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AGGREGATE SKEWNESS AND THE BUSINESS CYCLE

Abstract

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JEL Classification: C22, C38, E32

Keywords: Business cycles, downside risk, skewness, business cycle anatomy

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Aggregate Skewness and the Business Cycle

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Abstract

We develop a data-rich measure of expected macroeconomic skewness in the US economy. Expected macroeconomic skewness is strongly procyclical, mainly reflects the cyclicality in the skewness of real variables, is highly correlated with the cross-sectional skewness of firm-level employment growth, and is distinct from financial market skewness. Revisions in expected skewness, and the associated macroeconomic response to those, are nearly indistinguishable from the *main business cycle* shock of Angeletos et al. (2020). This result is robust to controlling for macroeconomic volatility and uncertainty, and alternative macroeconomic shocks. Our findings highlight the importance of higher-order dynamics for business cycle theories.

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1 Introduction

> *"FOMC participants (Board members and Reserve Bank presidents) indicated that considerable uncertainty surrounded the outlook for economic growth and that they saw the risks around that outlook as skewed to the downside."*
>
> Monetary Policy Report to Congress, Federal Reserve Board, Feb. 2008 (p.2)

> *"The outlook for the UK and global economies remains unusually uncertain.* [...] *The risks are skewed to the downside."*
>
> Monetary Policy Report, Bank of England, Aug. 2020 (p.1)

Assessing macroeconomic risks and analysing their potential impact on the economy is a key focus of economic policy institutions. Such risks are often not balanced around the baseline outlook, and the concept of skewness has been a device for policy-makers to communicate their beliefs about the evolution of risks. The academic literature has also used skewness to characterize the asymmetric effects of economic shocks due to, for instance, non-linearities (e.g. Petrosky-Nadeau et al., 2018; Jensen et al., 2020; Mumtaz and Theodoridis, 2020) or particular adverse events (e.g. Barro, 2009; Gourio, 2012; Fernández-Villaverde and Levintal, 2018). Yet it remains unclear to what extent business cycles exhibit large swings in the asymmetry of risk and, most importantly, whether those matter for our understanding of the macroeconomy. In this paper, we develop a new measure of expected macroeconomic skewness for the US economy, reflecting variations in the balance of risks of a large number of (nominal and real) macroeconomic and financial indicators. We contrast this measure with alternative measures of macro and micro skewness, and investigate the relationship between fluctuations in aggregate skewness and the business cycle.

A long-standing literature has argued that macroeconomic fluctuations are plagued by asymmetries, highlighting that recessions tend to be relatively deeper and more pronounced than expansions (Neftci, 1984; Hamilton, 1989; Sichel, 1993; Morley and Piger, 2012). More recent work has studied the asymmetry of the *conditional* distribution of GDP growth, documenting the presence of procyclical GDP growth skewness related to the state of macro-financial conditions (e.g. Adrian et al., 2019; Loria et al., 2020; Delle Monache et al., 2021; Forni et al., 2021).[1] These studies focus on measuring (expected) asymmetry of a single macroeconomic variable, namely GDP growth. While GDP is one of the most representative measures of the business cycle, it is unclear to what extent conditional skewness in GDP growth summarizes fluctuations in downside risk for the broader macroeconomy. We derive a new measure of aggregate expected skewness, which represents a common factor driving

[1]Theoretical and empirical contributions highlighting the role of time-varying skewness include, for example, Colacito et al. (2016), Dew-Becker et al. (2019), Jensen et al. (2020) and Fève et al. (2021) at the macro level, and Busch et al. (2018), Salgado et al. (2019), and Dew-Becker (2022) at the micro level.

the individual conditional skewness series of a large number of macroecoeconomic and financial indicators. Individual measures of skewness are computed using robust asymmetry measures (Kelley, 1947), where time-varying asymmetry derives from the relative movements of the conditional quantiles of the distribution captured using quantile regression techniques (Koenker and Bassett, 1978; Engle and Manganelli, 2004). This procedure allows us i) to derive summary measures that refer to different subgroups (e.g. prices, labor market indicators and financial variables) and ii) to understand which variables contribute most to overall skewness.[2]

The common skewness factor is strongly procyclical and explains only a limited part of the dynamics in expected skewness for most of the macroeconomic indicators. It explains more of the skewness variation of the real economy variables (including income, labor markets, orders and sales, and production indicators) compared to, for example, prices. Moreover, the factor accounts for a non-negligible fraction of the conditional asymmetry in some of the financial indicators, in particular non-household balance sheet and stock market indicators. Our measure of skewness is far from perfectly correlated with the conditional skewness of GDP growth, meaning that the latter may not always capture economy-wide risks. Aggregate skewness also comoves with the GDP growth skewness that conditions on financial conditions (Adrian et al., 2019). This is in spite of the fact that our measure captures common movements in conditional asymmetry across a large number of indicators, where the skewness of each variable is not forced to move together with financial conditions and is derived using only information contained in past observations of the variable itself. Our expected skewness factor relates closely to a summary measure of Fed economists' perception of risks to the economic outlook distilled from verbal information contained in the "Greenbook" documents prepared for Federal Open Market Committee (FOMC) meetings (Aruoba and Drechsel, 2022). In addition, aggregate skewness also highly correlates with the cross-sectional skewness of employment growth computed at the firm level by Salgado et al. (2019). Both findings are remarkable since the data and methodologies used to construct these indicators are extremely different. By contrast, our measure displays a limited correlation with indicators of financial market skewness, including stock return skewness, either computed at the market level (Dew-Becker, 2022) or the firm level (Salgado et al., 2019).

Our second contribution relates to investigating the role of our skewness factor in the US business cycle. In recent studies, Salgado et al. (2019) and Forni et al. (2021) demonstrate that shocks to the cross-sectional skewness of firm-level stock returns and the predictive GDP growth distribution, respectively, can produce contractionary movements in macroe-

[2]The simple and transparent derivation of our measure of aggregate expected skewness means that it can be updated seamlessly when new data becomes available. Monthly updates of the skewness factor can be downloaded from the authors' websites.

conomic and financial indicators. We show that revisions in expected skewness, which are associated with an increase in perceived downside risk, lead to a substantial contraction in output, consumption, and investment, while leaving prices and TFP broadly unaffected. Remarkably, revisions in expected skewness largely overlap with the *main business cycle* (MBC) shock identified in Angeletos et al. (2020) and give rise to nearly identical IRFs. This finding is robust to various sensitivity exercises. Specifically, revisions in expected skewness are distinct from movements in aggregate volatility and uncertainty, and appear unrelated to alternative shocks capturing credit risk, productivity, fiscal policy, and monetary policy.

Our empirical results highlight that any model that has the ambition to explain the main force of macroeconomic fluctuations needs to allow for higher-order dynamics and possibly relate those to economic agents' varying perception of downside risk. In this regard, within theories that suggest that a single shock is driving the business cycle, this key driver of macroeconomic fluctuations also needs to account for the bulk of the variation in revisions of perceived macroeconomic risk. Theories allowing for i) confidence or sentiment shocks (Angeletos and La'O, 2013; Angeletos et al., 2018); ii) the possibility of rare disasters (Rietz, 1988; Barro, 2006; Barro and Ursúa, 2008; Gabaix, 2008; Barro, 2009; Gourio, 2012; Wachter, 2013; Petrosky-Nadeau et al., 2018; Jordà et al., 2020); iii) informational frictions and learning asymmetries (Veldkamp, 2005; Ordonez, 2013); or iv) left-skewed uncertainty of households or firms (Salgado et al., 2019), could provide promising avenues.

2 A data-rich skewness measure for the US economy

This section presents a new measure of expected asymmetry based on a large dataset of macroeconomic and financial variables. To construct the skewness measure, we use the quarterly version of the McCracken and Ng (2016) dataset (FRED-QD) that contains 246 time series starting from 1959 and categorized into 14 groups.[3] All variables are transformed to make them stationary by using the transformations suggested by the authors. We remove those series that have missing observations over our sample period 1960:Q1–2022:Q3, which reduces the number of variables to $N = 210$. Next, we estimate for each (de-meaned) variable y_i and each quantile level $p = \{10\%, 50\%, 90\%\}$, the following autoregressive quantile regression as developed in Engle and Manganelli (2004)

$$Q_{i,t}^{p} = \beta_0^p + \beta_1^p Q_{i,t-1}^{p} + \beta_2^p y_{i,t-1}\mathbb{I}(y_{i,t-1} > 0) + \beta_3^p y_{i,t-1}\mathbb{I}(y_{i,t-1} < 0), \tag{1}$$

[3]These are *national income and product accounts (NIPA)*; *industrial production*; *employment and unemployment*; *housing*; *inventories, orders, and sales*; *prices*; *earnings and productivity*; *interest rates*; *money and credit*; *household balance sheets*; *non-household balance sheets*; *stock markets*; *exchange rates*; and *other*.

where $i = 1, ..., N$ and $t = 2, ..., T$. This *asymmetric slope* model (Engle and Manganelli, 2004) allows for a different impact of past observations on the respective quantiles, depending on whether they lie above or below the unconditional mean of the series. This permits an asymmetric impact of contractions and expansions in each variable on the different quantiles, so that, for instance, a recession can affect downside risk without necessarily affecting upside risk. In addition, the model allows the quantiles to be persistent, which seems appropriate given the well-documented persistence of the first two moments of many macroeconomic series (see, e.g., Antolin-Diaz et al., 2017).[4] The conditional quantile autoregressive model belongs to the class of observation-driven models, for which the trajectories of the time-varying parameters are perfectly predictable one-step-ahead given past information (Cox, 1981). Using the estimated model parameters from these quantile regressions, and assuming that agents' use Equation (1) to form their expectations, we compute for each variable the one-step-ahead expected, or predicted, Kelley skewness (Kelley, 1947)

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

Since each quantile estimate is computed as a (variable-specific) moving average of a non-linear function of the variable itself, there is no reason ex-ante to expect that the skewness of any series displays a particular cyclical behaviour or comoves across indicators. Our overall measure of expected asymmetry is then constructed as the first principal component obtained from the set of series-specific expected skewness measures, where each measure is first standardized by subtracting the series-specific mean and dividing by its standard deviation (see, e.g., Stock and Watson, 2002).[5] Since the skewness factor is based on PCA, its sign is not identified. We identify the sign by assuming a positive correlation between the skewness factor and the skewness of GDP growth. The factor reflects common movements of skewness across a large number of macroeconomic and financial indicators and does not necessarily overlap with the skewness of any specific indicator, e.g. the skewness of GDP growth. Moreover, the common factor should be relatively immune to idiosyncrasies and noise in the measurement of expected skewness for each of the individual series arising, for instance, from the estimation of the time-varying quantiles. In fact, our measure is also extremely robust to large variation in the underlying data, such as those observed during

[4]The model parameters are estimated by regression quantiles (Koenker and Bassett, 1978) and further details can be found in Engle and Manganelli (2004). Since we are interested in capturing cyclical movements in skewness rather than slow-moving trends, we restrict the degree of persistence, i.e. $0 < \beta_1^p < 0.8$.

[5]While somewhat different from our approach, Chen et al. (2021) is another example of combining quantile regression and factor analysis to measure, in their case, comovement across quantiles.

2020, when many of the underlying skewness indicators exhibit instabilities.[6] One should be concerned if our procedure was to predict large variation in aggregate asymmetry when in fact this is not a feature of the data. Appendix A presents a simulation exercise showing that our two-step approach to construct the skewness factor does not yield spurious results, i.e. the factor collapses to zero if the DGP does not feature conditional skewness.

Table 1: Descriptive statistics of skewness variation explained by first principal component (in %)

Group	Variables	Mean	Median	Max.	Min.	Corr. w/o group
Inventories, orders, and sales	6	21.0	23.5	38.3	0.6	0.99
National income and product accounts	22	17.9	13.5	50.3	0.0	0.98
Employment and unemployment	44	15.7	12.6	43.3	0.1	0.95
Industrial production	15	14.8	8.9	59.7	1.1	0.99
Stock markets	5	13.5	9.0	31.5	2.0	1.00
Non-household balance sheets	11	13.3	12.1	30.2	0.1	0.99
Housing	6	8.1	4.2	19.8	0.0	1.00
Interest rates	18	7.8	5.7	42.4	0.0	0.99
Prices	46	7.6	2.7	51.5	0.0	0.98
Earnings and productivity	10	7.1	2.3	26.4	0.1	1.00
Exchange rates	4	6.4	6.7	11.1	1.2	0.99
Household balance sheets	9	6.0	3.9	26.3	0.0	1.00
Money and credit	13	6.0	3.9	21.4	0.1	0.99

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. The grouping follows McCracken and Ng (2020). The group *Other* is dropped from this table as it only contains one variable.

This skewness factor explains around 12% of the variation across the individual skewness series, reflecting the presence of many series with a small degree of asymmetry that load only weakly on the common factor.[7] Table 1 illustrates this point by showing the share of variation explained by the skewness factor for each group of variables. The skewness factor tends to explain more of the skewness variation of the real economy variables including NIPA, labor markets, and production indicators compared to, for example, prices. Moreover, the factor accounts for a non-negligible fraction of the conditional asymmetry in some financial indicators such as non-household balance sheets and stock markets. The last column of Table 1 highlights that our expected skewness factor is robust to the data composition. Specifically, the factor remains largely unaffected by the omission of any of the groups of

[6] Figure D-3 in Appendix D shows our skewness factor estimated with different data vintages, indicating that data revisions and the re-estimation of the model only have a very limited impact on the estimated factor.

[7] For comparison, the first principal component of the actual data accounts for around 24% of the variation, while a common factor of the volatilities accounts for around 29% of the variation in dispersion. Lastly, a common factor of a quantile-based dispersion measure (expected interquartile range), accounts for around 26% of the variation.

variables in the dataset.[8]

Existing studies have largely focussed on the conditional asymmetry of a single variable, i.e. GDP growth (see, for example, Adrian et al., 2019; Jensen et al., 2020; Loria et al., 2020; Forni et al., 2021; Castelnuovo and Mori, 2022). This is different from our data-rich approach where the skewness factor reflects variation in risks of a large number of macroeconomic and financial indicators. The top left panel of Figure 1 compares the expected skewness factor with the individual (de-meaned) skewness series of GDP growth obtained from different conditional quantile models. Aggregate expected skewness is highly procyclical: it drops strongly during recessions and increases/stabilises during the expansionary phases of the cycle. Our skewness factor is positively correlated with the skewness series of GDP growth retrieved using the autoregressive quantile model described above. In spite of their similarities, there are also differences between our measure of aggregate skewness and the expected skewness of GDP growth. The latter features a distinct downward trend in the last part of the sample, which is in line with the findings of Delle Monache et al. (2021) and appears to be a feature not shared by other indicators.

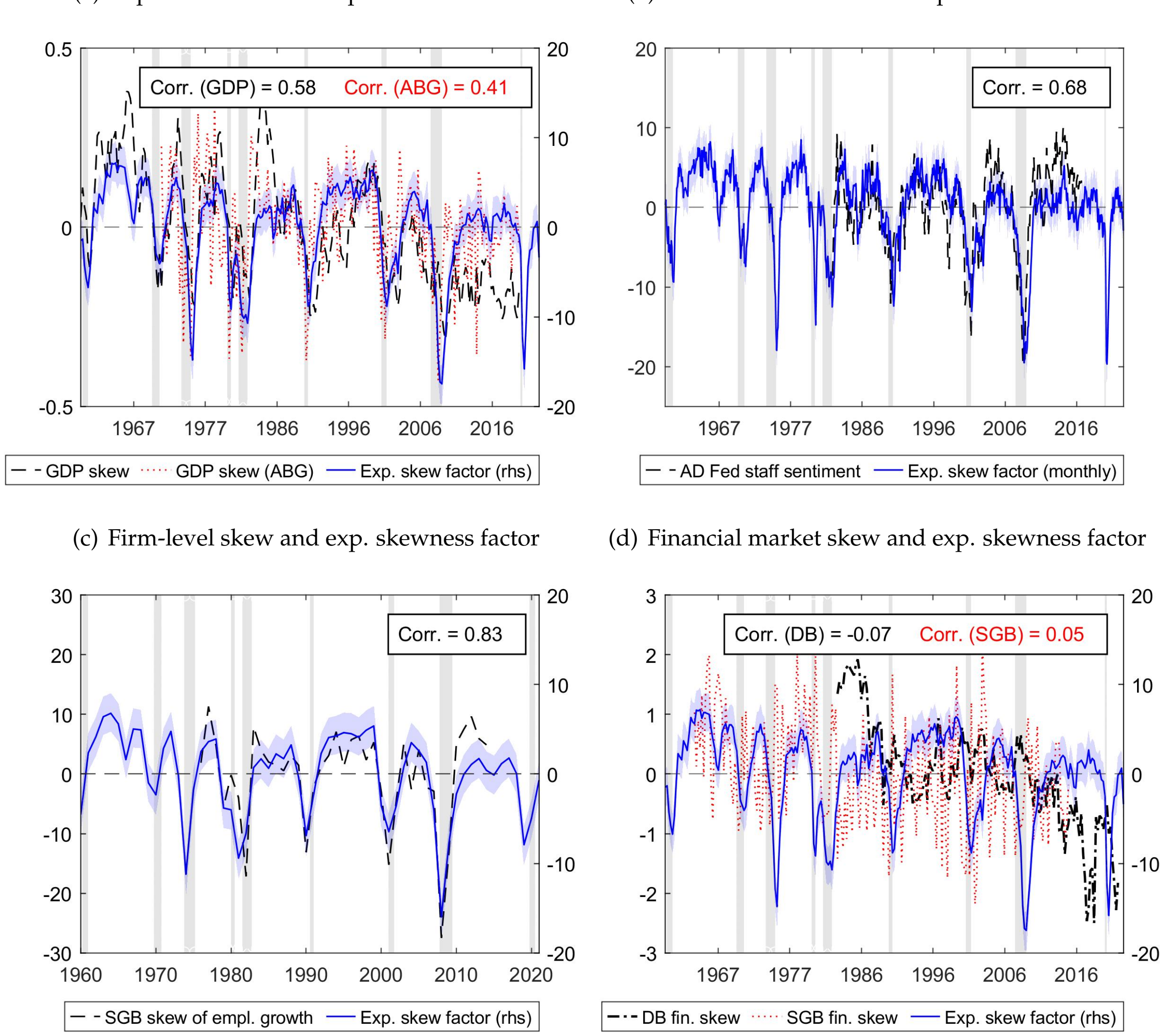
Quantile regressions that include financial conditions imply a more asymmetric conditional growth distribution and a longer left tail during recessions (Adrian et al., 2019). We document a correlation of around 0.4 between our expected skewness factor and the (Kelley) skewness of GDP growth which conditions on financial conditions. This highlights that elevated asymmetry during downturns is a feature shared by a number of economic indicators and not necessarily related to fluctuations in financial conditions. Note also that we report the comparison with GDP growth skewness with the latter estimated over a sample ending before the Covid pandemic. When including data for the pandemic period, both estimates reported in Figure 1(a) change substantially, with especially the Adrian et al. (2019) measure becoming unstable. By contrast, our skewness factor is not affected by this issue.[9] Moreover, the VAR analysis in Section 3 shows that unexpected changes in aggregate macro skewness and GDP growth skewness exert different effects on the macroeconomy.

Documents of economic policy institutions often contain a verbal assessment of the underlying risks to the economy. In case of the US, the language with which Fed economists describe the subtleties around the economic outlook reflects such an informal economic risk assessment and provides valuable information beyond what is contained in purely numerical predictions (see, for example, Aruoba and Drechsel, 2022; Cieslak et al., 2022).

[8]Figure D-1(b) in Appendix D shows alternative factors when omitting selected groups of variables. We have also computed an alternative skewness factor based on a subset of 101 variables, that largely match those used in Stock and Watson (2012). Figure D-1(a) in Appendix D compares the two skewness factors which are highly correlated.

[9]Figure D-2 in Appendix D shows the two GDP growth skewness measures estimated over the full sample.

Figure 1: Skewness factor vs. other (skewness) measures



(a) Exp. GDP skew and exp. skewness factor

(b) Fed staff sentiment and exp. skewness factor

(c) Firm-level skew and exp. skewness factor

(d) Financial market skew and exp. skewness factor

Note: Figure 1(a) shows the expected skewness factor together with the individual (Kelley) skewness series of quarter-over-quarter real GDP growth derived based on the quantile specification in Equations (1)-(2) and the approach of Adrian et al. (2019) (ABG), respectively. The latter series is based on quantile regressions of real GDP growth on lagged growth and the lagged National Financial Conditions Index (NFCI) computed by the Chicago Fed. Figure 1(b) shows the monthly version of the skewness factor together with the first principal component of all sentiment indicators (Oct. 1982–Dec. 2016) computed in Aruoba and Drechsel (2022) (AD). Figure 1(c) shows the skewness factor (annual avg.) together with the (employment-weighted) cross-sectional Kelley skewness of firms' log employment growth (1976–2014) obtained from Salgado et al. (2019) (SGB). Figure 1(d) shows the skewness factor together with i) the monthly option-implied measure of market skewness for the S&P 500 developed in Dew-Becker (2022) (DB, quarterly avg., 1983:Q2–2021:Q4), and ii) the cross-sectional (Kelley) skewness of firms' daily stock returns within a month computed in Salgado et al. (2019) (SGB, quarterly avg., 1964:Q1–2015:Q1). All alternative skewness series are de-meaned and the scale of the SGB financial skewness measure is adjusted for comparability with the DB measure. The blue shaded areas are the bootstrapped confidence bands (90%) around the skewness factor based on Gonçalves and Perron (2020). Gray areas are NBER recessions.

Figure 1(b) highlights the close relationship between the skewness factor and Fed economists' perception of risks to the economic outlook. The latter is constructed as the first principal component of more than 250 sentiment indicators extracted using natural language processing techniques from the Fed "Greenbook" documents by Aruoba and Drechsel (2022).[10]

We also compare our measure of macro skewness with micro-level and financial market measures of asymmetry. Figure 1(c) compares the cross-sectional (Kelley) skewness of firms' employment growth (Salgado et al., 2019) with our expected skewness factor.[11] Both series move together closely and share a correlation of around 0.8. Given the different underlying methodologies, we interpret this result as i) potential evidence that the same shocks or mechanisms drive both firm-level and aggregate skewness and ii) an affirmation of our interpretation of the skewness factor as an economy-wide skewness measure. Figure 1(d) contrasts our expected skewness factor with two measures of financial market skewness. Specifically, we show the option-implied skewness of the S&P 500 index computed at the market level by Dew-Becker (2022), and the cross-sectional firm-level series of stock return skewness of Salgado et al. (2019). The correlation between the skewness factor and, respectively, option-implied market-level skewness and cross-sectional return skewness is relatively low. This provides further support to the interpretation of the aggregate skewness factor as a measure of macroeconomic skewness which is distinct from financial market skewness.[12]

Lastly, our skewness measure correlates with – but is still quite distinct from – aggregate volatility and uncertainty.[13] Table D-1 in Appendix D shows a correlation matrix including the expected skewness factor, the first principal component of the actual data (X) and squared data (X^2) akin to Gorodnichenko and Ng (2017), a common factor of the expected interquartile ranges derived from Equation (1), an expected volatility (GARCH) factor, and two popular measures of uncertainty (Jurado et al., 2015; Ludvigson et al., 2021).[14] Given the procyclicality of the skewness factor, it is not surprising to find negative comovement with

[10]To maintain close comparability with Aruoba and Drechsel (2022), we have also constructed a monthly version of our indicator using the FRED-MD dataset (see McCracken and Ng, 2016). The quarterly average of the monthly skewness is consistent with the skewness factor extracted from the quarterly data. Different from our measure, which can be computed in real time, the sentiment measures of Aruoba and Drechsel (2022) are only available with a five-year lag given the publication delay of the "Greenbook" documents.

[11]To preserve the forward-looking character of the skewness factor, we compute the annual average for each year t over the period Q4 (t) to Q3 ($t + 1$). However, this implies that for the annual series, expectations about skewness in $t + 1$ are no longer formed conditional on information in year t only. The firm-level skewness series was directly taken from the replication files provided by Salgado et al. (2019). The authors compute this series based on the US Census Bureau's Longitudinal Business Database.

[12]This result echoes the one of Ludvigson et al. (2021), who highlight a similar disconnect between macro and financial market uncertainty.

[13]Orlik and Veldkamp (2014) highlight how within a Bayesian learning framework, where agents attempt to learn the evolving distribution of GDP growth, uncertainty, skewness and therefore downside risk, are naturally related to one another.

[14]The fact that the quantile-based volatility measure is strongly correlated with the GARCH factor (> 0.9) and macroeconomic uncertainty (> 0.8) provides reassurance that our procedure also reliably measures skewness.

uncertainty, which moves countercyclically (see, e.g., Jurado et al., 2015).

3 Macroeconomic effects of shifts in aggregate skewness

In this section we investigate the dynamic relationships between expected skewness and the macroeconomy. To do that, we add our measure of skewness to an otherwise standard VAR model.[15] The empirical specification, the variables included, as well as the estimation approach largely follow Angeletos et al. (2020). Within this set up, we study the relationship between revisions in expected skewness and the *main business cycle* shock of these authors.

The baseline VAR contains the following variables: the expected skewness factor, real GDP per capita, real investment per capita, real consumption per capita, hours worked per person, unemployment rate, labor share, effective federal funds rate, inflation, labor productivity (non-farm business sector), and a measure of TFP. The analysis is conducted over the period 1960:Q1–2019:Q4.[16] Details on the variables can be found in Appendix B. The VAR model has the following representation:

$$y_t = \sum_{p=1}^{P} \Theta_p y_{t-p} + u_t, \quad u_t \sim \mathcal{N}(\mathbf{0}, \Sigma) \tag{3}$$

where $\Theta_p \; \forall \; p = 1, ..., P$ are the matrices of VAR coefficients, and u_t is a vector of reduced-form disturbances, which are linear combinations of the underlying structural (orthogonal) shocks $u_t = A_0 \varepsilon_t$. A_0 is the matrix containing the contemporaneous responses, where $A_0 A_0' = \Sigma$. Due to the relatively large dimension of the VAR model, we adopt a Bayesian estimation approach and employ a Minnesota-type prior. The parameter controlling the tightness of this prior is set to $\lambda = 2$, a commonly used value in studies with US data. Section 4 shows that the results hold even for looser configurations. Appendix C contains details on the prior specification and the Bayesian estimation approach (Gibbs sampling). We choose a lag length of $P = 2$ and demonstrate robustness with respect to this choice in Section 4.

Identifying exogenous variation in expected skewness is challenging, with theory providing little guidance. Our baseline approach imposes zero restrictions on the matrix containing the contemporaneous responses. Specifically, A_0 is identified as the lower trian-

[15] Note that a linear VAR would still be the appropriate framework to recover the conditional expectation function, hence the impulse response function, even in the presence of non-Gaussianity in the underlying data.

[16] We end the sample in 2019:Q4 and use the latest data vintage before the Covid-19 pandemic for all variables in the VAR (including the TFP series of Fernald (2014)) to avoid that the results are affected by this period (see, for example, Lenza and Primiceri, 2022). The expected skewness factor for the VAR exercise is extracted from the FRED-QD "2020-02" vintage, and thus slightly differs from the one shown in Figure 1. However, both vintages of the skewness factor have a correlation of 0.95. In addition, all key results hold when excluding the Great Recession, i.e. ending the sample in 2007:Q2.

gular matrix obtained from a Cholesky decomposition of Σ. Ordering our skewness measure first, this simple identification scheme provides us with an intuitive interpretation of the identified shock as the revision, i.e. the 'unexpected change', in expected skewness: $\mathbb{E}_t[Skew_{t+1}] - \mathbb{E}_{t-1}\left[\mathbb{E}_t[Skew_{t+1}]\right]$ where the expectation $\mathbb{E}_{t-1}$ is conditional on the information set spanned by the VAR. We loosely refer to this as a "skewness shock". However, this should not be interpreted as a *structural* shock, but is better understood as the (fixed) linear combination of (structural) shocks, i.e. the *skewness anatomy* following the lexicon of Angeletos et al. (2020), which explains unexpected changes in aggregate skewness. Section 4 shows that an alternative approach which relaxes the zero restrictions and identifies the shock that explains the largest share of unexpected variation in skewness over the medium horizon based on Uhlig (2003) yields very similar results.

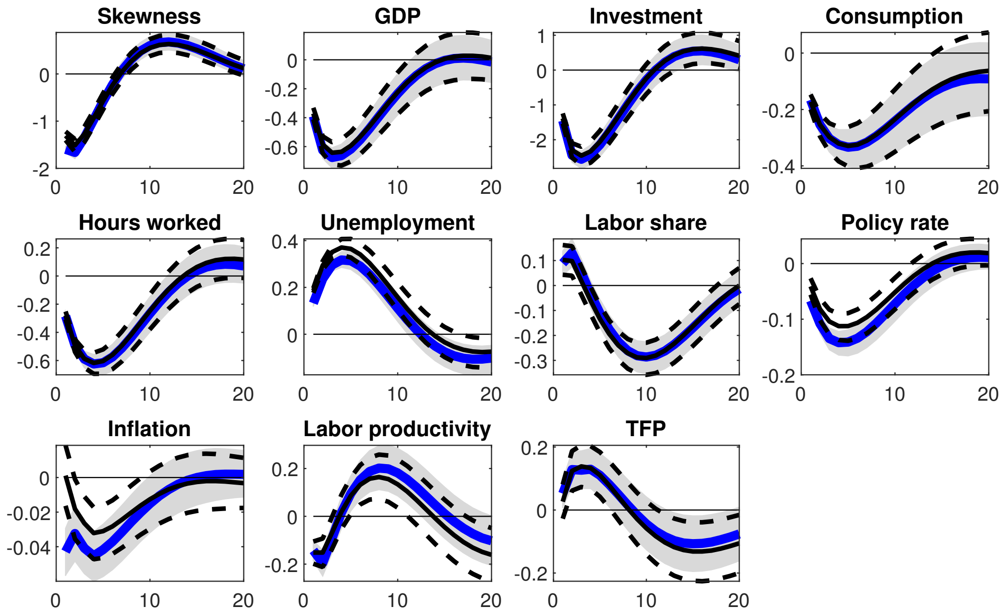
Revisions to expected skewness are 'small' compared to the overall variation of aggregate skewness, which highlights a certain sluggishness of underlying risks in the macroeconomy.[17] Figures 2 and 3 show the impulse response functions following a negative shock to expected skewness, i.e. a downward revision of expected skewness, and the corresponding forecast error variance contributions, together with those of the MBC shock of Angeletos et al. (2020). The latter is identified as the shock that explains the bulk of the variation of unemployment using the max-share approach of Uhlig (2003), targeting four quarters in the time domain. Both shocks are identified within the same VAR specification. A revision in expected skewness generates business cycle dynamics that are very similar to the *business cycle anatomy* documented in Angeletos et al. (2020). These dynamics reflect a sizeable, but relatively short-lived, comovement between GDP, investment, consumption, hours worked, and unemployment, without meaningful movements in inflation and TFP.

Table 2 shows that the (unconditional) correlation between the MBC shock and our skewness shock is around 0.8.[18] Angeletos et al. (2020) use the *business cycle anatomy* to shed light on the transmission of macro shocks and, in particular, on the drivers of the business cycle. Our evidence underlines that the key source of business cycle variation in the data also accounts for short-term revisions in expected macroeconomic asymmetries. Put differently, while the MBC and the skewness shock are likely no structural shocks – but rather a combination of such shocks – our results suggest that the same combination of structural shocks explains both revisions in expected skewness and business cycle fluctuations.

[17] The left panel of Figure D-4 in Appendix D illustrates this by contrasting the skewness factor and its revisions.

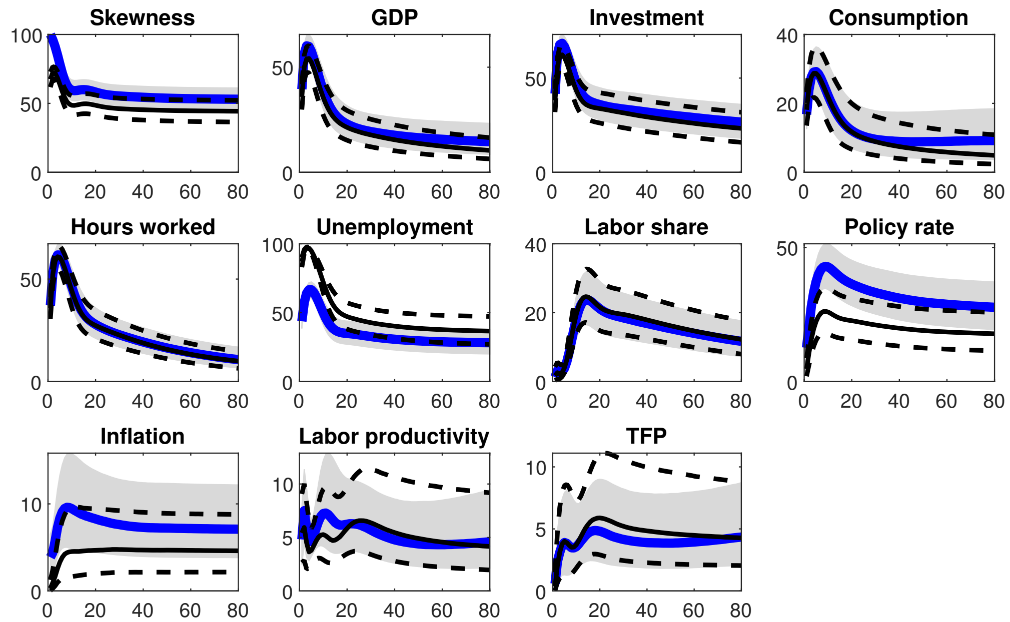
[18] The right panel of Figure D-4 in Appendix D contrasts revisions in skewness and the MBC shock visually.

Figure 2: Baseline model: Impulse response functions



Note: The blue lines are the posterior mean responses to a negative one S.D. shock to expected skewness along with the 68% highest density interval. The skewness shock is identified through a Cholesky decomposition. The black lines are the responses to a one S.D. shock to unemployment, i.e. the MBC shock of Angeletos et al. (2020). This shock is identified using the approach of Uhlig (2003). Sample period: 1960:Q1–2019:Q4.

Figure 3: Baseline model: Forecast error variance contributions



Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval for a shock to expected skewness (blue) and the MBC (unemployment) shock (black).

Table 2: Correlation of revisions in (exp.) skewness and MBC shock for different specifications

				MBC shock	
	Baseline model			**MBC shock**	
a)	Exp. skewness factor	**Skew. shock** (1960:Q1–2019:Q4)	Median	**0.82**	
			95% HDI	0.77	0.87
	Other skewness measures			**MBC shock**	
b)	Exp. GDP skewness	**Skew. shock** (1960:Q1–2019:Q4)	Median	**0.52**	
			95% HDI	0.43	0.60
c)	Exp. GDP skewness (ABG)	**Skew. shock** (1971:Q1–2019:Q4)	Median	**0.58**	
			95% HDI	0.49	0.66
d)	S&P 500 skewness	**Skew. shock** (1983:Q2–2019:Q4)	Median	**-0.30**	
			95% HDI	-0.43	-0.17
e)	Firm-level stock return skewness	**Skew. shock** (1964:Q1–2015:Q1)	Median	**0.15**	
			95% HDI	0.03	0.27
	Robustness checks			**MBC shock**	
f)	Orthog. to GARCH volatility	**Skew. shock** (1960:Q1–2019:Q4)	Median	**0.66**	
			95% HDI	0.55	0.75
g)	Orthog. to macro and financial unc.	**Skew. shock** (1960:Q1–2019:Q4)	Median	**0.63**	
			95% HDI	0.52	0.72
h)	Orthog. to geopolitical risk	**Skew. shock** (1960:Q1–2019:Q4)	Median	**0.82**	
			95% HDI	0.76	0.87
i)	Orthog. to excess bond premium	**Skew. shock** (1973:Q1–2019:Q4)	Median	**0.69**	
			95% HDI	0.60	0.78
j)	Orthog. to total factor productivity	**Skew. shock** (1960:Q1–2019:Q4)	Median	**0.83**	
			95% HDI	0.77	0.88
k)	Orthog. to fiscal policy	**Skew. shock** (1960:Q1–2015:Q4)	Median	**0.81**	
			95% HDI	0.75	0.86
l)	Orthog. to monetary policy	**Skew. shock** (1990:Q1–2016:Q4)	Median	**0.80**	
			95% HDI	0.72	0.87

Note: Each row corresponds to a VAR specification and shows the correlation between downward revisions in (expected) skewness and the (contractionary) MBC shock (Angeletos et al., 2020). We report the median correlation across MCMC draws along with the 95% highest density interval (HDI). Revisions in (expected) skewness are identified through a Cholesky decomposition by ordering skewness first if no alternative shock/variable is included and second/third otherwise. Specification a) is our baseline model whereas in b), c), d) and e) the skewness factor is replaced with the exp. skewness of GDP growth, the exp. skewness of GDP growth based on the approach of Adrian et al. (2019), the option-implied skewness of the S&P 500 (quarterly avg.) computed by Dew-Becker (2022), and the cross-sectional firm-level skewness of stock returns (quarterly avg.) computed by Salgado et al. (2019), respectively. The alternative variables/shocks are: f) a data-rich measure of expected volatility based on a GARCH(1,1); g) the macroeconomic and financial uncertainty indices of Jurado et al. (2015) and Ludvigson et al. (2021); h) the (historical) geopolitical risk index (quarterly avg.) of Caldara and Iacoviello (2022); i) the excess bond premium (EBP) (Gilchrist and Zakrajšek, 2012); j) the (annualized) growth rate of the utilization-adjusted TFP measure of Fernald (2014); k) the government spending shock of Ramey and Zubairy (2018); and l) the monetary policy surprises of Jarociński and Karadi (2020).

In Section 2 we show that our skewness factor is correlated with alternative measures of macroeconomic skewness. It is therefore natural to ask whether revisions of these alternative measures also display a close connection with the *business cycle anatomy* and whether introducing a broader measure of skewness through our principal component approach is crucial to obtaining this result. As a first exercise, we replace the expected skewness factor with the individual expected skewness series of GDP growth. The results of this specification are shown in Figures D-5 and D-6 in Appendix D. Despite producing sizeable comovement among all key macroeconomic quantities, the IRFs display less similarity with the *business cycle anatomy*. The correlation between revisions in this skewness measure and the MBC shock remains well-below the baseline result (Table 2). When comparing our results with the impact of revisions in expected GDP growth skewness computed based on the approach of Adrian et al. (2019), the conclusion remains similar. Specifically, revisions in this measure of expected growth skewness, largely reflecting revisions related to financial conditions, have a much more short-lived impact on macroeconomic asymmetry (Figures D-7 and D-8 in Appendix D). While slightly higher than before, the correlation with the MBC shock remains again significantly below the baseline result (Table 2). This is evidence that our skewness factor is a broader measure of risk and that the additional information it contains matters when analysing the impact of changing risks.

We also investigate whether revisions in financial market skewness produce dynamics consistent with the ones reported above. To this end, we replace the skewness factor with the option-implied market skewness series of Dew-Becker (2022) as well as the cross-sectional stock return series of Salgado et al. (2019), both shown in Figure 1(d). First, Table 2 shows that revisions to the S&P 500 skewness series are negatively correlated with the MBC shock. In fact, a downward revision in this skewness measure is associated with an expansionary response of the main business cycle indicators, and non-negligible positive inflation (Figures D-9 and D-10). This result is in line with Dew-Becker (2022), who finds financial market skewness to move countercyclically. Second, when including the cross-sectional firm-level measure of stock return skewness, we only find a minor correlation between revisions in this series and the MBC shock (see Table 2, and Figures D-11 and D-12).

To conclude this section, we explore the impact of revisions in expected skewness beyond the baseline set of macroeconomic variables through augmented specifications, including selected financial variables (see Appendix E). We consider three augmented models that, in addition to the baseline variables, include either i) excess returns and the term premium (Figures E-1 and E-2); ii) real house prices and real stock prices (Figures E-3 and E-4); or iii) yields of 10-year government bonds (Figures E-5 and E-6). A downward revision of expected skewness is associated with lower stock prices, excess returns and 10-year government bond yields while the term premium, and to a lesser extent house prices, are higher. Moreover, revisions in skewness contribute to a non-negligible share of the variation in 10-year government bond yields, the term premium and stock prices. Yet in line with the original evidence in Angeletos et al. (2020), a revision in expected macroeconomic skewness appears to matter somewhat more for macroeconomic than financial variables.

4 Robustness checks

In this section we check the robustness of our baseline results along different dimensions. Detailed results can be found in Appendix F. First, the baseline results are robust to a change in the identification scheme. In particular, to be closer to Angeletos et al. (2020), we also identify skewness shocks using the Uhlig (2003) approach which maximizes the explained share of skewness variation over four quarters in the time domain. The results (Figures F-1 and F-2) are very similar to those based on the recursive identification.

Second, we augment our baseline specification with measures of macroeconomic volatility, uncertainty and geopolitical risk. Figures F-3 and F-4 present the effects of a revision in expected skewness when controlling for aggregate expected volatility, achieved by ordering this measure first in the Cholesky identification.[19] This isolates the contribution associated with the revision in expected macroeconomic skewness that is orthogonal to variations in overall volatility. Both the IRFs and the variance contributions of a skewness shock remain very similar and the correlation between revisions in expected skewness and the MBC shock remains quite strong (Table 2). In a related exercise, we control for macro and financial uncertainty (Jurado et al., 2015; Ludvigson et al., 2021). While the IRFs (Figure F-5) and variance contributions (Figure F-6) change somewhat more in this case, they still remain similar to the baseline results. The positive comovement between output and uncertainty after a downward revision in expected skewness implies that the transmission of skewness revisions is clearly distinct from the transmission of an uncertainty shock, which is generally characterized by a negative comovement between output and uncertainty. Table 2 shows that the correlation between the skewness shock and the MBC shock remains sizeable. These results are largely consistent with those in Forni et al. (2021), who show that the transmission of downside uncertainty and skewness shocks is distinct from that of a standard (symmetric) uncertainty shock, with a widening of the left tail causing economic contractions (see also Segal et al., 2015). Moreover, to test whether revisions in expected skewness relate to geopolit-

[19]The volatility measure is also based on a data-rich approach to match the derivation of the skewness factor. Specifically, we estimate a GARCH(1,1) model on each (de-meaned) data series of the McCracken and Ng (2020) dataset and obtain the first principal component of all standardized expected volatility (conditional standard deviation) series.

ical risk, we augment our baseline specification with the Geopolitical Risk Index of Caldara and Iacoviello (2022). Here, we find that the IRFs (Figure F-7) and variance contributions (Figure F-8), as well as the correlation with the MBC shock, remain nearly unchanged.

Third, we show that revisions in expected skewness are unrelated to other standard shocks. We control for: i) (credit-)risk shocks measured as the exogenous variation in the Gilchrist and Zakrajšek (2012) excess bond premium (Figures F-9 and F-10); ii) productivity shocks measured as the exogenous variation in the growth rate of the Fernald (2014) TFP series (Figures F-11 and F-12); iii) shocks to government expenditure as identified in Ramey and Zubairy (2018) (Figures F-13 and F-14); and iv) monetary policy shocks measured by the surprise series of Jarociński and Karadi (2020), which is purged of the central bank information component (Figures F-15 and F-16). In all cases the IRFs and FVDs are similar to the baseline model and range from being nearly identical (TFP and fiscal policy) to showing some differences (EBP and monetary policy). The skewness shock continues to be highly correlated with the MBC shock across specifications (Table 2), which highlights that the revision in expected skewness is roughly orthogonal to this set of shocks.

Finally, we change the lag order in the VAR model and the Minnesota prior. Figures F-17 and F-18 present the results using a lag order of $P = 4$, which remain very similar compared to the baseline model. Figures F-19 and F-20 show that applying an even looser configuration of the Minnesota prior ($\lambda = 10$) leaves the baseline results essentially unchanged.

5 Conclusion and direction for future research

We construct a factor that summarizes expected macroeconomic skewness. This factor is the first principal component of the time-varying expected skewness indicators of a large number of macroeconomic series. Aggregate macroeconomic skewness is strongly procyclical, comoves with, but is quite distinct from, the expected GDP growth skewness series based on the approach of Adrian et al. (2019), and is highly correlated with the cross-sectional skewness of firm-level employment growth (Salgado et al., 2019). In addition, our skewness factor comoves with the economic risks perceived by Fed staff economists (Aruoba and Drechsel, 2022). We then document that the impulse responses of a set of macroeconomic variables associated with a revision in expected macroeconomic skewness, and the corresponding variance contributions, closely match the *business cycle anatomy* of Angeletos et al. (2020). In fact, expected skewness revisions largely overlap with the *main business cycle* shock identified in Angeletos et al. (2020). The results are robust to changes in the identification scheme, controlling for macroeconomic volatility, uncertainty, and frequently considered alternative shocks.

Our results highlight the importance of accounting for a procyclical variation in conditional skewness of macroeconomic data. Variation in conditional skewness requires the presence of non-linearities in the transmission of Gaussian shocks (see, e.g., Fernández-Villaverde and Guerrón-Quintana, 2020), or can directly derive from skewed shocks hitting the economy (Bekaert and Engstrom, 2017; Salgado et al., 2019). Angeletos and La'O (2013) and Angeletos et al. (2018) highlight how waves of optimism and pessimism regarding both firms' expected employment and production decisions as well as consumers' beliefs about future employment opportunities and income generate dynamics of output, employment, spending and prices akin to the business cycle patterns observed in the data. The former could potentially arise from learning asymmetries in the presence of informational frictions as in Veldkamp (2005). To the extent that fluctuations in *sentiment* or *confidence* are associated with a reassessment of upside and downside risk over the cycle, and hence shifts in expected skewness, our results help addressing the problem that "a direct, empirical counterpart to the confidence shock is hard, if possible at all, to obtain" (Angeletos et al., 2018, p. 1692). Our results are also consistent with a relevant role for expectations of rare disasters in explaining economic fluctuations (Rietz, 1988; Barro, 2006, 2009; Gabaix, 2008; Gourio, 2012; Wachter, 2013; Petrosky-Nadeau et al., 2018; Jordà et al., 2020). In particular, our results highlight the importance of allowing for time variation in the severity (Gabaix, 2008) and/or probability of such rare disasters (see, e.g., Gourio, 2012; Wachter, 2013; Giglio et al., 2021), which could generate sizeable variation in expected skewness.Most importantly, our results provide useful insights for macroeconomic theories that search for shocks and propagation mechanisms behind macroeconomic fluctuations. Any such theory will need to be able to reproduce variations in aggregate skewness whose revisions are strongly affected by the main source of business cycle fluctuations.

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Appendix A Monte Carlo exercise

This section addresses the concern that our two-step approach to constructing an aggregate skewness factor could yield spurious results, i.e. indicate time-varying conditional skewness in cases, where in fact there is none. For this, we conduct a Monte Carlo exercise and generate 500 datasets of size $N = 70$ and $T = 250$ from two different data generating processes (DGP), both of which do not feature conditional skewness. The first DGP has a time-varying mean and volatility, which both have a factor structure. Specifically, DGP 1 is defined as

$$
\begin{aligned}
y_{i,t} &= \mu_{i,t} + e^{h_{i,t}/2}\varepsilon_{i,t}, & \varepsilon_{i,t} &\sim \mathcal{N}(0,1), && \text{(A-1)}\\
\mu_{i,t} &= \lambda_i^f f_t + \omega_{i,t}, & & && \text{(A-2)}\\
h_{i,t} &= \lambda_i^h \bar{h}_t + \nu_{i,t}, & & && \text{(A-3)}\\
f_t &= \rho^f f_{t-1} + z_t, & z_t &\sim \mathcal{N}(0,\sigma_z^2), && \text{(A-4)}\\
\bar{h}_t &= \rho^h \bar{h}_{t-1} + u_t, & u_t &\sim \mathcal{N}(0,\sigma_u^2), && \text{(A-5)}\\
\omega_{i,t} &= \rho_i^\omega \omega_{i,t-1} + \epsilon_{i,t}, & \epsilon_{i,t} &\sim \mathcal{N}(0,\sigma_{\epsilon,i}^2), && \text{(A-6)}\\
\nu_{i,t} &= \rho_i^\nu \nu_{i,t-1} + \kappa_{i,t}, & \kappa_{i,t} &\sim \mathcal{N}(0,\sigma_{\kappa,i}^2). && \text{(A-7)}
\end{aligned}
$$

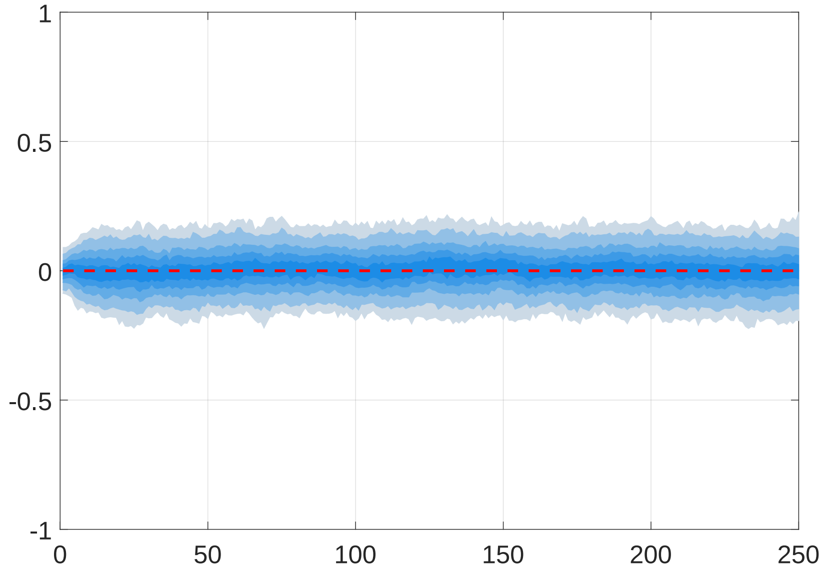
The parameters of the DGP are set to: $\rho^f = 0.9$, $\rho^h = 0.98$, $\rho_i^\omega = 0.9$, $\rho_i^\nu = 0.98$, $\sigma_z^2 = 1$, $\sigma_u^2 = 0.1$, $\sigma_{\epsilon,i}^2 = 1$, and $\sigma_{\kappa,i}^2 = 0.1\ \forall\, i = 1, ..., N$. The factor loadings in the mean and log-volatility equation, λ_i^f and λ_i^h, are drawn from independent normal distributions with the moments chosen such that the average variation explained of the mean and log-volatility of the variables is 20% and 25%, respectively.

DGP 2 is similar to DGP 1 but includes the so-called leverage effect, i.e a negative contemporaneous correlation between the innovations to the mean and volatility factors, as well as the innovations to the idiosyncratic mean and volatility components. Under this assumption, it is well-known that the model remains conditionally Gaussian, but features unconditional left-skewness (e.g. Omori et al., 2007). In particular, in this case, we assume that z_t and u_t follow a multivariate normal distribution with correlation $\rho_{z_t,u_t} = -0.9$. A similar assumption is introduced for the correlation between $\epsilon_{i,t}$ and $\kappa_{i,t}$ is chosen randomly from a uniform distribution $[0, -0.9]$ for each variable $i = 1, ..., N$.

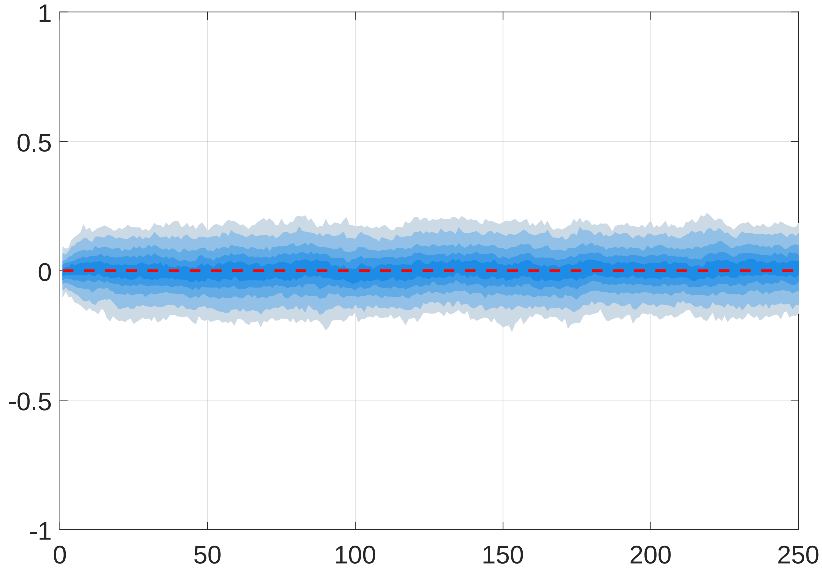
For each simulated dataset and both DGPs, we estimate the skewness factor as outlined in Section 2. Since the scale of the skewness factor is not identified, and since in this case we are interested in assessing how far the retrieved factor is from the zero line, we normalize the factor so that its standard deviation matches the mean value of the standard deviation of the individual skewness series in the dataset. Figure A-1 presents the distribution of the estimated skewness factors across the Monte Carlo samples. The results provide evidence for the strong performance of the model and show that our two-step approach to construct the skewness factor does not capture "spurious skewness". In particular, since both DGPs do not feature conditional skewness, the distribution of the estimated factors across Monte Carlo samples is centred around the zero line with only limited dispersion.

Figure A-1: Results of Monte Carlo simulation

(a) DGP 1: (Un-)conditionally Gaussian



(b) DGP 2: Cond. Gaussian with uncond. skew



Note: The largest shaded area corresponds to the 90% confidence interval, with shades corresponding to increasing probability ranges of $10\%, 20\%, ..., 90\%$.

Appendix B Data

Table B-1: Data descriptions, transformations and sources

Dataset used to derive the skewness factor

McCracken and Ng (2016) / McCracken and Ng (2020) datasets: https://research.stlouisfed.org/econ/mccracken/fred-databases/

Vintage: December 2022 (February 2020 for VAR analysis).

Variables in baseline VAR

Name	**Description**	**Transformation**	**Source**
GDP	Real GDP per capita	100*log(X)	(AL)FRED
Investment	Real investment per capita	100*log(X)	(AL)FRED
Consumption	Real consumption per capita	100*log(X)	(AL)FRED
Hours worked	Hours worked per person	100*log(X)	(AL)FRED
Unemployment	Civilian unemployment rate	–	(AL)FRED
Labor share	Labor share in the non-farm business sector	100*log(X)	(AL)FRED
Policy rate	Effective federal funds rate	$X/4$	(AL)FRED
Inflation	Percentage change in GDP deflator	100*log(X_t/X_{t-1})	(AL)FRED
Labor productivity	Real (non-farm) output per hours of all persons	100*log(X)	(AL)FRED
TFP	Level of total factor productivity	100*log(X)	Fernald (2014)

Variables in augmented VARs

Name	**Description**	**Transformation**	**Source**
Excess returns	Change of S&P 500 minus 3-month treasury yield	–	FRED
Term premium	Treasury term premium for 10-year gov. bonds	–	FRBSF/Adrian et al. (2013)
House prices	Real house prices (nominal HPI divided by CPI)	100*log(X)	FRED
S&P 500	Real stock prices (S&P 500 index divided by CPI)	100*log(X)	FRED
Government bond yield	10-year government bond yield	–	FRED

Note: The variables in the baseline VAR match those included by Angeletos et al. (2020) and more details can be found in that reference.

Appendix C VAR model and prior choice

This appendix contains additional details on the VAR model used in the main part of the paper and the prior specification employed in the Bayesian estimation of this model. Since the presentation here is relatively brief and does not outline every step of the Bayesian treatment of a VAR model, we refer to standard references for further details (e.g. Koop and Korobilis, 2010; Chan, 2020). The starting point of our empirical analysis is a vector autoregressive model of order P denoted as VAR(P)

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

where u_t is a $N \times 1$ vector of reduced-form errors that is normally distributed with zero mean and covariance matrix Σ. The regression-equation representation of this system is

$$Y = X\Theta + U, \tag{C-2}$$

where $Y = [y_{h+1}, ..., y_T]$ is a $N \times T$ matrix, $X = Y_{-h}$ is a $(NP) \times T$ matrix containing the h-th lag of Y, $\Theta = [\Theta_1, ..., \Theta_P]$ is a $N \times (NP)$ matrix, and $U = [u_{h+1}, ..., u_T]$ is a $N \times T$ matrix of disturbances.

The Bayesian estimation of VAR models has become standard in empirical macroeconomics. Specifically, we use a Minnesota-type prior (Doan et al., 1984; Litterman, 1986). It is assumed that the prior distribution of the VAR parameters has a Normal-Wishart conjugate form

$$\theta|\Sigma \sim \mathcal{N}(\theta_0, \Sigma \otimes \Omega_0), \quad \Sigma \sim \mathcal{IW}(v_0, S_0), \tag{C-3}$$

where θ is obtained by stacking the columns of Θ. In contrast to Litterman (1986), the covariance matrix Σ in the prior described in Equation (C-3) is not replaced by an estimated and thus known (diagonal) counterpart. Therefore, sampling from the conditional posterior distributions described below requires Gibbs sampling (see also Mumtaz and Zanetti, 2012). Our results are based on 25,000 draws and we discard the initial 5,000 draws as burn-in. The (Minnesota) prior moments of θ are given by

$$\mathbb{E}[(\Theta_p), i, j] = \begin{cases} \delta_i & i = j, p = 1 \\ 0 & \text{otherwise} \end{cases}, \quad Var[(\Theta_p), i, j] = \lambda \sigma_i^2 / \sigma_j^2, \tag{C-4}$$

and, as outlined in Bańbura et al. (2010), they can be constructed using the following T_D

dummy observations

$$Y_D = \begin{pmatrix} \frac{diag(\delta_1\sigma_1,...,\delta_N\sigma_N)}{\lambda} \\ 0_{N\times(P-1)N} \\ .... \\ diag(\sigma_1,...,\sigma_N) \\ .... \\ 0_{1\times N} \end{pmatrix} \text{ and } X_D = \begin{pmatrix} \frac{J_P\otimes diag(\sigma_1,...,\sigma_N)}{\lambda} \\ 0_{N\times NP} \\ .... \\ 0_{1\times NP} \end{pmatrix}, \tag{C-5}$$

where $J_P = diag(1,2,...,P)$ and $diag$ denotes the diagonal matrix. The prior moments in Equation (C-3) are functions of Y_D and X_D, $\Theta_0 = Y_D X_D'(X_D X_D')^{-1}$, $\Omega_0 = (X_D X_D')^{-1}$, $S_0 = (Y_D - \Theta_0 X_D)(Y_D - \Theta_0 X_D)'$ and $v_0 = T_D - NP$. Finally, the hyper-parameter λ controls the tightness of the prior and our baseline choice is $\lambda = 2$.

Since the normal-inverse Wishart prior is conjugate, the conditional posterior distribution of this model is also normal-inverse Wishart (Kadiyala and Karlsson, 1997)

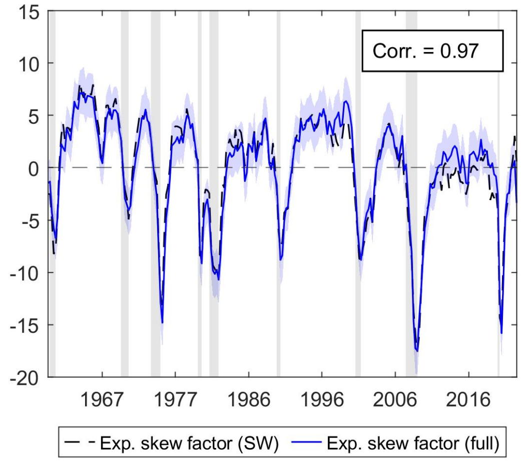
$$\theta|\Sigma, Y \sim \mathcal{N}(\bar{\theta}, \Sigma \otimes \bar{\Omega}), \quad \Sigma|Y \sim \mathcal{IW}(\bar{v}, \bar{S}), \tag{C-6}$$

where variables with a bar denote the parameters of the posterior distribution. Defining $\hat{\Theta}$ and $\hat{U}$ as the OLS estimates from Equation (C-2), the parameters of the conditional posterior distribution can be computed as $\bar{\Theta} = (\Omega_0^{-1}S_0 + YX')(\Omega_0^{-1} + X'X)^{-1}$, $\bar{\Omega} = (\Omega_0^{-1} + X'X)^{-1}$, $\bar{v} = v_0 + T$, and $\bar{S} = \hat{\Theta}XX'\hat{\Theta}' + \Theta_0\Omega_0^{-1}\Theta_0 + S_0 + \hat{U}\hat{U}' - \bar{\Theta}\bar{\Omega}^{-1}\bar{\Theta}'$. Lastly, as in Mumtaz and Zanetti (2012), the values of the persistence parameter δ_i and the error standard deviation σ_i of the AR(1) model are obtained from its OLS estimation.

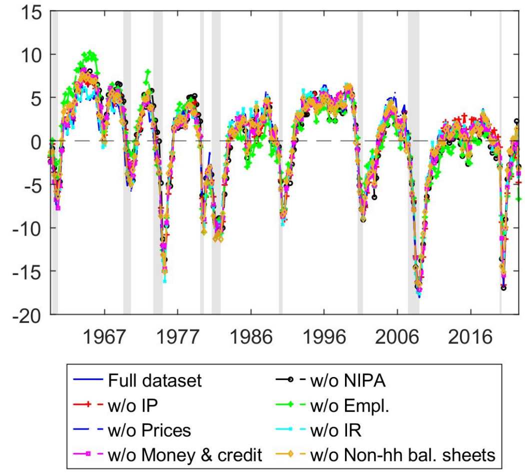
Appendix D Additional results

Figure D-1: Skewness factor based on different datasets

(a) Smaller subset of variables

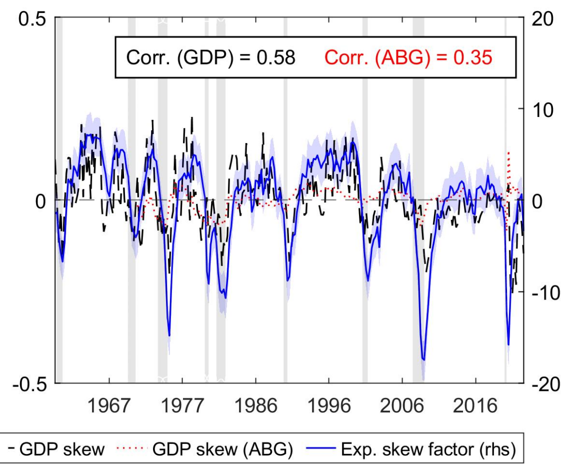


(b) Excluding groups of variables



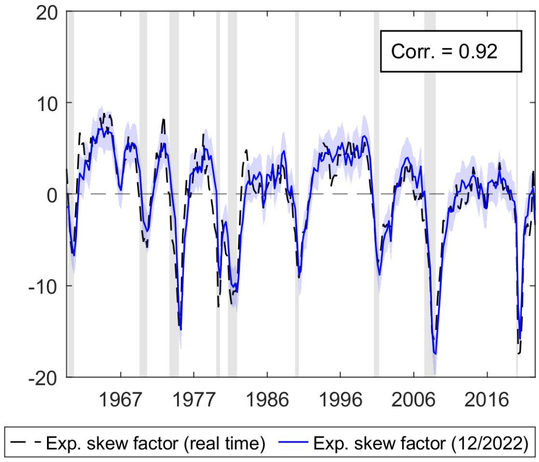
Note: Figure D-1(a) shows the skewness factor based on the full McCracken and Ng (2020) dataset and an alternative skewness factor based on a subset of variables similar to those used in Stock and Watson (2012). The blue shaded areas are the bootstrapped confidence bands (90%) around the skewness factor based on Gonçalves and Perron (2020). Figure D-1(b) shows the skewness factor based on the full dataset together with alternative skewness factors obtained from the original dataset where one group of variables is omitted at a time. In both figures, the scale of the alternative skewness factors is adjusted to match the one of the original factor.

Figure D-2: Exp. GDP growth skewness (until 2022:Q3) and exp. skewness factor



Note: This figure shows the expected skewness factor together with the individual skewness measures of GDP growth when, also for the latter, using the full estimation sample until 2022:Q3. See also Figure 1.

Figure D-3: Skewness factor (full sample) vs. real-time factor



Note: This figure shows the expected skewness factor estimated over the full sample (using the FRED-QD "2022-12" vintage (McCracken and Ng, 2020)) together with an alternative skewness factor that is estimated in real-time using FRED-QD vintages since May 2018 (earliest available vintage). Specifically, the latter starts by using the "2018-05" vintage to estimate the skewness factor over the period 1960:Q1–2018:Q1. After that, the real-time estimation uses four vintages per year (January, April, July, and October), re-estimating the model repeatedly using the latest vintage, and adding one observation at a time. The last re-estimation is done using the "2022-10" vintage.

Table D-1: Correlation of skewness factor and different volatility/uncertainty measures

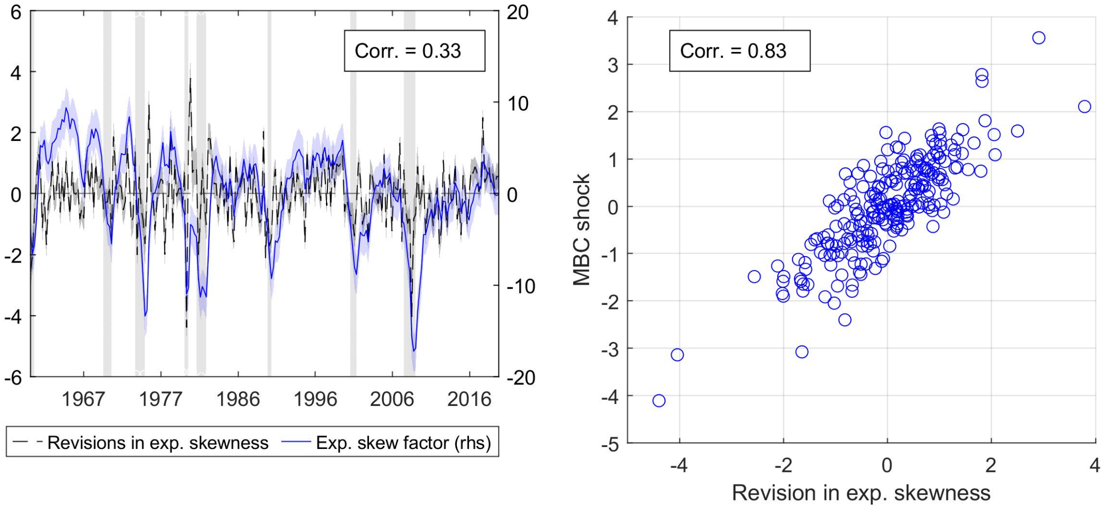
	PC (skew)	PC (X)	PC (X^2)	PC (P_{75}-P_{25})	PC (GARCH)	Macro unc.	Fin. unc.
PC (skew)	1.00	-	-	-	-	-	-
PC (X)	0.43	1.00	-	-	-	-	-
PC (X^2)	-0.37	-0.51	1.00	-	-	-	-
PC (P_{75}-P_{25})	-0.72	-0.69	0.82	1.00	-	-	-
PC (GARCH)	-0.64	-0.47	0.91	0.93	1.00	-	-
Macro unc.	-0.70	-0.44	0.56	0.83	0.76	1.00	-
Fin. unc.	-0.48	-0.34	0.29	0.54	0.45	0.61	1.00

Note: This table contains correlations of the exp. skewness factor *PC (skew)* and different measures of volatility and uncertainty. *PC (X)*, *PC (X^2)*, *PC (P_{75}-P_{25})*, and *PC (GARCH)* are, respectively, the first principal component of the McCracken and Ng (2020) dataset, the first principal component of the squared observations (Gorodnichenko and Ng, 2017), the first principal component of the expected interquartile ranges, and the first principal component of the expected individual GARCH standard deviations. Macro unc. and Fin. unc. are the macroeconomic and financial uncertainty indices developed in Jurado et al. (2015) and Ludvigson et al. (2021).

Figure D-4: Revisions in expected skewness

(a) Exp. skewness factor and its revisions

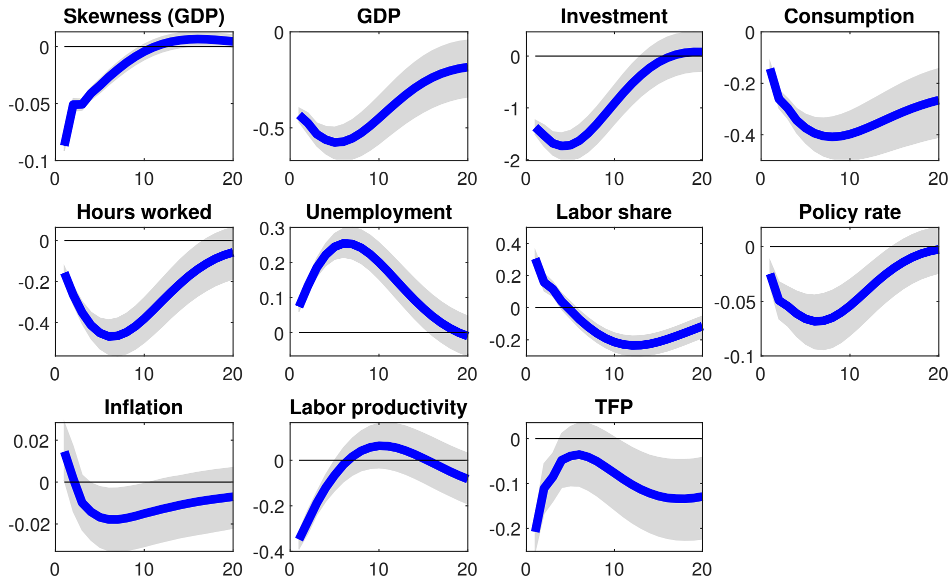
(b) Revisions in exp. skewness and MBC shock



Note: The left panel shows the expected skewness factor and its revisions obtained from the VAR analysis. The blue shaded areas are the bootstrapped confidence bands (90%) around the skewness factor based on Gonçalves and Perron (2020). The dark gray shaded areas are the 90% HDI of the skewness revisions across all MCMC draws. Light gray areas are NBER recessions. The right panel contrasts revisions in expected skewness with the MBC shock obtained following Angeletos et al. (2020). The reported correlation reflects the one of the median shocks computed across all MCMC draws.

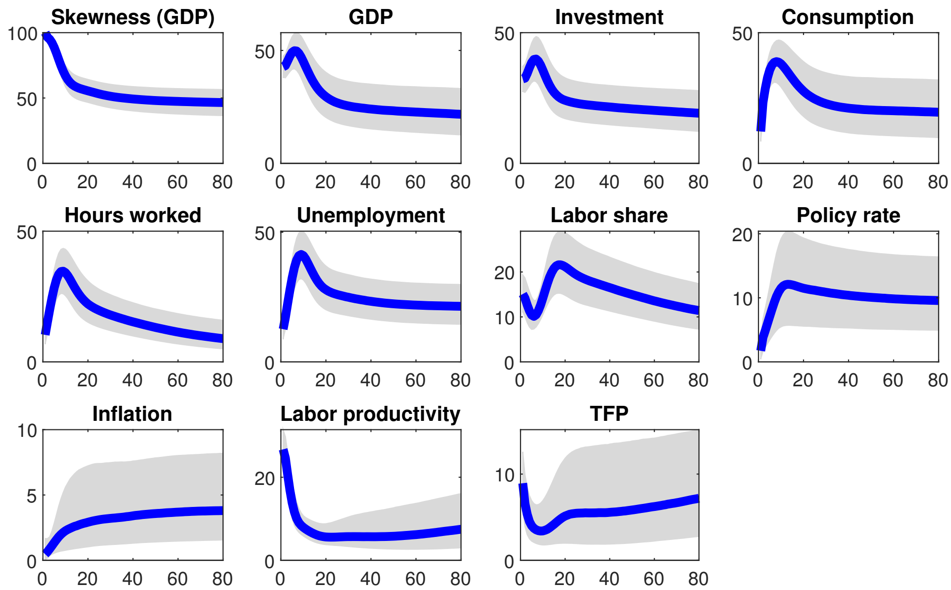
Results of baseline model with GDP skewness

Figure D-5: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to expected GDP skewness along with the 68% highest density interval. Identification through Cholesky decomposition. Sample period: 1960:Q1–2019:Q4.

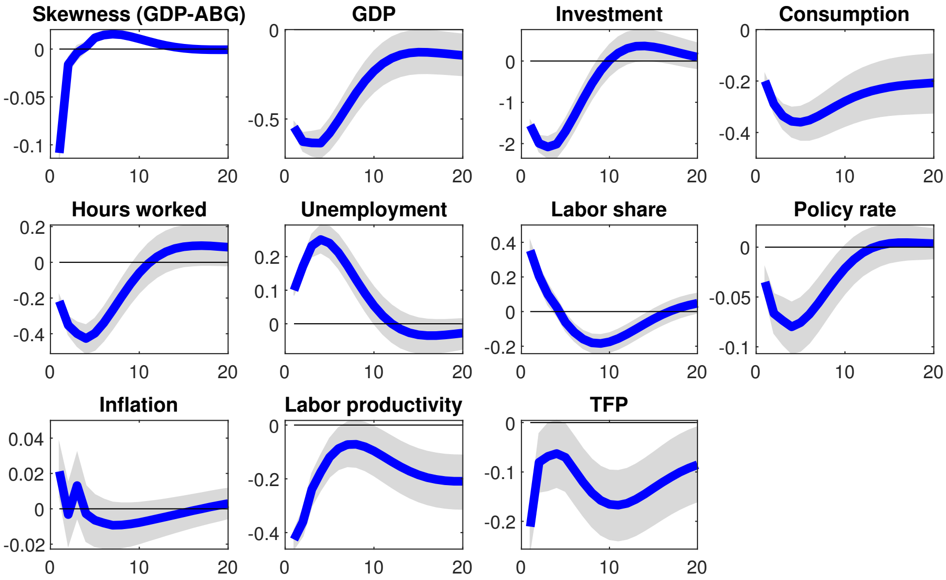
Figure D-6: Forecast error variance contributions



Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.

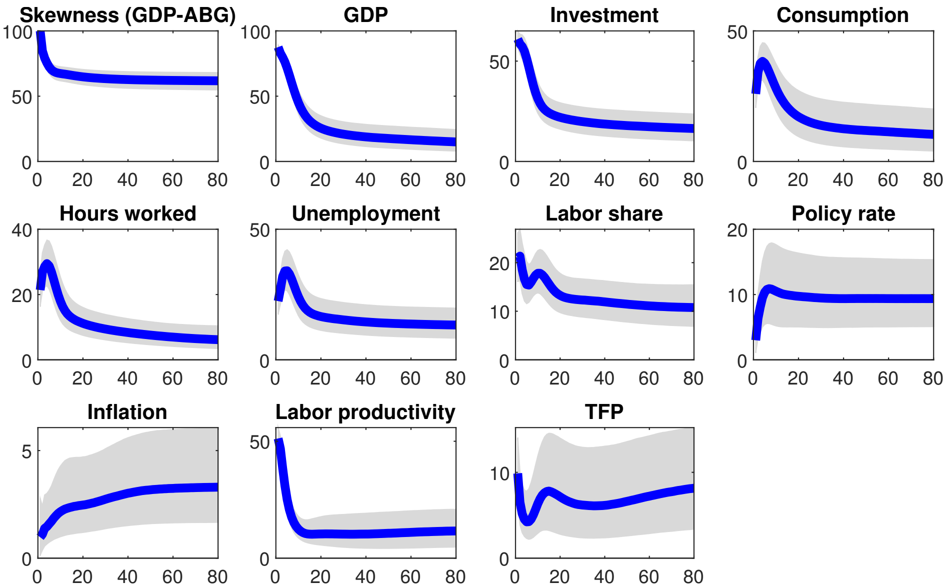
Results of baseline model with GDP skewness (Adrian et al., 2019)

Figure D-7: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to expected GDP skewness (Adrian et al., 2019) along with the 68% highest density interval. Identification through Cholesky decomposition. Sample period: 1971:Q1–2019:Q4.

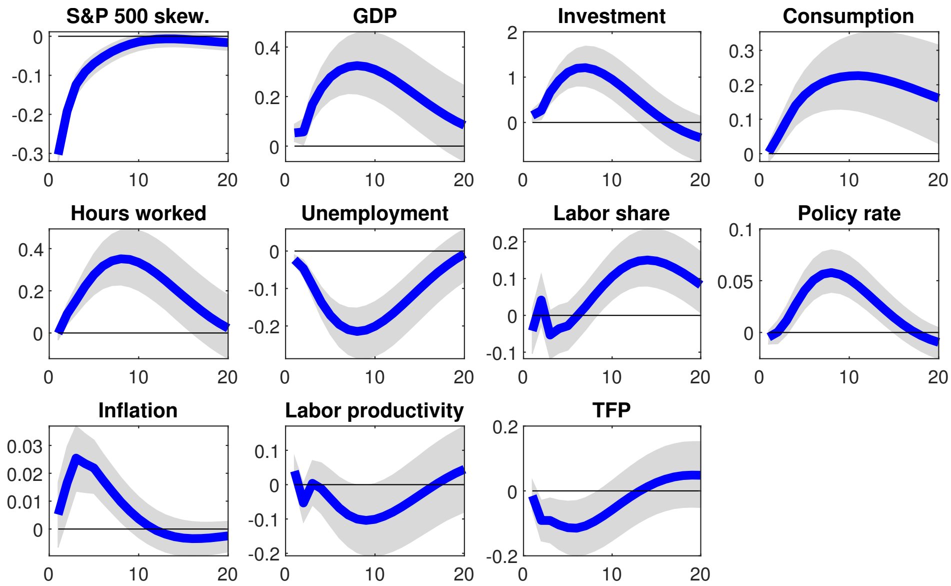
Figure D-8: Forecast error variance contributions



Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.

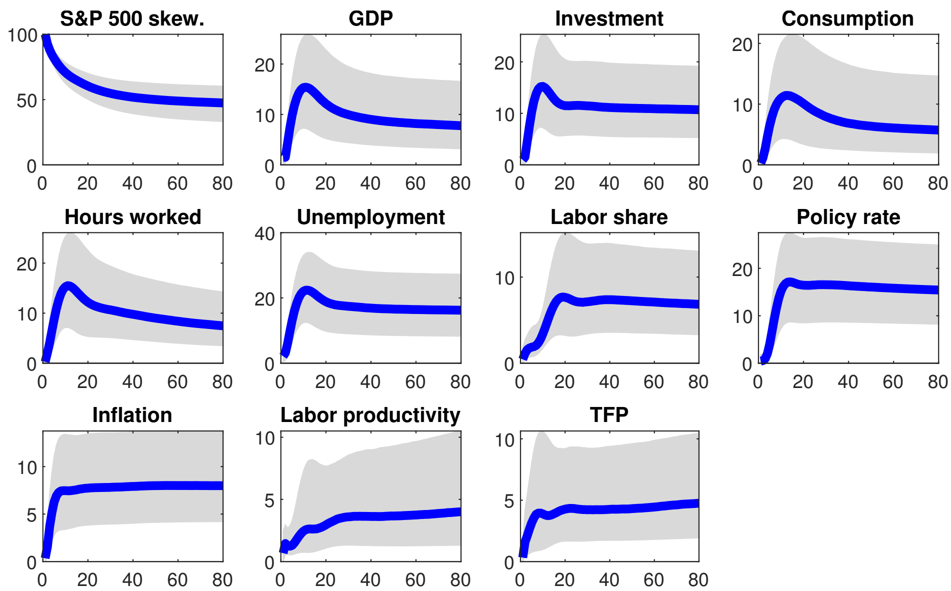
Results of baseline model with S&P 500 skewness (Dew-Becker, 2022)

Figure D-9: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to option-implied S&P 500 skewness (Dew-Becker, 2022) along with the 68% highest density interval. Identification through Cholesky decomposition. Sample period: 1983:Q2–2019:Q4.

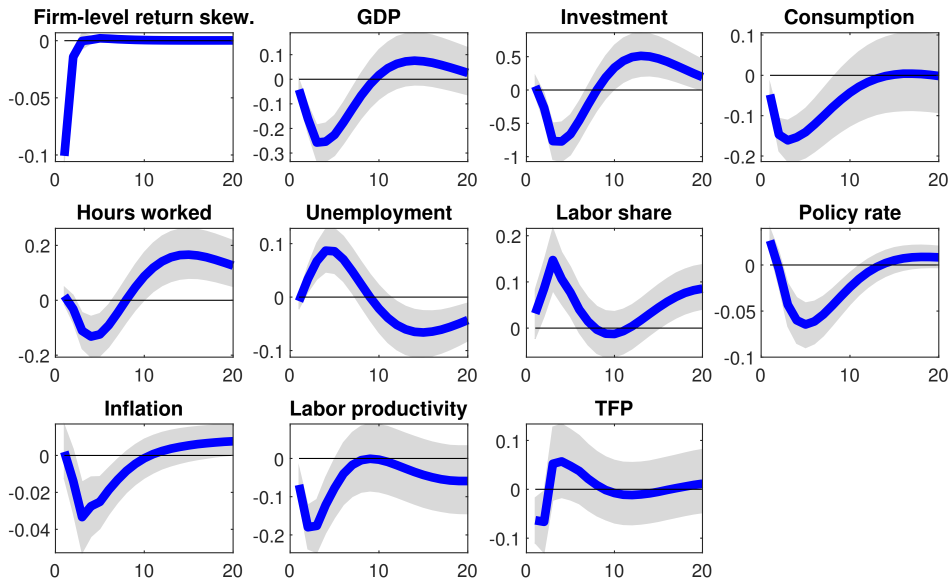
Figure D-10: Forecast error variance contributions



Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.

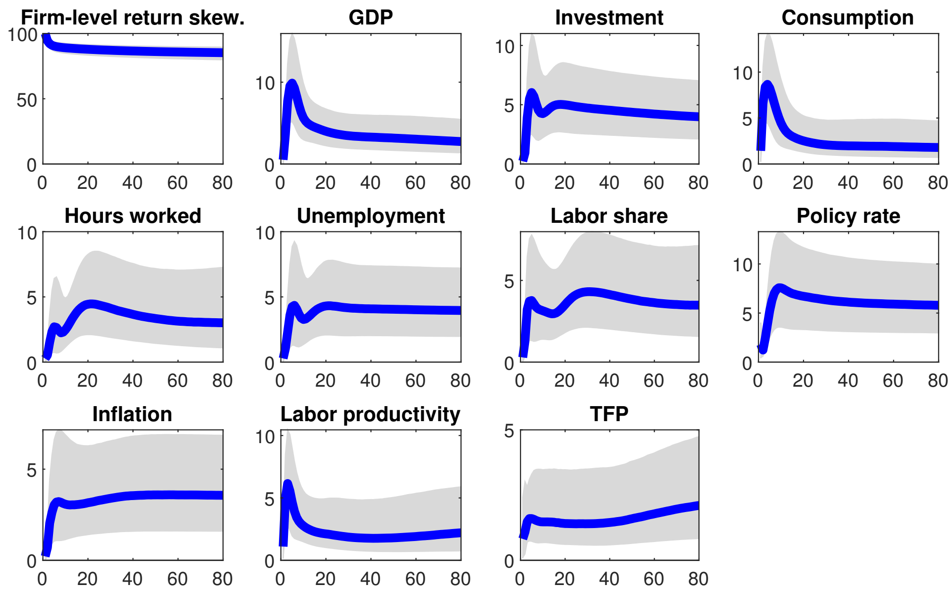
Results of baseline model with firm-level return skewness (Salgado et al., 2019)

Figure D-11: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to the cross-sectional firm-level skewness of stock returns (Salgado et al., 2019) along with the 68% highest density interval. Identification through Cholesky decomposition. Sample period: 1964:Q1–2015:Q1.

Figure D-12: Forecast error variance contributions

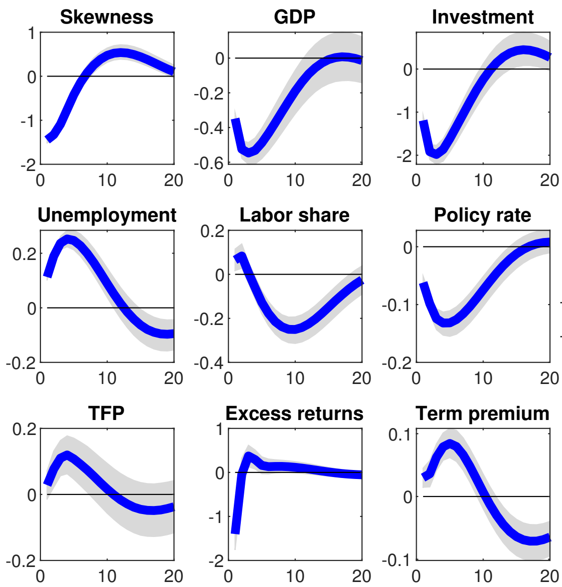


Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.

Appendix E Augmented models including financial variables

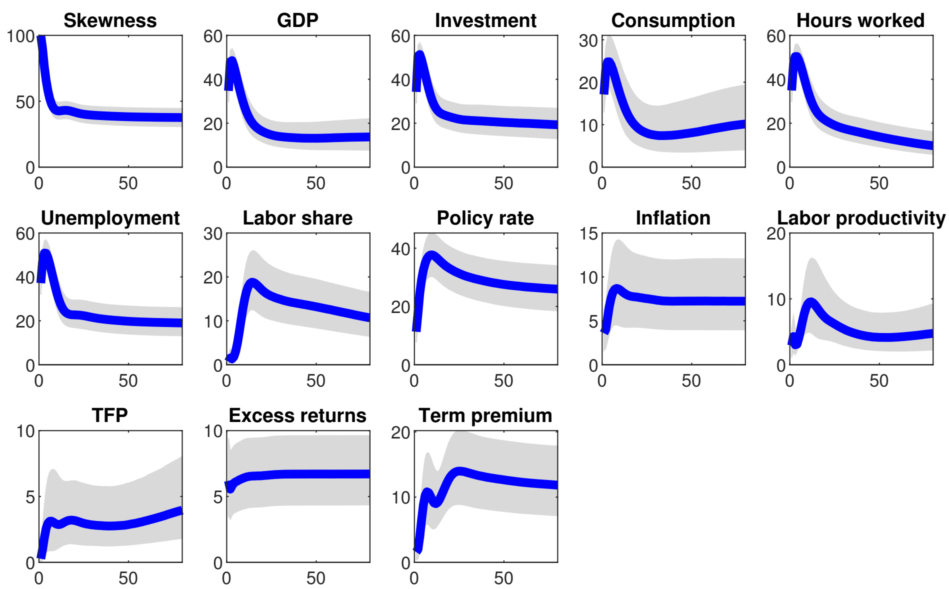
Results of model augmented with excess returns and term premium

Figure E-1: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to expected skewness along with the 68% highest density interval. Identification through Cholesky decomposition. Sample period: 1961:Q3–2019:Q4.

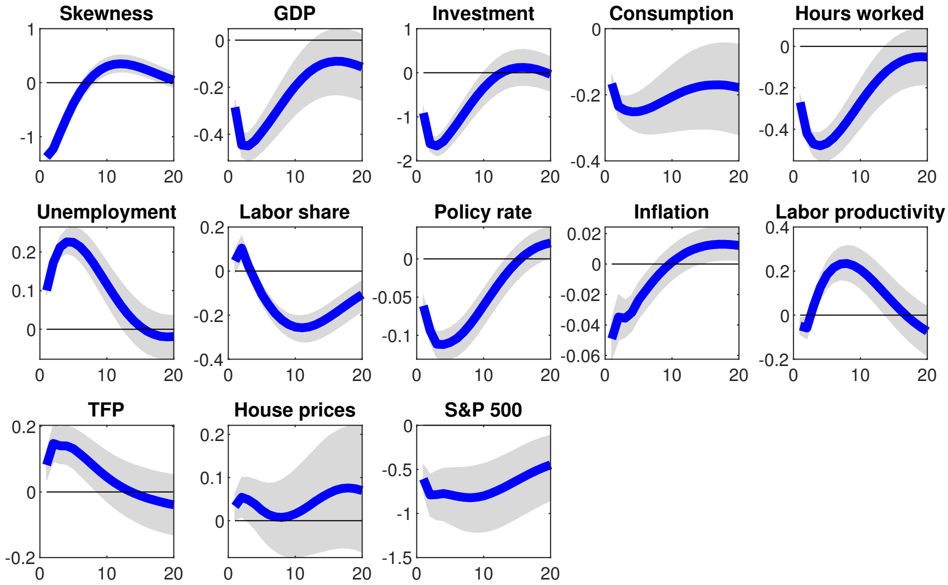
Figure E-2: Forecast error variance contributions



Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.

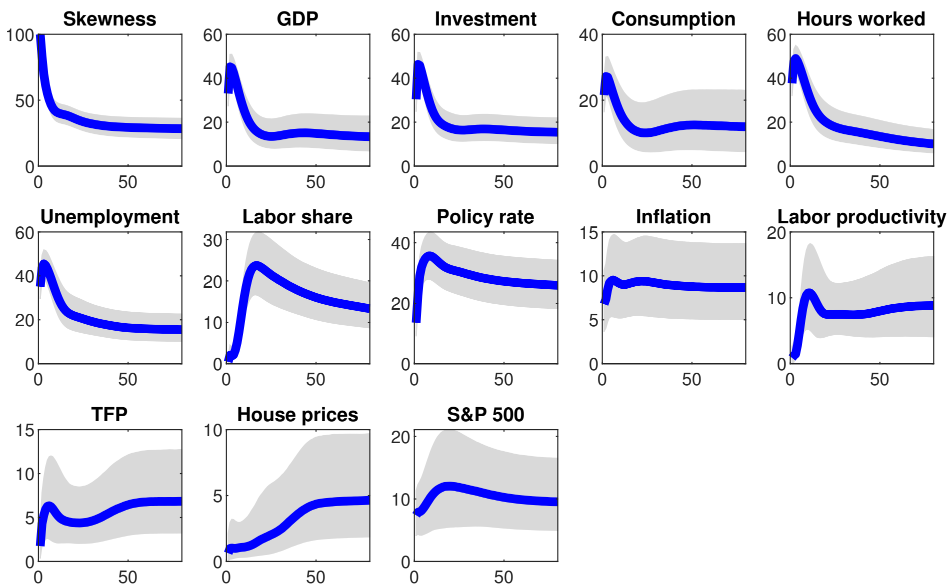
Results of model augmented with house prices and stock prices

Figure E-3: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to expected skewness along with the 68% highest density interval. Identification through Cholesky decomposition. Sample period: 1975:Q1–2019:Q4.

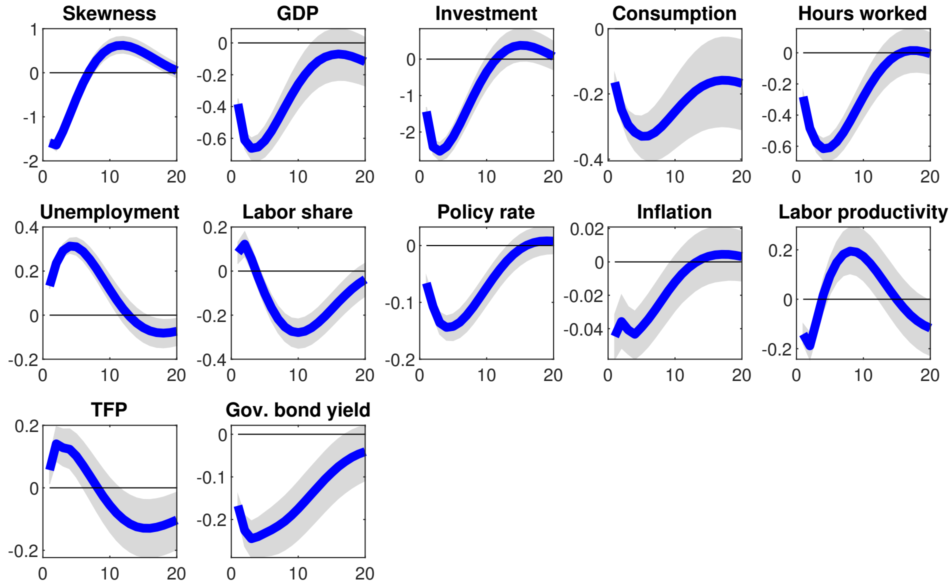
Figure E-4: Forecast error variance contributions



Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.

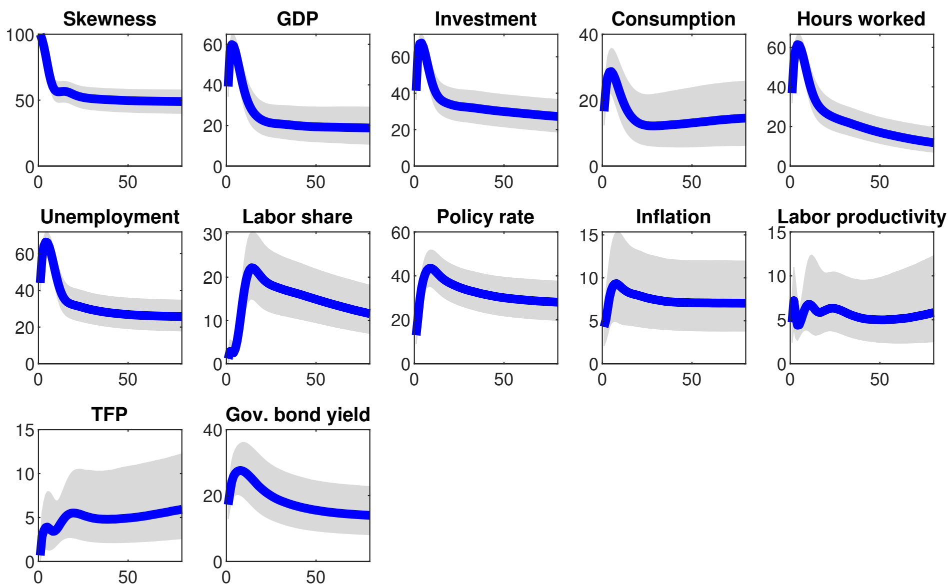
Results of model augmented with government bond yields

Figure E-5: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to expected skewness along with the 68% highest density interval. Identification through Cholesky decomposition. Sample period: 1960:Q1–2019:Q4.

Figure E-6: Forecast error variance contributions

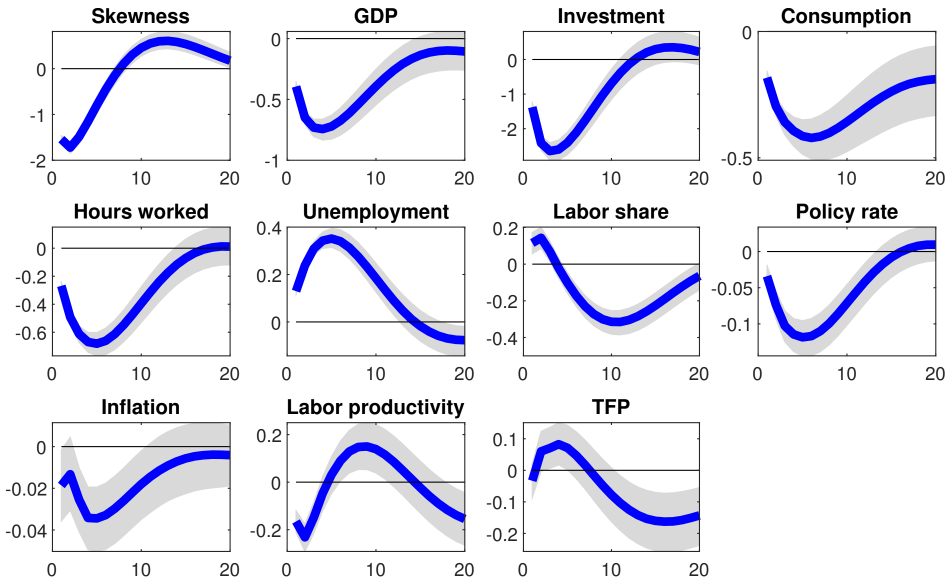


Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.

Appendix F Robustness checks

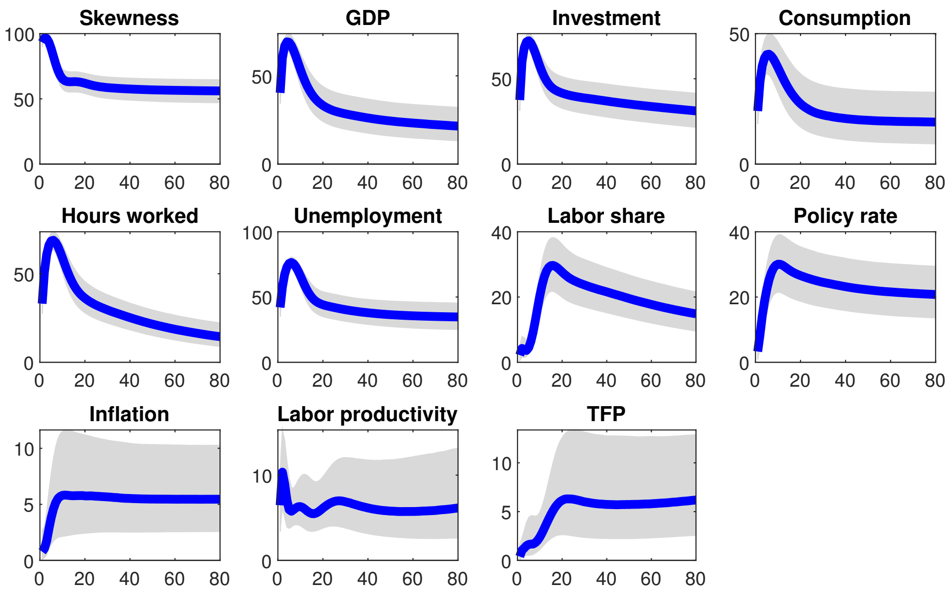
Results of baseline model with max-share identification approach

Figure F-1: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to expected skewness along with the 68% highest density interval. Identification through max-share approach (Uhlig, 2003). Sample period: 1960:Q1–2019:Q4.

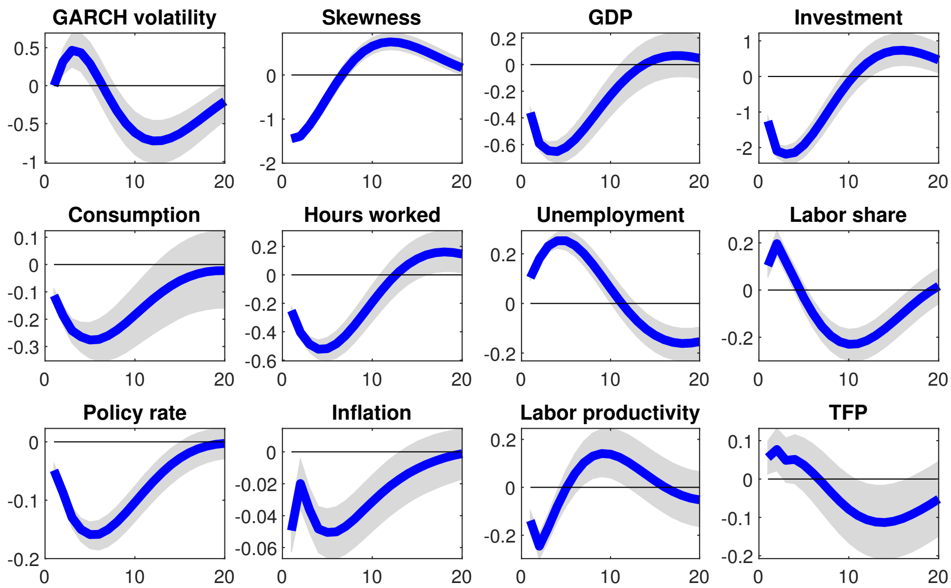
Figure F-2: Forecast error variance contributions



Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.

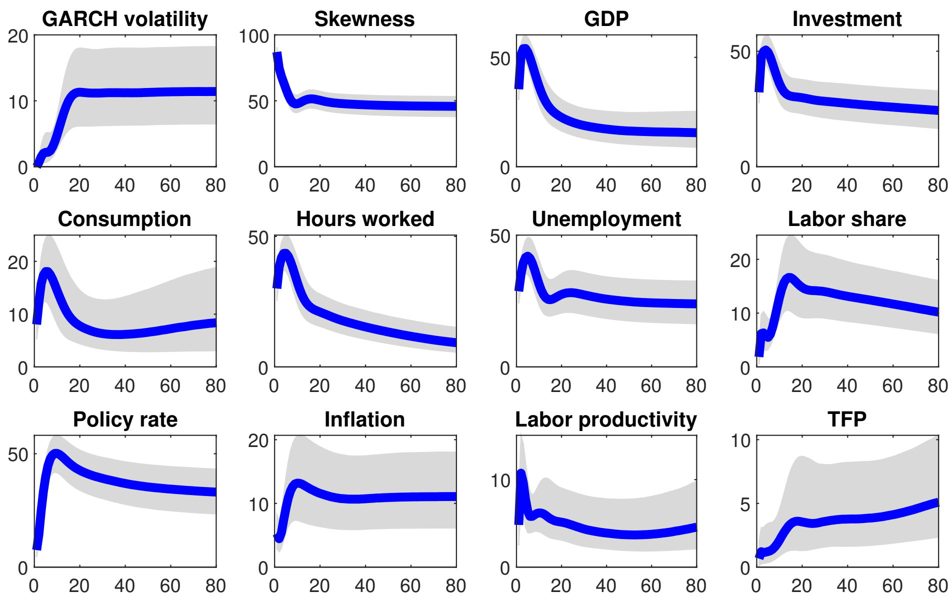
Model results controlling for (GARCH) volatility

Figure F-3: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to expected skewness along with the 68% highest density interval. Identification through Cholesky decomposition. Sample period: 1960:Q1–2019:Q4.

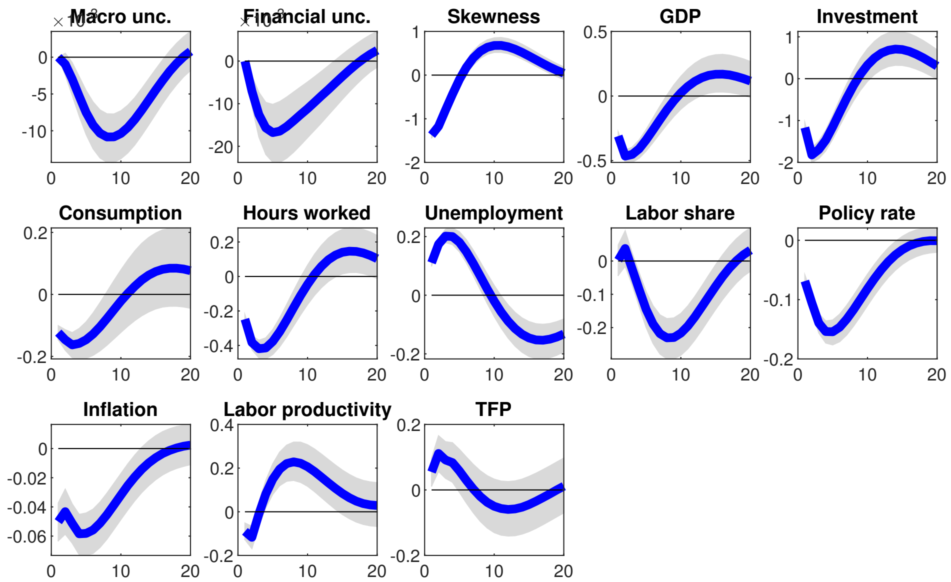
Figure F-4: Forecast error variance contributions



Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.

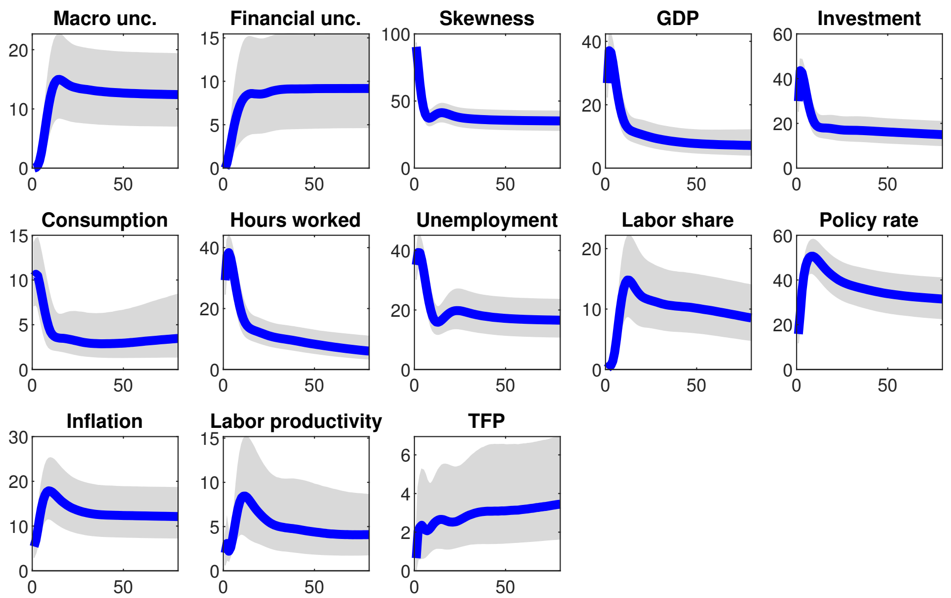
Model results controlling for macroeconomic and financial uncertainty

Figure F-5: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to expected skewness along with the 68% highest density interval. Identification through Cholesky decomposition. Sample period: 1960:Q3–2019:Q4.

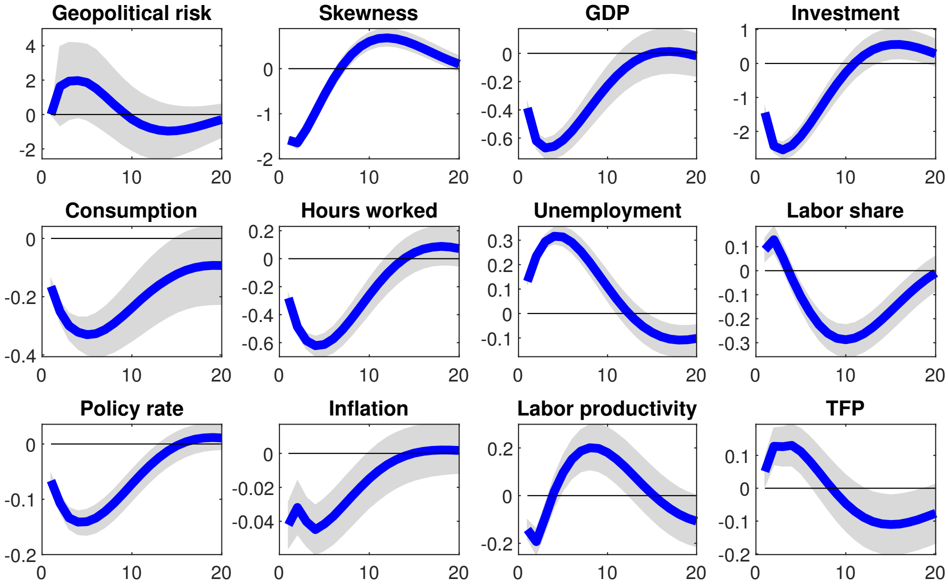
Figure F-6: Forecast error variance contributions



Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.

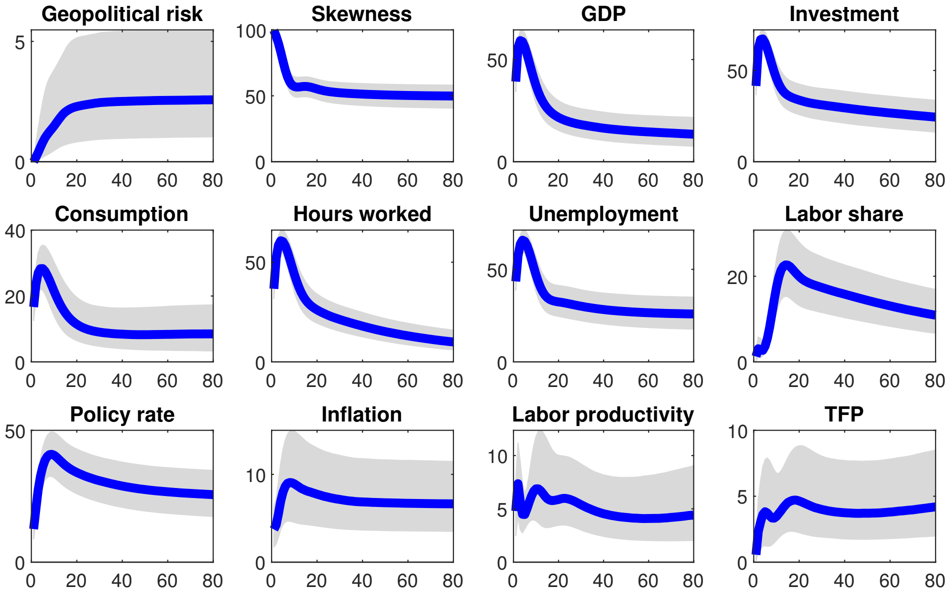
Model results controlling for geopolitical risk

Figure F-7: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to expected skewness along with the 68% highest density interval. Identification through Cholesky decomposition. Sample period: 1960:Q1–2019:Q4.

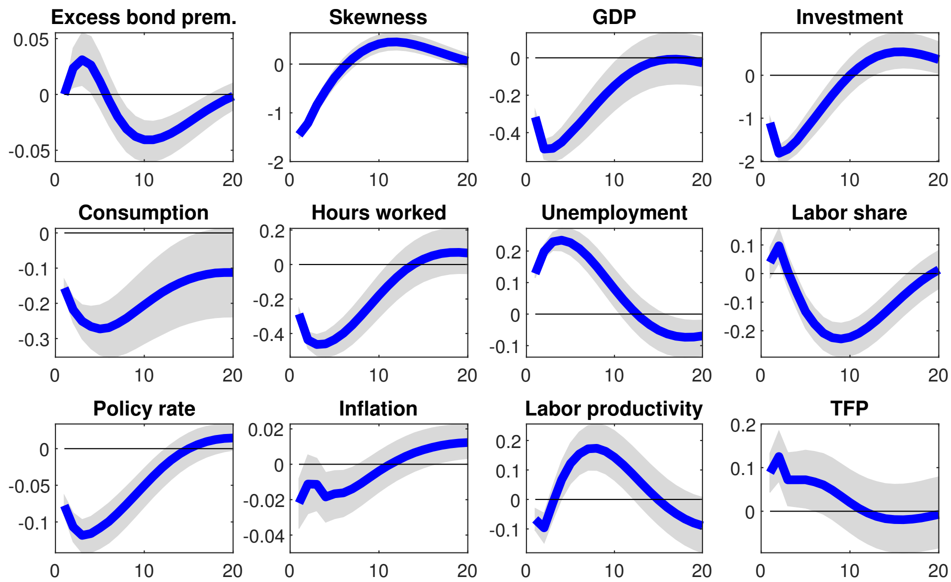
Figure F-8: Forecast error variance contributions



Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.

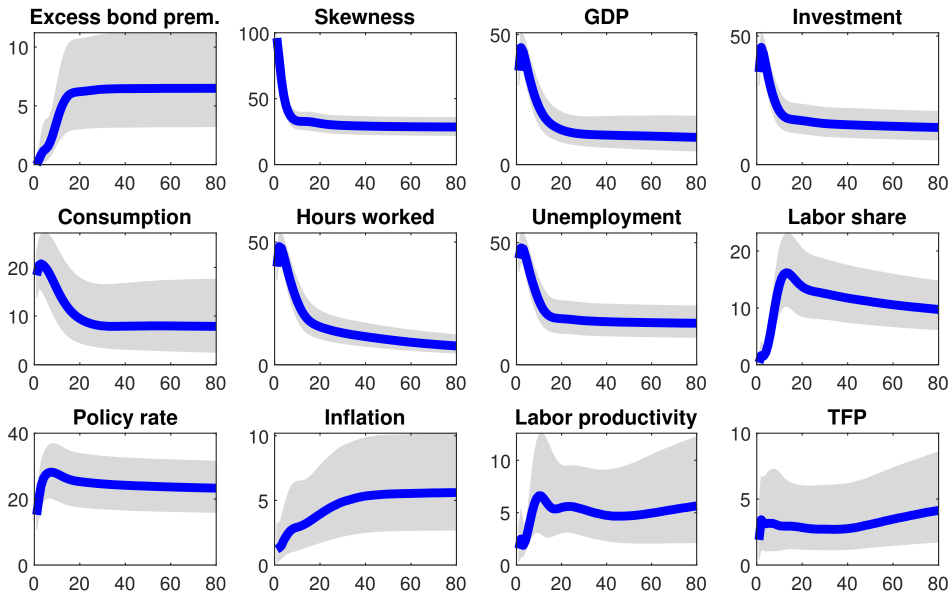
Model results controlling for excess bond premium

Figure F-9: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to expected skewness along with the 68% highest density interval. Identification through Cholesky decomposition. Sample period: 1973:Q1–2019:Q4.

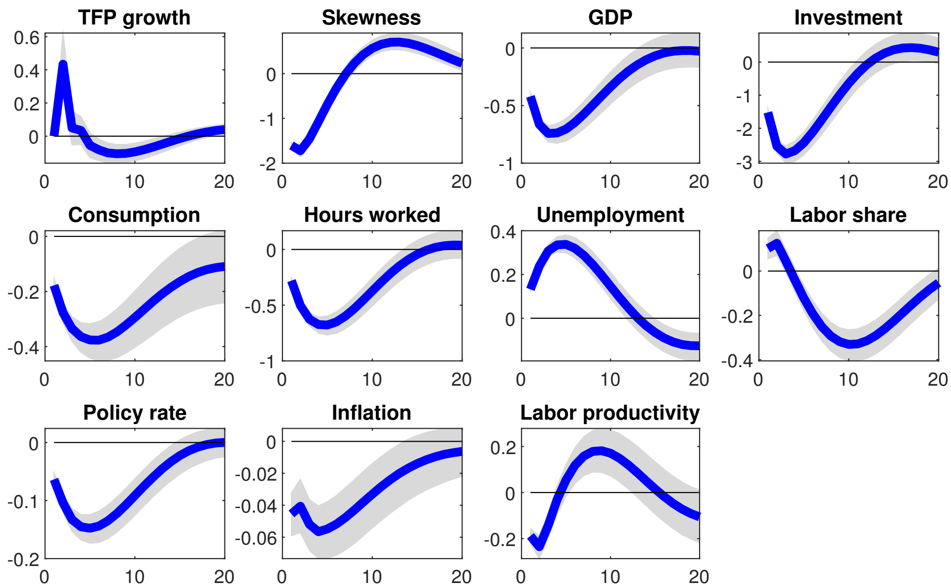
Figure F-10: Forecast error variance contributions



Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.

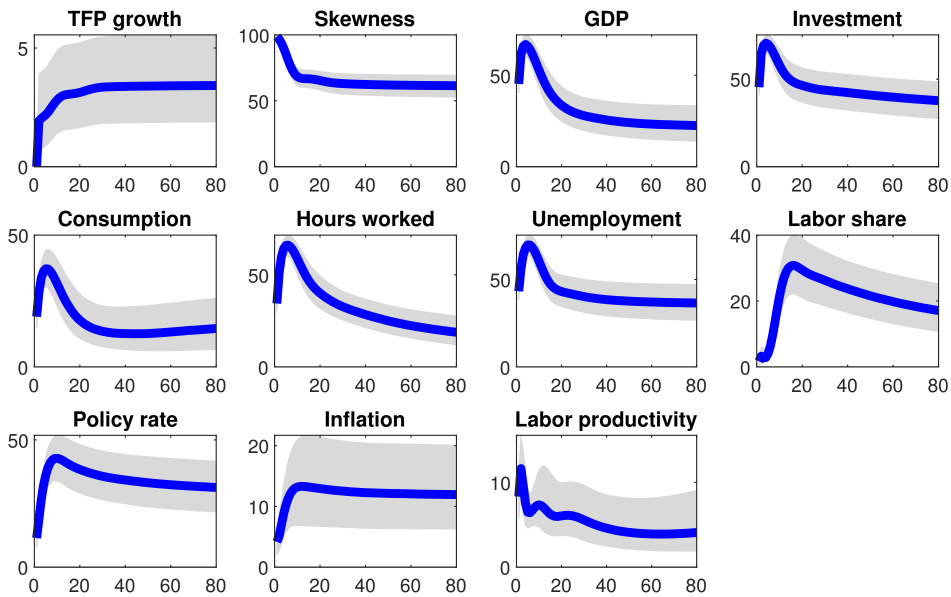
Model results controlling for TFP growth

Figure F-11: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to expected skewness along with the 68% highest density interval. Identification through Cholesky decomposition. Sample period: 1960:Q1–2019:Q4.

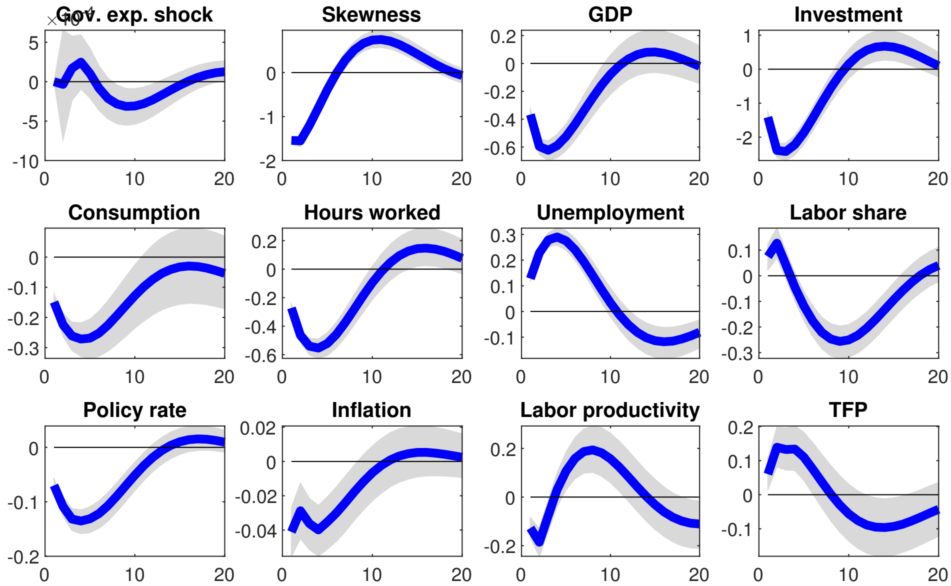
Figure F-12: Forecast error variance contributions



Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.

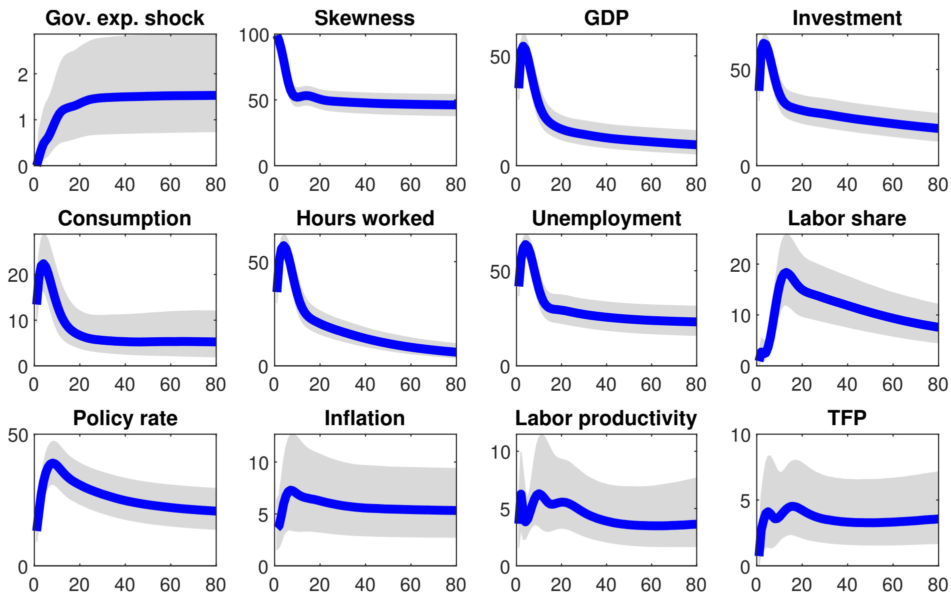
Model results controlling for fiscal policy shocks

Figure F-13: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to expected skewness along with the 68% highest density interval. Identification through Cholesky decomposition. Sample period: 1960:Q1–2015:Q4.

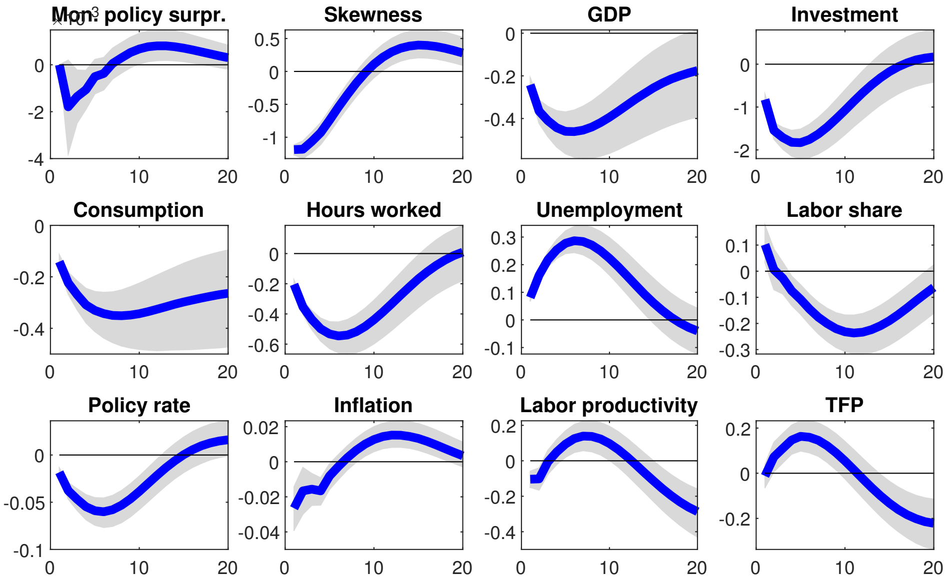
Figure F-14: Forecast error variance contributions



Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.

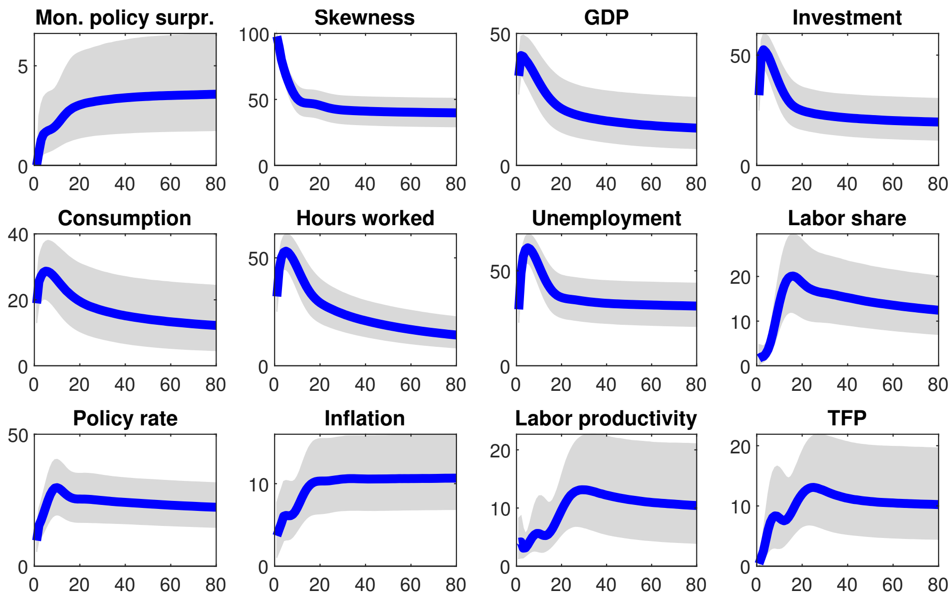
Model results controlling for monetary policy shocks

Figure F-15: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to expected skewness along with the 68% highest density interval. Identification through Cholesky decomposition. Sample period: 1990:Q1–2016:Q4.

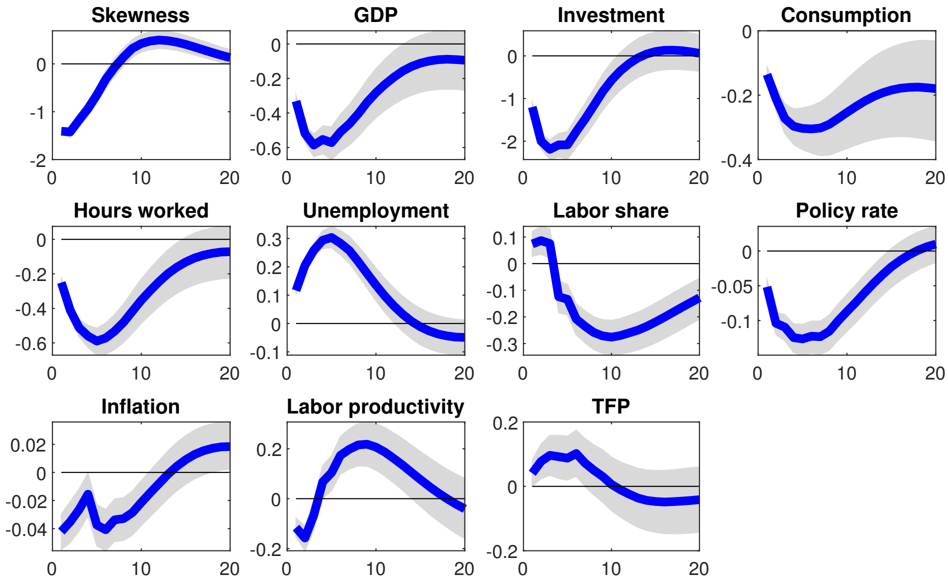
Figure F-16: Forecast error variance contributions



Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.

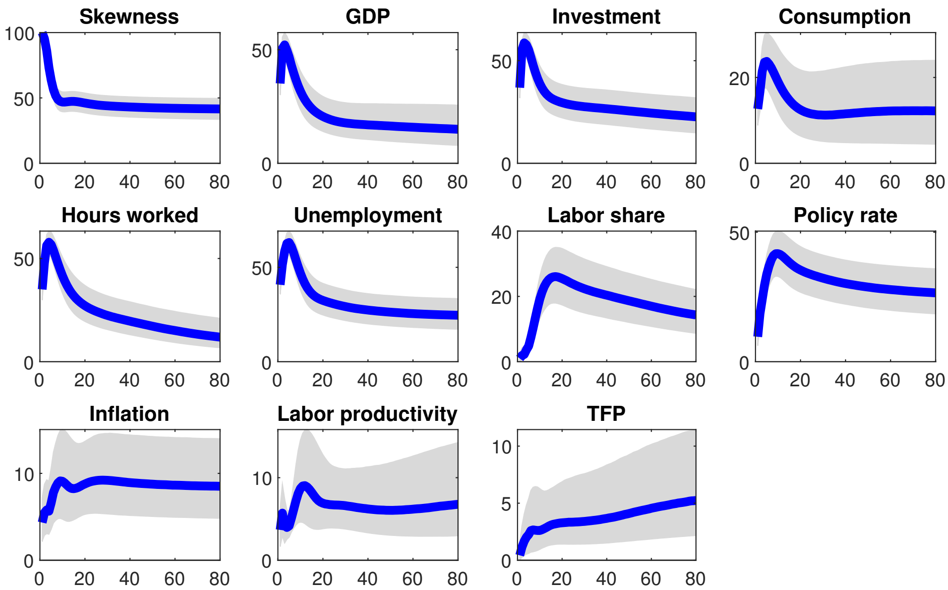
Results of baseline model with lag order $P = 4$

Figure F-17: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to expected skewness along with the 68% highest density interval. Identification through Cholesky decomposition. Sample period: 1960:Q1–2019:Q4.

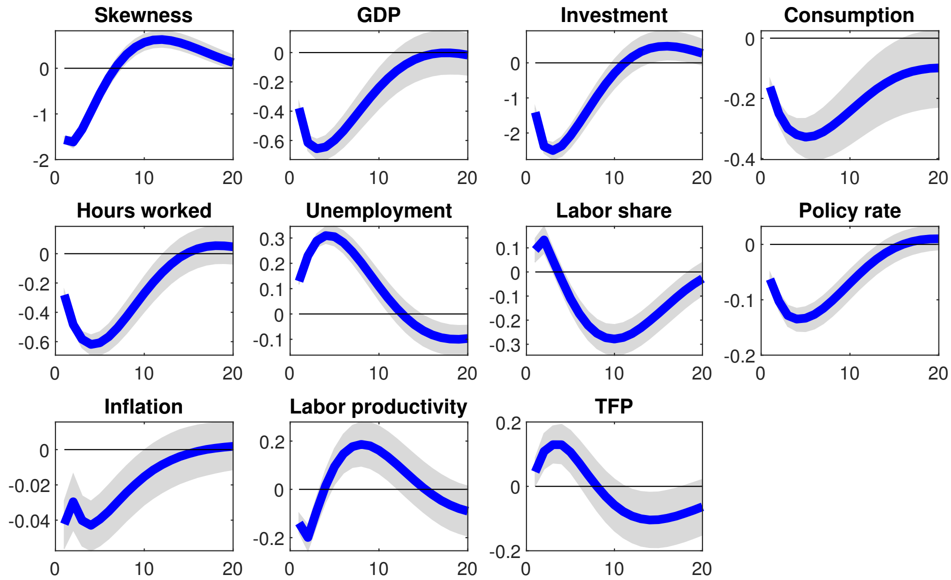
Figure F-18: Forecast error variance contributions



Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.

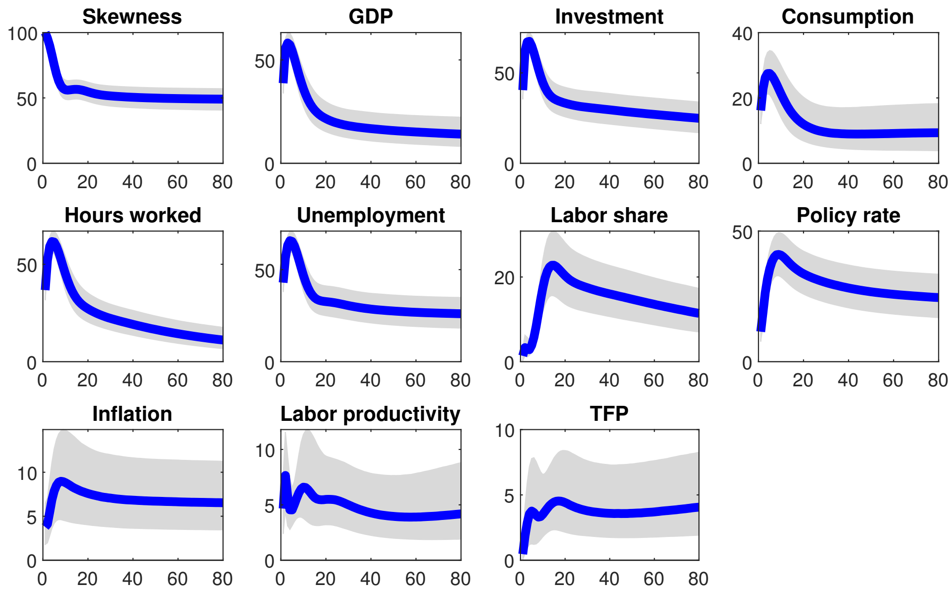
Results of baseline model with looser prior configuration in VAR ($\lambda = 10$)

Figure F-19: Impulse response functions



Note: Posterior mean responses to a negative one S.D. shock to expected skewness along with the 68% highest density interval. Identification through Cholesky decomposition. Sample period: 1960:Q1–2019:Q4.

Figure F-20: Forecast error variance contributions



Note: Posterior mean of the forecast error variance contributions along with the 68% highest density interval.