Financial Shocks in an Uncertain Economy

By Chiara Scotti[1]

Abstract

The past 15 years have been eventful. The Global Financial Crisis (GFC) reminded us of the importance of a stable financial system to a well-functioning economy, one with low and stable inflation and maximum employment. Given the recent banking stress, we ponder this issue again. The pandemic was a huge shock surrounded by much uncertainty, making precise forecasts within traditional models difficult. And more recently, there has been continuous talk of a soft landing and recession risks.

In this paper, I focus on some of the lessons we have learned over the years: (i) uncertainty and tail risk have cyclical variation; (ii) financial shocks can have a significant effect on macroeconomic outcomes; (iii) the impact of shocks is stronger in periods of high volatility.

These lessons have important implications for policymakers in today's environment.

1 The Background

Over the past few years, the profession has come to the realization that financial market stress can significantly affect the broader macroeconomy, and elevated leverage and uncertainty can intensify the impact. These insights are the result of the rapidly growing theoretical and empirical literature in these key areas.

In his Nobel lecture, former Federal Reserve Chair Ben Bernanke highlighted how financial (credit) market stress can have significant macroeconomic effects and act as both a source and an amplifier of macroeconomic stress (Bernanke, 2023). Credit markets are characterized by imperfect and asymmetric information—frictions that can at times create market stress with unusually costly intermediation for businesses and/or households. Examples include times when there is fear that a financial institution may fail, which could lead to it being cut off from credit, or when there are runs on banks, something that we experienced first-hand just a few months ago.

In such situations, an institution may be forced to sell assets quickly at "fire sale" prices, incurring losses and potentially becoming insolvent, as well as causing additional price declines that can create stress across markets and at other

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institutions (Board of Governors of the Federal Reserve System, 2023). When this happens against the backdrop of excessive leverage, either within the financial sector or among households and businesses, the risks to economic activity may be further amplified.

Bernanke (2023) also talked about the cost of credit intermediation, defined as the cost—net of the safe rate of interest—of channelling funds from savers to borrowers, which is also referred to as external finance premium. Empirically, this cost has been measured with the excess bond premium of Gilchrist and Zakrajšek (2012) or simply by a corporate credit spread. Gilchrist and Zakrajšek (2012) show how an increase in the excess bond premium reflects a reduction in the financial sector's risk-bearing capacity, which induces a contraction in the supply of credit and a deterioration in macroeconomic conditions, consistent with the financial accelerator mechanism (see Bernanke and Gertler, 1989, 1990; Kiyotaki and Moore, 1997; Bernanke, Gertler, and Gilchrist,1999; and Hall, 2011 among others). The latter helps explain why comparatively large and persistent fluctuations in the economy can result from relatively small and temporary shocks.

In addition to financial conditions, uncertainty has also been recognized as playing an important role in the economy. Much of the early literature focused on trying to understand the macroeconomic effects of an exogenous uncertainty shock (see Bloom, 2014, for a survey of this literature and the channels through which uncertainty can transmit to the macroeconomy). More recently, the literature has shown that uncertainty can also be endogenous and respond to macroeconomic conditions. Information and labour market frictions are the two main sources of uncertainty emphasized in literature (see, for example, Fajgelbaum et al., 2017, Ilut and Schneider, 2014, Ilut et al., 2018, and Bernstein et al., 2022).

Given the importance of financial stress and uncertainty, it is important to understand how they can impact macroeconomic forecasting. In doing so, in the remainder of this paper, I will focus on recent work with Dario Caldara and Molin Zhong (2023), henceforth referred to as CSZ (2023). The paper is particularly well suited to address these issues. It investigates the drivers of uncertainty and the tail risk of future GDP growth and corporate credit spreads—our empirical counterpart of Bernanke's external finance premium. In the next sections, I will draw some lessons from the paper especially given the experiences of the past 15 years, which I am sure you will agree remain relevant given recent developments.

2 Lesson I: Uncertainty and tail risk have cyclical variation

Uncertainty about future economic outcomes is crucial for economic decisions and for policymaking. A highly uncertain and risky economic outlook can cause concern among policymakers and influence policy decisions. For instance, a study by Evans et al. (2015) found evidence of risk management considerations—the assessment of what could go wrong with the economy and judging whether policy should be adjusted to minimize risks—in one-third of the Federal Open Market Committee

(FOMC) monetary policy decisions between 1993 and 2008.[2] The FOMC's Summary of Economic Projections (SEP) shows the evolution of the balance of FOMC participants' assessment of uncertainty and risk related to their projections.

The most recent SEP, released on June 14, 2023, shows that the participants' assessment of the uncertainty attached to their projections of GDP, unemployment, and inflation is high relative to the past 20 years and has been elevated since 2020.[3] In addition to the uncertainty assessment, the SEP also shows the so-called risk weights, which give information about the participants' assessment of downside risk, defined as the risk of particularly large adverse events materializing.[4]

The importance of uncertainty and downside risk clearly calls for looking at forecast distributions rather than a point forecast. In CSZ (2023), we study the joint conditional distribution of GDP growth and corporate credit spreads using a stochastic volatility vector autoregression (SV-VAR). We define uncertainty as the standard deviation of the conditional distributions of future GDP growth and credit spreads (the volatility implied by the conditional distributions), and tail risk as the size and location of the tails of these distributions.[5] Modelling first and second moments allows us to understand the behaviour of uncertainty and tail risk and their evolution over time.[6]

Within our model, the mean of the endogenous variables influences their volatility and, similarly, volatility feeds back into their mean. The nonlinear interaction between mean and volatility gives rise to predictive distributions that are state-dependent, with mean and volatility varying over time. Chart 1 shows an example from a simple univariate SV model where shifts in mean and volatility generate an asymmetric shift in the distribution. The red line shows a distribution with lower mean and greater uncertainty compared to the blue one, and whose tails have not shifted symmetrically: The right tails practically coincide, but the left tails show a greater downside risk for the red distribution.

[2] See also Cieslak et al (2021).

[3] See figure 4.D. in the FOMC projections material at www.federalreserve.gov. The diffusion index data was first published following the December 2020 FOMC meeting, with a history going back to October 2007. Each point in the diffusion uncertainty index represents the number of participants who responded that uncertainty relative to the average over the past 20-years is ``Higher'' minus the number who responded ``Lower,'' divided by the total number of participants.

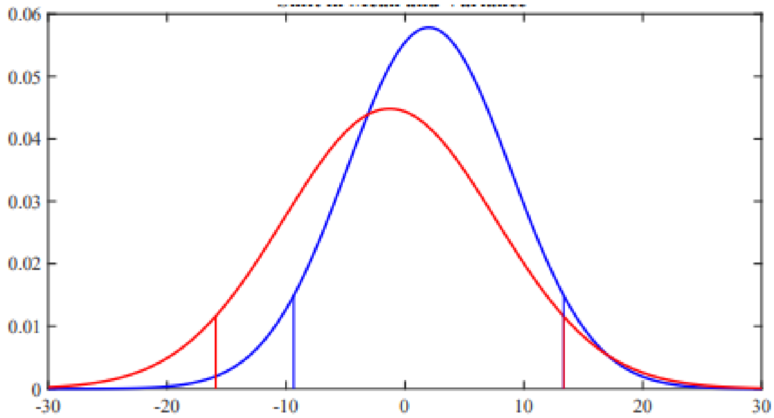
[4] See Figure 4.E. in the FOMC projection material at www.federalreserve.gov. For each SEP, participants provided responses to the question: "Please indicate your judgment of the risk weighting around your projections." Each point in the diffusion indexes represents the number of participants responding "Weighted to the Upside" minus the number responding "Weighted to the Downside," divided by the total number of participants.

[5] There are two main ways of measuring uncertainty: aggregate uncertainty (forecast error volatility of macroeconomic aggregates) and micro uncertainty (cross sectional dispersion in firm level outcomes).

[6] The simultaneous changes in mean and volatility are able to produce the asymmetric shift in uncertainty and tail risk.

Chart 1

Predictive distributions with a shift in mean and volatility

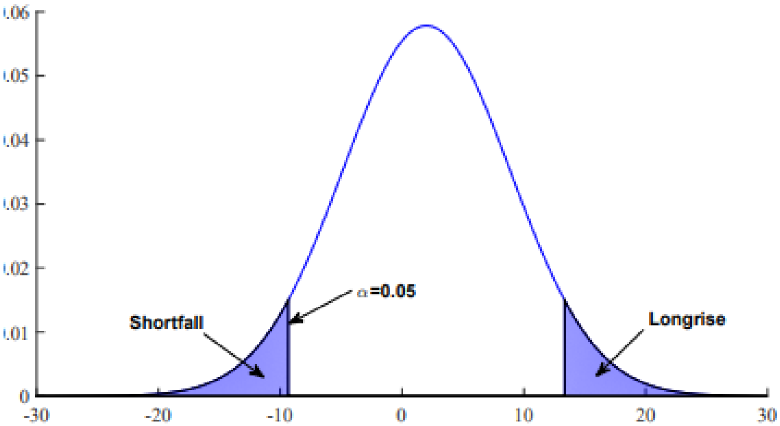


Sources: Author’s calculations.
Notes: The red line in the figure shows the distribution following a shift in mean and volatility from a univariate SV model that generates asymmetric movement in the distribution.

Chart 2

Shortfall and Longrise

(Percentage points)



Sources: Author’s calculations.
Notes: Shortfall and longrise at the 5 percent level.

The tails measure the probability of extreme good or bad events. In the case of the GDP distribution, the shortfall (longrise) measures the probability of low (high) growth. Shortfall and longrise are normally associated with a number, α in Chart 2, that defines the size of the tail (5 percent in our example). Looking back at Chart 1, the red distribution shows a higher downside risk, with the shortfall at about -16 versus -9 for the blue distribution.

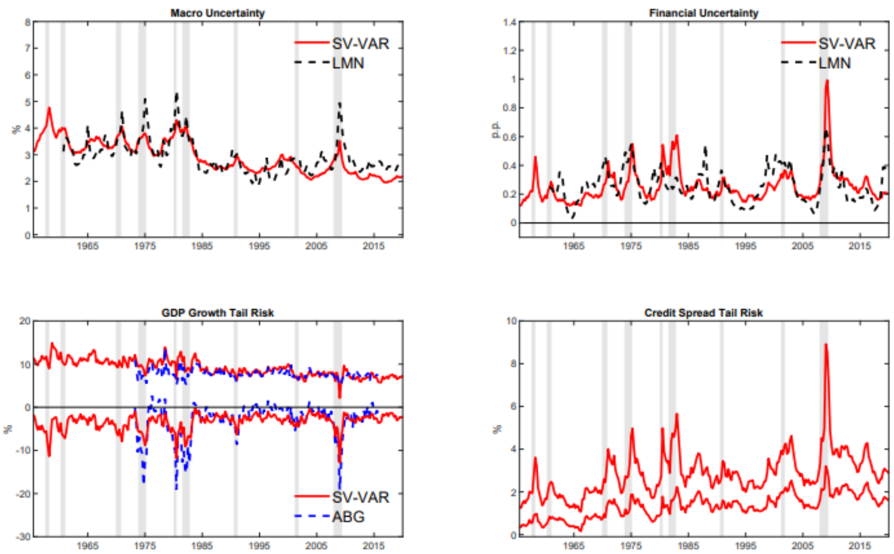
Uncertainty and risk measures from our model are reminiscent of indicators that have been developed in the literature on growth-at-risk and uncertainty, such as the GDP growth-at-risk from Adrian et al. (2019) and the macroeconomic and financial volatility indices as in Ludvingson et al. (2020). Chart 3 shows in red the one-quarter ahead GDP growth and spread uncertainty in the top row and the one-quarter ahead GDP growth and spread tail risk (shortfall and longrise) in the bottom row produced by the SV-VAR model.

Chart 3

Uncertainty and risk measures

Comparison with Adrian et al (2019) and Ludvigson et al (2021)

(Percentage points)



Sources: CSZ (2023)
Notes: The upper panels plot our estimates of one-quarter ahead GDP growth and spread uncertainty (solid red lines) and the quarterly average of the three-month ahead real and financial uncertainty measures from Ludvigson et al. (2021) (dashed black lines), standardized to have the same sample mean and standard deviation as our uncertainty series. The lower panels plot our estimates of one-quarter ahead (left panel) GDP growth tail risk (solid red lines) against estimates of GDP growth tail risk from Adrian et al. (2019). The right panel plots one-quarter ahead spread tail risk. Grey shaded areas are recession dates as defined by the National Bureau of Economic Research,

The measures of GDP growth and spread uncertainty are characterized by a clear pattern of cyclical variation. They spike during recessions and slowly ease afterward.[7] The second row shows GDP growth and spread shortfall and longrise. GDP growth shortfall is especially volatile in recessions, whereas GDP growth longrise is more stable. The GFC features large declines in the shortfall, but not unprecedentedly so relative to the historical record. Spread longrise also spikes during recessions, consistent with the spike in spread uncertainty. In contrast with the behaviour of GDP growth shortfall, the GFC has the largest spike in the spread

[7] This is consistent with the asymmetric effects on uncertainty of adverse versus good shocks. There are two main reasons for this behaviour. First, we model the volatility processes in logs, as is standard in the literature (Clark, 2011). Shocks that move log volatility symmetrically have asymmetric effects on uncertainty. Second, estimation uncertainty increases overall uncertainty no matter whether the shock is positive or negative. This channel amplifies the effects of adverse shocks that raise uncertainty while muting the effects of good shocks that lower it.

longrise, highlighting the important role that tight financial conditions played in the crisis.[8]

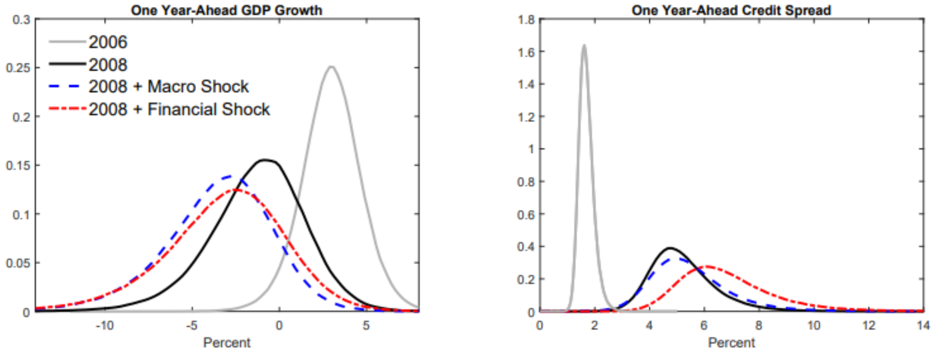
3 Lesson II: Financial shocks can have a relatively large impact

Chart 4 illustrates the main findings in CSZ (2023), plotting the distributions for one-year-ahead GDP growth and corporate credit spreads conditioned on data available at the end of 2008. The black solid lines show the baseline forecast, while the blue dashed and red dotted lines depict two counterfactual forecasts, which assume that at the beginning of 2009 the economy was hit by either a two-standard deviation macroeconomic or a two-standard deviation financial shock.

Chart 4

The impact of macro and financial shocks on conditional distributions

(Percentage points)



Sources: CSZ (2023)
Notes: The figure plots one year-ahead conditional distributions of average GDP growth and corporate credit spreads generated by our stochastic volatility VAR model. The grey distributions are computed conditioning on 2006:Q4 data, corresponding to a quarter of low volatility; the black distributions are computed conditioning on 2008:Q4 data, a quarter of high volatility. The blue (red) distributions are computed by running a counterfactual that adds to the baseline forecast in 2008:Q4 a two-standard deviation macro (financial) shock in 2009:Q1.

We emphasize two results. First, we find that adverse macroeconomic and financial shocks simultaneously move future GDP growth and corporate spreads. However, while macro and financial shocks can similarly impact the conditional distribution of average GDP growth, the financial shock primarily moves the conditional distribution of corporate credit spreads. While not shown in the figure, the financial shock plays a

[8] The dashed black lines in the figure show the macro and financial uncertainty series of Ludvigson et al. (2021), LMN henceforth, and the dashed blue lines show the GDP growth tail risk series of Adrian et al. (2019) for comparison. Despite the varying data and methodologies used, our measures of uncertainty and tail risk largely cohere with those in the literature. The correlation between macroeconomic uncertainty measures is about 0.8, and the two measures share major spikes. The correlation between the financial uncertainties is lower at 0.6. The measures share only some spikes---during the 1970s and during the GFC---while differing in the 1980s and 1990s. The difference, in part, reflects the choice of underlying financial variables. We use corporate credit spreads, while the LMN measure mostly loads on stock returns. As a result, for example, our spread volatility measure does not spike during the stock market crash of October 1987 while the LMN measure does. Turning to GDP growth tail risk, the correlation between shortfall measures is around 0.9 at the one-quarter horizon. The correlation for the longrise is lower, at 0.7 one quarter ahead, although the two models share some spikes.

dominant role at longer horizons, while the macro shock has its largest effect within one year.

Second, these shocks generate an increase in uncertainty and downside tail risk to future GDP growth and spreads, but only a small reduction in upside tail risk. This is visible in the counterfactual distributions, which are more dispersed than the baseline distributions and place higher probability around particularly bad outcomes relative to good outcomes. The differential response of downside and upside risk happens because in our model shocks that lower the mean forecast also raise uncertainty around the forecast, thus increasing the probability of adverse tail outcomes relative to positive outcomes.

4 Lesson III: Effects of shocks are stronger in periods of high volatility

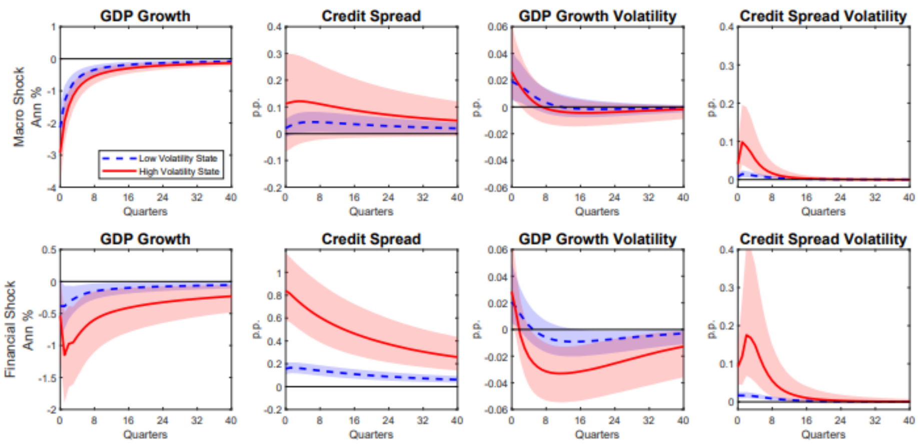
Chart 4 also shows that low volatility periods such as 2006 feature substantially lower uncertainty and risk about future outcomes than periods of high volatility.

A different way to understand the importance of high and low volatility is with the impulse responses to one-standard deviation adverse macro and financial shocks shown in Chart 5. The GDP growth responses show annualized average GDP growth between horizon *1* and *f*, where *f* denotes the forecast horizon. The spread responses are the average spreads in percentage points between horizon *1* and *f*. The blue dashed lines plot median responses conditioning on 2006:Q4 data, a quarter characterized by low volatility, while the red solid lines plot median responses conditioning on 2008:Q4 data, a quarter characterized by high volatility. The shaded areas are 80 percent credible sets reflecting uncertainty around volatility states and model parameters.

Chart 5

Impulse response functions in high and low volatility states

(Percentage points, annualized)



Sources: CSZ (2023)
Notes: The red (blue) lines in the top panel depict the median impulse responses to a one-standard deviation macro and financial shock conditioning on 2008:Q4 (2006:Q4), a quarter of high (low) volatility. Shaded areas denote 80 percent credible sets. The volatility responses of the reduced form innovations are in percentage points.

The effects of both shocks are larger during periods of high volatility, but the amplification generated by the high volatility state is stronger for financial shocks than for macro shocks. The GDP growth response to a financial shock is tripled after four quarters, while the spread response is quadrupled on impact.

5 Inflation at risk

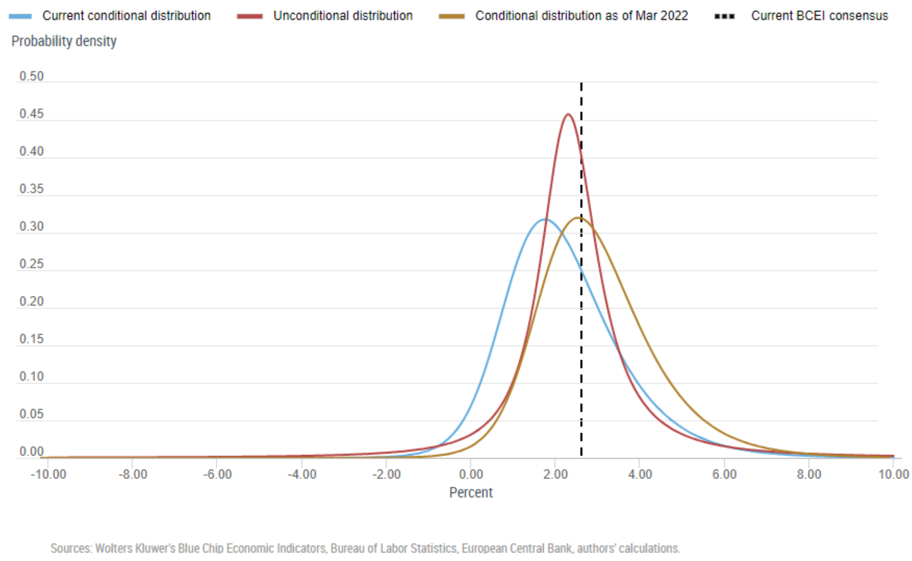
While I have so far focused on corporate credit spreads and GDP, there is a growing literature looking at inflation or employment at-risk (Adrian et al., 2019; Lopez-Salido and Loria, 2020; Kiley, 2021; Federal Reserve Bank of New York, 2023).

The Federal Reserve Bank of New York publishes updates of its “outlook-at-risk” covering GDP, unemployment, and inflation. Chart 6 shows the most recent update of CPI inflation at-risk. In particular, the chart shows predictive distributions of average CPI inflation over the next four quarters at different forecast dates. When comparing the predictive distribution of average CPI inflation one-year ahead computed in March 2022 at the beginning of the tightening cycle (in red) versus May 2023 (in blue), we see that the latter distribution is broadly symmetric around 2 percent, with modestly more risk of higher inflation than lower inflation. These updates can be useful tools to monitor the evolution of risks to the forecast on a continuous basis.[9]

[9] Updates are regularly posted at https://www.newyorkfed.org/research/policy/outlook-at-risk#root:overview.

Chart 6
Inflation at risk

(Percent)



Source: Federal Reserve Bank of New York.
Notes: The chart shows selected quantiles of the predicted distribution of average CPI inflation over the next four quarters (10th and 90th in blue, 25th and 75th in grey) at each forecast date, together with the median forecast (red) and, when available, the realized four-quarter-average CPI inflation (black).

6 What lessons for policymakers and forecasters in today's environment?

If these are the lessons from the past 15 years, how do we use them in today's world?

First, the banking stress that emerged in March has complicated the outlook and raised uncertainty. While the Fed has increased the federal funds rate range over the past 15 months with the intent of curbing inflation, additional credit tightening or a pullback in bank lending due to stresses in financial markets could generate additional uncertainty and downside risk to the economic outlook. Surveys of banks show that lending standards were already tightening before March—an expected consequence of the monetary policy tightening over 2022.

As of May, the tightening in lending conditions does not appear to have accelerated much and financial conditions have not tightened considerably. Through the lens of our empirical model, this implies that the financial shock emanating from the March bank failures should not dramatically shift the predictive distribution of future GDP growth, at least as of now. However, these models' conditional distributions depend on corporate spreads (or financial conditions indexes in the case of the outlook at risk), and there has recently been a disconnect between tightening credit standards (as measured by bank surveys) and corporate risk premia. Normally, the sharp increase in the lending standards index is associated with higher risk premia and, therefore, a deterioration in macroeconomic outcomes. However, the first link has been much more muted recently, calling into question the strength of the second link. Regardless, policymakers and forecasters need to be mindful of the impact that financial shocks could have on the macroeconomy, especially as it interacts with monetary policy goals.

Second, our results show a strong tie between the macroeconomy and the financial system. Shocks that generate on one side can propagate and amplify risks on the other side. In addition, the effects of both macro and financial shocks are greater in periods of high volatility, and the amplification generated by the high volatility state is stronger for financial shocks than for macro shocks, as shown in lesson III. Because financial shocks in a high volatility environment can notably amplify the impact on GDP growth and volatility, it is important to think of ways to limit financial market volatility.

While CSZ (2023) does not explicitly include monetary policy, the results appear to suggest that risks related to macro fundamentals could be addressed by changing the stance of monetary and fiscal policy, while risks originating in the financial sector could be more directly tackled with macroprudential tools. Good macroprudential policies that work ex-ante by limiting financial system vulnerabilities and liquidity tools that work ex-post by containing the impact of adverse financial shocks could make monetary policy easier to conduct.[10] To this end, it is important to recognize that such policies and tools hardly existed before the GFC but are now readily available for central banks to use.[11]

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[10] In linear models similar to the one used in CSZ, stochastic volatility would not matter for optimal policy under the conventional quadratic objective function, unless policy itself is the source of endogenous volatility (e.g. because of financial spill-overs). However, even in the case when there are financial spillovers induced by monetary policy, it is important to have macroprudential tools because else monetary policy should internalize these spillovers. With the right macroprudential tools, the only reason to change monetary policy in the wake of volatility changes (financial or macro) is if policymakers care directly about higher order moments of inflation or unemployment.

[11] There are situations in which the same tool could in principle be used for both financial and price stability. This occurred during the pandemic, when financial risks materialized in a way that did not create a trade-off between financial stability and monetary policy objectives. But there are situations in which financial stability and monetary policy tools should be separated. Let’s think at the past year, when central banks around the globe started sharply raising their policy rates, perhaps catching many by surprise with respect to the speed of the increase. The BOE announced a strictly time-limited and targeted backstop purchase facility in line with its statutory financial stability objective. It specified that it would carry out purchases of long-term UK sovereign bonds to restore market functioning and that these purchases would later be reversed in a timely but orderly manner via asset sales. The BOE was able to restore market functioning quickly through its interventions, while it also managed to start active asset sales from its monetary policy portfolio. Earlier this year, the Fed announced the bank term funding program (BTFP), through which we lend based on the collateral’s par value, even if rising interest rates have reduced its market value. The program effectively increased banks’ access to funding.

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