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Recent Developments in Financial Risk and the Real Economy

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Abstract

In this article, we review recent developments in macroeconomics and finance on the relationship between financial risk and the real economy. We focus on three specific topics: (*a*) the term structure of uncertainty, (*b*) time variation—specifically, the long-term decline—in the variance risk premium, and (*c*) time variation in conditional skewness. We also introduce two new data series: implied volatility from one-day options on grains for the period 1906–1936 and prices of cliquet options, which provide insurance against single-day crashes on the S&P 500. Both series give some context to the recent rise in trade in extremely short-dated options. Finally, we discuss new avenues for future research.

1. INTRODUCTION

Financial risk plays an important role in both macroeconomics and finance, with a large literature investigating both how it affects the macroeconomy and how it is priced in financial markets. This article surveys recent developments in asset pricing and macroeconomics that have implications about our understanding of the relationship between financial risk—by which we mean variation in volatility and skewness of asset prices and returns—and the real economy.

There are two main reasons why research in asset pricing plays a crucial role for this goal: First, while risk/uncertainty is a multifaceted concept (e.g., sector-specific uncertainty, uncertainty about inputs, uncertainty about prices, and so on), financial uncertainty is the one that is most easily and precisely measured at high frequency and for a variety of levels of aggregation, and because of this, it has most often been used as a proxy for uncertainty more generally.[1] Second, financial markets give direct insights into how people perceive risk that can help us better understand how it affects the economy: For example, in macrofinance models, a link exists between the effects of conditional volatility on macroeconomic aggregates (e.g., consumption) and the risk premium that investors require for bearing volatility risk.

Early research in this area of macroeconomics typically studied the relation between risk and the macroeconomy by relating, typically through a vector autoregression (VAR), one proxy for uncertainty (e.g., the VIX) to various macroeconomic outcomes; in finance, a corresponding literature studied the risk premium associated with the VIX itself, measuring how investors perceive the risk associated with short-term realized variance. The core of this review focuses on three new insights developed in the recent literature in this area:

1. **A focus on the term structure of volatility.** Volatility and uncertainty can differ markedly across horizons: In finance, it is well-known that investors may perceive long-term and short-term risks very differently; in macroeconomics, new research has also begun to distinguish their effects, often emphasizing the importance of financial frictions.
2. **Observed declines in the variance risk premium (VRP) and options premia more generally.** The VRP—the large (negative) compensation for exposure to variance, implying that investors are highly averse to high-volatility states—has long been viewed as a robust empirical regularity in the finance literature, with a range of models developed to understand it. More recent research, however, has begun to question whether this premium still exists, with papers arguing that it has fallen to nearly zero. One interpretation of these results is that the measured VRP may not have been due to investors' aversion to uncertainty and volatility, but instead it reflected the effects of intermediation frictions, which have changed over time.
3. **The recognition of variation in conditional skewness as a driving force in the economy.** While some evidence suggests that financial uncertainty might not have large real effects (and, consistent with this, that the risk premia associated with it have decreased dramatically), recent research has shown that measures of higher-order risk—skewness in particular—may be strongly associated with macroeconomic outcomes. Specifically, while there is a long history of studying unconditional skewness, more recent work has focused on changes in skewness over time. Understanding skewness, even more so than volatility, requires tackling nonlinearity in the economy.

[1] For a variety of other measures, some of which directly analyze macroeconomic uncertainty, see the recent review by Cascaldi-Garcia et al. (2023). In addition to the distinction between real and financial uncertainty, even within financial uncertainty, Chang, d'Avernas & Eisfeldt (2024) emphasize the difference between levered and unlevered uncertainty.

In addition, this article presents two new data series that are novel to the literature and may be of interest in future work. One gives measures of implied volatility during the period 1906–1936 and helps shed light on the historical cyclicality of risk. The second is the time series of prices for options that isolate one-day crash probabilities. Both are of potential interest additionally because they give historical context for the recent rise in trade in one-day (and even zero-day) options—single-day options were traded long before Robinhood.

After tackling these three points in Sections 2–4, we conclude with a discussion of important new avenues for research. As suggested by the above summary, one path is to understand better how financial intermediaries affect the transmission of risk between the financial and real sides of the economy. It is well-known that the link between GDP and measures of financial risk like the VIX is weak at best, but in some episodes, they move together extremely strongly. The question is: What drives the conditional variation in that relationship?

The second path is to better understand nonlinearity in both macroeconomics and finance. Countercyclical volatility is pervasive through both the real and financial sectors, but standard models usually do not have a channel through which it can arise. Capturing that feedback requires allowing nonlinearity. We discuss some recent work on that idea, along with promising avenues for future research, but view it as still very much open to new analyses.

2. THE TERM STRUCTURE OF FINANCIAL RISK

Risk is not the same at all horizons, and it changes dynamically over time; understanding the dynamics and maturities of risk is important both for asset pricing and for macroeconomics. Borovička & Hansen (2016), for example, provide a thorough review. Both macroeconomics and finance have recently started studying in greater depth the term structure of risk in the economy. We begin by thinking of risk as being measured by volatility (and subsequently move on to higher-order risk). When thinking about the dynamics of volatility and its pricing and real effects, it is useful to start by distinguishing realized volatility from uncertainty. They have often been used interchangeably in existing research, especially in macroeconomics, but they correspond to very different concepts with potentially very different real effects. Consider some economic variable, perhaps stock returns or GDP growth. Its reduced-form innovation, x_t, can be decomposed as

$$x_t = \sigma_{t-1}\varepsilon_t, \tag{1.}$$

where ε_t is some mean-zero unit standard deviation innovation and σ_{t-1} is the conditional volatility. We refer to realized volatility as the squared realization of the shock, $x_t^2 = \sigma_{t-1}^2\varepsilon_t^2$, a measure of the size of the realized shock. Realized volatility is, therefore, backward-looking—it describes how large the shocks were during period t.[2] We refer to uncertainty or risk at some horizon j as $\text{var}_t[x_{t+j}]$. That captures the forward-looking uncertainty about the future values of x_t.[3]

An immediate but key result that links the two is that

$$\text{var}_t\left[x_{t+j}\right] = E_t x_{t+j}^2.$$

That is, uncertainty is the same as the expectation of future realized volatility.

To see the distinction empirically, **Figure 1** plots monthly realized volatility for the S&P 500 against 30- and 365-day at-the-money implied volatility for S&P 500 options. While the series are

[2]In empirical work, realized volatility is often aggregated to lower frequencies, e.g., a month. In that case, it is typically computed as the sample realized volatility over that month, and again, it describes how large shocks were during that period.

[3]In a very similar analysis, Rossi, Sekhposyan & Soupre (2020) refer to the forward-looking uncertainty as the ex ante component and realized volatility as the ex post component.

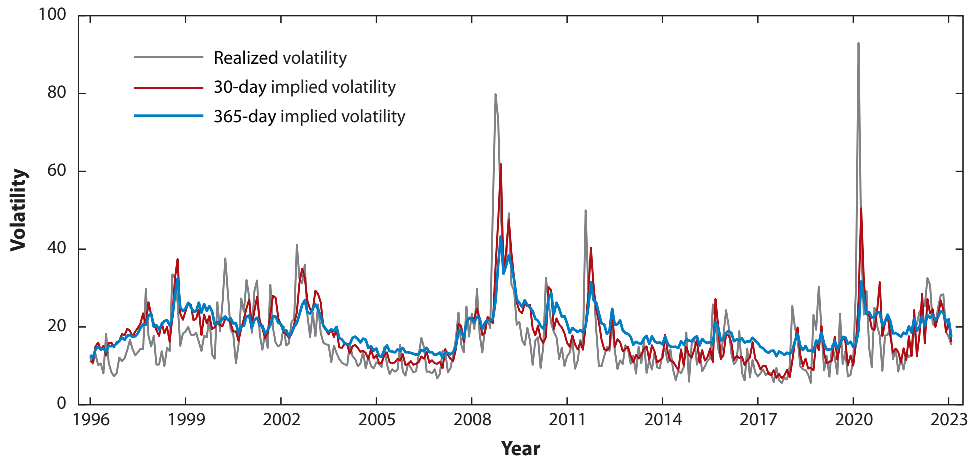

Figure 1

Realized and implied volatility. The figure plots monthly realized volatility (*gray*), together with 30-day (*red*) and 365-day (*blue*) at-the-money implied volatility for S&P 500 options. Data from Optionmetrics.

naturally strongly correlated, they also have significant independent variation. Their correlations are listed in **Table 1**.

The two implied volatilities are very strongly, though imperfectly, correlated, while realized volatility has significant independent variation from the two implied volatilities. It is therefore not surprising that the conclusions drawn from the various series might be different. Of course, all the above can also be extended to other moments—e.g., realized, short-run, and longer-run conditional skewness, which we study in Section 4. The remainder of this section reviews recent work on the term structure of uncertainty, in terms both of risk premia and effects on the macroeconomy.

2.1. Finance Literature

In this section, we review recent empirical and theoretical studies of volatility in the finance literature.

2.1.1. Empirical analyses. While the VRP has been studied since the 1990s, and work on the dynamics of volatility—implying a term structure—extends at least to the 1980s,[4] studies of how the VRP varies across the term structure only began to arise relatively recently. The work by

Table 1 Correlations between realized volatility (RV), 30-day implied volatility (IV), and 365-day IV

	RV	30-day IV	365-day IV
RV	1	–	–
30-day IV	0.70	1	–
365-day IV	0.61	0.93	1

[4]For more on the pricing of volatility, see Jackwerth & Rubinstein (1996); Coval & Shumway (2001); Bakshi & Kapadia (2003); Broadie, Chernov & Johannes (2009); and Carr & Wu (2009). For more on volatility dynamics, see Engle (1982) and many subsequent papers; volatility dynamics has been reviewed in several papers, such as Bollerslev, Engle & Nelson (1994) and Engle (2004).

Egloff, Leippold & Wu (2010) is perhaps the earliest contribution. They estimate a two-factor model of volatility dynamics and focus on portfolio choice, finding that premia are isolated at the short end of the term structure (see also, later, Feunou et al. 2014; Filipović, Gourier & Mancini 2016; Eraker & Wu 2017; Johnson 2017; Aït-Sahalia, Karaman & Mancini 2020). Choi, Mueller & Vedolin (2017) find a similar result for the term structure of bond variance risk premia.

Dew-Becker et al. (2017) study the term structure of volatility risk premia implied by variance swaps. The main innovation in that paper relative to the other related work on the term structure is distinguishing premia for shocks to realized volatility from shocks to implied future volatility (again, date-t shocks to x_t^2 versus to $E_t[x_{t+j}^2]$). Dew-Becker et al. (2017) find that only shocks to realized volatility carry a significant risk premium. Claims to forward volatility (that is, expectations of future volatility) carry no risk premium at all. In the context of **Figure 1** and correlations from the previous section, the results imply that it is the part of realized volatility that is uncorrelated with the two implied volatilities that investors have historically been averse to.

Dew-Becker et al. (2017) argue that that fact is difficult to reconcile with standard consumption-based asset pricing models (though they also present a disaster model that can fit the data). A potential alternative explanation is that segmentation in the derivatives market might cause the models that fit the variance term structure (and options markets) to differ from those that fit prices in other markets like equities. That idea is discussed in Section 3.2.

Dew-Becker, Giglio & Kelly (2021) extend Dew-Becker et al.'s (2017) results to show that large negative premia for shocks to realized volatility and small or insignificant premia for shocks to implied volatilities or uncertainty are pervasive across a number of other markets, including bonds, currencies, and commodities (see also Hollstein, Prokopczuk & Würsig 2020).

Johnson (2017) extends the results in Dew-Becker et al. (2017), looking at variation over time in variance risk premia (see also Cheng 2019; Andries, Eisenbach & Schmalz 2023). Time variation in the VRP is discussed further in Section 3.

2.1.2. Models. Numerous papers have developed models to fit the VRP at short maturities. However, because shocks to realized volatility (which is the payoff of the derivatives from which the VRP is computed) are correlated with uncertainty shocks (shocks to expected future volatility), the VRP could reflect investors' aversion to either of the two shocks. Therefore, the fact that a model successfully matches the VRP is no guarantee that the model correctly prices both realized volatility and uncertainty shocks. Only a few studies draw out the implications for the two types of shocks for the entire term structure of volatility risk, which allows separate identification of the two risk premia. As noted above, Dew-Becker et al. (2017) both compare their empirical results to predictions of earlier models (like those of Drechsler & Yaron 2011; Du 2011; Wachter 2013; Christoffersen, Du & Elkamhi 2017) and propose a disaster-based model that can fit the evidence. Eraker & Wu (2017) also present an equilibrium model to match the behavior of variance claims.

The literature has also developed models based on deviations from standard preference specifications to try to match the term structure of uncertainty risk premia. Babiak (2020) shows that a model in which agents have generalized disappointment aversion can fit the variance term structure. While they do not report detailed estimates, Andries, Eisenbach & Schmalz (2023) suggest that their model of horizon-dependent risk aversion would explain the variance term structure.

This work complements a much larger literature that tries to explain the empirical term structures of risk premia in the equity markets [documented starting from van Binsbergen, Brandt & Koijen (2012); van Binsbergen et al. (2013)], and of course, the vast literature on the term structure of bond yields.

2.2. Financial Uncertainty and the Macroeconomy

Financial market volatility has been widely used as proxy for uncertainty in macroeconomic models. The empirical evidence on the potential role of uncertainty in driving macroeconomic activity comes first of all from the observed negative correlation between measures of financial uncertainty (like the VIX) and macroeconomic downturns. Additional empirical evidence in the literature has come from trying to identify the causal effects of uncertainty shocks and the macroeconomy (mostly via VARs). In parallel with this empirical work, the theoretical literature has focused on understanding the potential mechanisms through which uncertainty could have real economic effects [a seminal paper in this literature is that by Bloom (2009)].

In this section, we highlight several recent advances in the empirical study of the relation between financial uncertainty and the macroeconomy. We focus on three main points: (*a*) We document novel historical evidence supporting the negative correlation between uncertainty and the business cycle; (*b*) we discuss the challenges to the identification of uncertainty shocks stemming from the endogeneity of uncertainty to macroeconomic shocks, and show how term structure information described in the previous section can be used for this purpose; and (*c*) we highlight the different cyclical properties of aggregate as opposed to idiosyncratic volatility, suggesting that they interact with economic activity through different mechanisms.

2.2.1. The correlation of financial uncertainty and the business cycle: new evidence from the early twentieth century. The most widely used measure of financial uncertainty is the VIX, which is computed from S&P 500 Index option prices and has been available since 1987, which is when monthly expirations for these options were introduced. Empirically, **Figure 2*b*** plots the VIX together with indicators of the National Bureau of Economic Research (NBER) recessions, showing the well-known countercyclicality of aggregate uncertainty.

That evidence is limited to a relatively short period of time, though, due to the available sample for the VIX. Several attempts have been made to extend the data before 1987. One approach that part of the literature has followed is to use realized volatility instead of the VIX for the time when the VIX is not available.[5] But as discussed above, measures of realized volatility are a poor proxy for forward-looking uncertainty, and the fact that uncertainty and realized volatility are priced differently in financial markets suggests that their relationship with the economy has important differences. Another approach is that of Manela & Moreira (2017), who extend the VIX back in time based on text from front-page articles in the *Wall Street Journal*.

Here, we provide novel evidence on historical uncertainty based on prices of options on grain futures from the early twentieth century. We essentially build an analogue to the VIX based on information from commodity markets—which were, at the time, of similar importance to the stock market now.

While options on stock market indexes were not traded before 1987, options on other macroeconomically important assets were traded in the early twentieth century. Among them, very short-term options on commodity futures—called privileges, bids, or offers—were traded at the Chicago Board of Trade (CBOT). Mehl (1934) and Lurie (1979) give extensive descriptions of the CBOT options market. To get a sense of magnitudes, aggregate dividends from stocks between 1925 and 1932 averaged $2.5 billion per year (NBER 2024a), while aggregate farm income (not

[5] For example, Bloom (2009) splices together the two series. Baker et al. (2021) examine the causes of large jumps since 1900 in the United States and, in more recent samples, in a range of other countries. Jumps are directly related to realized volatility but correlate with uncertainty via generalized auto regressive conditional heteroskedasticity (GARCH) effects, since jumps are typically followed by more volatility. See additional discussion of this in Section 2.2.2.

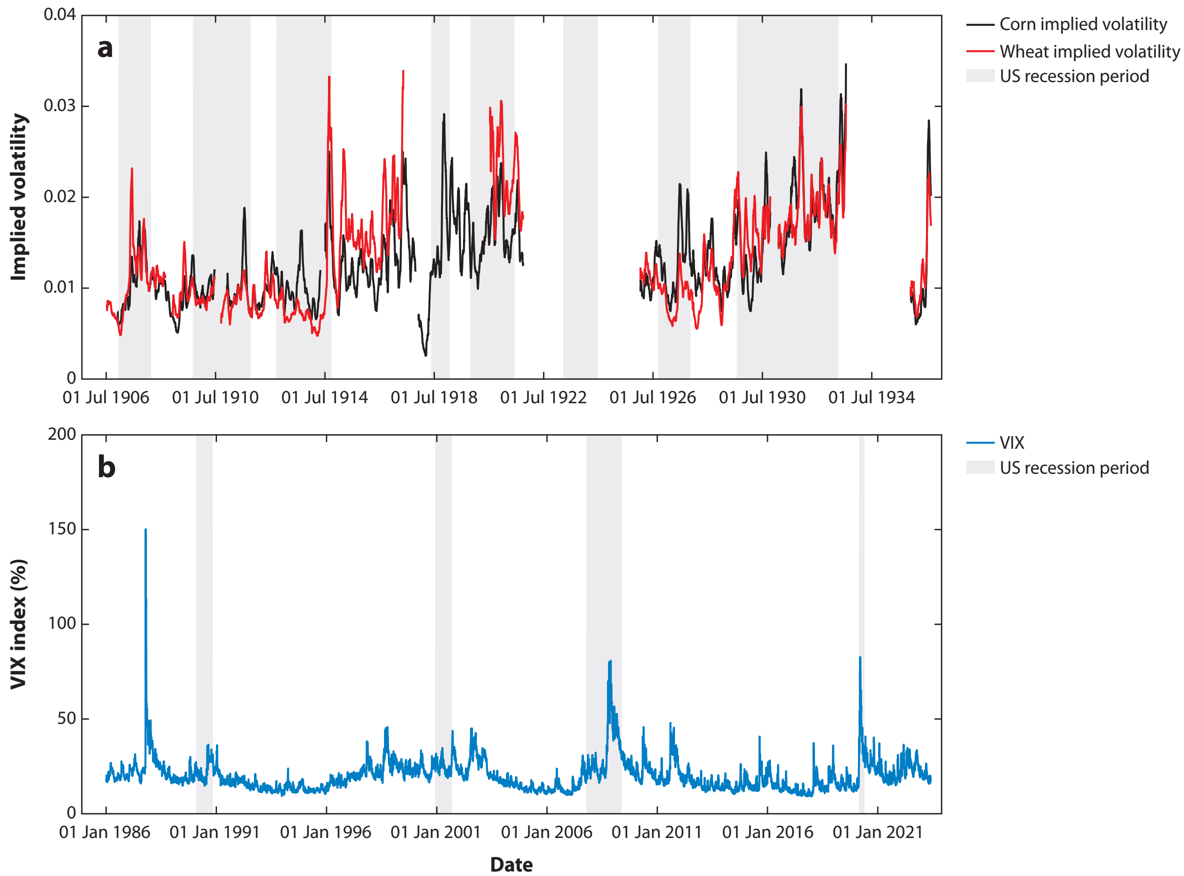

Figure 2

Financial uncertainty and recession. Panel *a* plots the implied volatility for corn and wheat over the period 1906–1936. Data are from the author's calculations based on data collected from the *Chicago Tribune*. Panel *b* plots the VIX for the period 1986–2023. VIX data are from the author's calculations based on data from Optionmetrics and the CME Group. The gray shaded areas are recessions in the United States as dated by the National Bureau of Economic Research.

including receipts of government payments) averaged \$8.6 billion (NBER 2024b). GDP between 1929 and 1933 averaged \$78 billion. Farm income was therefore approximately 11% of aggregate income in the period this data covers, compared to 5% for corporate dividends since 2013.

The CBOT options market structure was different from the current structure in two important ways. First, the options traded had maturities of either one day or one week, with the dailies being traded more consistently over time. So the recent rise of daily options is actually not unprecedented historically. Second, instead of the strike of an option being fixed, it was the price (or premium) that was fixed, at \$5 per 5,000 bushels (of wheat or corn), and what varied was the strike. On any given day, there was a put and a call available, each with the same price, and their strikes were then reported in newspapers along with futures prices.

We obtained data on privilege prices from scans of the *Chicago Tribune* over the period 1906–1936 (with some gaps when trading was not allowed). While data are available for both daily and weekly options, we focus just on dailies here for simplicity. **Figure 2*a*** plots implied volatilities for corn and wheat over the sample period and shows NBER-dated recessions, while as mentioned above, **Figure 2*b*** plots, for context, the VIX and recessions for the period 1986–2023. For each of these series, evidence shows that option-implied volatility is higher during recessions (with the statistical strength being weaker for the earlier sample).[6]

The series here are positively correlated, though somewhat weakly, with that of Manela & Moreira (2017). Corn and wheat implied volatilities have a correlation of 0.79 with each other in our sample and correlations of 0.22 and 0.17, respectively, with Manela & Moreira's (2017) News-Implied Volatility Index (NVIX).

One might ask why a person would ever want to trade extremely short-term options. Aren't they just gambling? The fact that we see them traded a century ago implies that single-day options are not just a phenomenon of online brokerages like Robinhood. Instead, there is a simple market-completeness explanation. It is well-known that the two key risks that cannot be spanned via dynamic trading are jumps and unspanned volatility. Bollerslev & Todorov (2011, 2014) show that at very short maturities, out-of-the-money option prices are driven by the distribution of jumps—intuitively, because at very short maturities diffusive risks are not large enough to create any probability of an out-of-the-money option paying off. So one-day options are useful for isolating jump risk, whereas longer maturity options mix that risk with diffusive risk—which can already be hedged via dynamic trading—and other higher-moment risks. In that sense, when trying to complete the market, short-maturity options may actually be most natural, consistent with their appearance long before modern equity options markets.[7]

The focus of this review is not economic history, so we do not take the analysis any further. The data in **Figure 2** are novel to the literature, though, and part of a broader data set that includes prices of futures and options from the CBOT over a 30-year period. They are now posted on our websites, along with documentation.[8]

2.2.2. Expected volatility and its macroeconomic effects. Going beyond simple correlations and trying to understand the causal effects of uncertainty on the macroeconomy requires thinking carefully about the dynamics of volatility, so that shocks to uncertainty can be measured and their causal effects identified. Early macroeconomic models often simplified the treatment of volatility—typically assuming that it follows a first-order autoregressive process [AR(1)]. In this case, news about volatility at all horizons are perfectly correlated and hence empirically indistinguishable. In addition, existing literature often ignored the distinction between realized volatility and future uncertainty that Dew-Becker et al. (2017) show is central to understanding risk premia.

Some early theoretical work (e.g., Hassler 1996) looks at how responses to uncertainty shocks might depend on their persistence, but little empirical analysis was initially done. More recently, a number of papers have looked at responses at different horizons, allowing a distinction of the real effects of realized and expected volatility. Finance has a long tradition of studying the dynamics of volatility in the context of volatility forecasting. That work goes back to early autoregressive conditional heteroskedasticity (ARCH) and GARCH studies (Engle 1982, Bollerslev 1986). More recently, for surveys, see Poon & Granger (2003) and Andersen et al. (2006); for studies of the ability of a broader array of variables to help forecast volatility, see Paye (2012) and Christiansen, Schmeling & Schrimpf (2012).

[6]Formally, the graphs plot the 1-month moving average of the implied volatility series. The point estimates are of higher volatility in recessions for all three series, with Newey-West t-statistics of 2.3 for corn, 0.7 for wheat, and 7.9 for the VIX.

[7]Note also that in modern markets, unspanned volatility, the other primary risk factor that cannot be hedged via dynamic trading, can now be hedged with VIX futures.

[8]See **dew-becker.org**.

Berger, Dew-Becker & Giglio (2020) focus not so much on the details of forecasting volatility but on understanding the distinction between realized and expected volatility in a macroeconomic setting. They use a standard VAR setup to understand the interaction of volatility and the macroeconomy, but with the innovation of treating an uncertainty shock as news about future volatility. This is closely related to the analysis above of the differential pricing of implied and realized volatility: Recall from above that uncertainty is fundamentally equivalent to expectations of future realized volatility. So, a shock to uncertainty is really news—it is a shock to $E_t x_{t+j}^2$. Berger, Dew-Becker & Giglio (2020) build on a large literature in macroeconomics on estimating the response of the economy to news shocks (see, e.g., Beaudry & Portier 2006; Barsky & Sims 2011; Barsky, Basu & Lee 2014) and apply these techniques to understanding the effects of news about future volatility onto the economy.

The key empirical finding of Berger, Dew-Becker & Giglio (2020) is that after controlling for realized volatility—thus, isolating the purely forward-looking component of uncertainty, as opposed to the part relating to shocks that have already been realized—uncertainty does not have a significant impact on the behavior of the economy. Interestingly, this result is consistent with those obtained in the finance literature and described in Section 2.1.1, in that uncertainty shocks, which appear not to have negative macroeconomic effects, also are not priced by investors in financial markets.

Importantly, this result is inconsistent with a number of other papers in the macroeconomics literature on the effects of uncertainty shocks, such as those by Bloom (2009), Basu & Bundick (2017), and Jurado, Ludvigson & Ng (2015). Similar to Berger, Dew-Becker & Giglio (2020), Ludvigson, Ma & Ng (2015) find an important role for feedback from the macroeconomy to uncertainty. The papers finding large effects of uncertainty typically shut off the reverse-causation channel, which can bias their results. Chang, d'Avernas & Eisfeldt (2024) provide evidence consistent with the importance of reverse causation from investment to uncertainty in the cross-section of firms. Rogers (2021) similarly emphasize biases that can arise both from ignoring reverse causation and also from constructing uncertainty forecasts from data that have a look-ahead bias.

Rossi, Sekhposyan & Soupre (2020) extend the results in Berger, Dew-Becker & Giglio (2020) studying various types of uncertainty. They refer to Berger, Dew-Becker & Giglio's (2020) expected and realized volatility as "ex ante" and "ex post" uncertainty and find, consistent with Berger, Dew-Becker & Giglio (2020), but across a wider range of variables and using somewhat different methods, that it is the ex post component that seems to drive the economy, as opposed to the ex ante uncertainty component.

2.2.3. Aggregate versus idiosyncratic uncertainty. Another important distinction that matters both empirically and theoretically is between aggregate and firm-level uncertainty. A recent paper focusing on the latter, and also emphasizing the importance of the term structure of volatility expectations in macro models, is that by Christiano, Motto & Rostagno (2014). Specifically, these authors take a standard New Keynesian business cycle model with financial frictions and allow for variation in firm-level risk over time. When firms face a broader distribution of shocks, they have a higher risk of bankruptcy, which essentially acts like a tax on capital due to bankruptcy costs. Increases in firm uncertainty can thus generate recessions in the model due to declines in investment demand. But Christiano, Motto & Rostagno (2014) also show that, in order to match the data, it is important to have not just contemporaneous shocks to firm risk but also news about variation in future firm risk.

Building on the work by Christiano, Motto & Rostagno (2014), Dew-Becker & Giglio (2023a) measure firm-level uncertainty based on implied volatility from options on individual stocks over the period 1980–2020 (that paper also gives a discussion of other related work in macroeconomics on cross-sectional uncertainty shocks). They find that in only some recessions—primarily 2008 and 2020—has firm-level uncertainty risen. Otherwise, it appears to be largely acyclical, and it was actually high during the late 1990s boom. From this point of view, firm-level uncertainty looks very different from aggregate uncertainty in the post-1980s sample but does resemble the early twentieth century data in that the relationship between uncertainty and the business cycle is somewhat weak and ambiguous overall.

2.2.4. Other related work. A number of other papers explore different aspects of the relation between term structures of uncertainty and the business cycle. Jurado, Ludvigson & Ng (2015) and Ludvigson, Ma & Ng (2021) construct uncertainty indexes capturing uncertainty at different horizons.[9] Their methods involve forward-looking data, though, making them difficult to use when trying to understand causation. Barrero, Bloom & Wright (2017) study how different types of investment respond to short- and long-run uncertainty, using firm-level option-implied volatilities as in Dew-Becker & Giglio (2023a). Other papers have exploited other identification schemes to identify the effects of uncertainty shocks and address the endogeneity of uncertainty to the state of the economy (see Bachmann, Elstner & Sims 2013; Cesa-Bianchi, Pesaran & Rebucci 2020; Rogers 2021; Alessandri, Gazzani & Vicondoa 2023).

Note that other concepts of financial risk are also connected to the macroeconomy, most importantly credit spreads. Gilchrist & Zakrajsek (2012), for example, find that a component of the credit spread has a strong relationship with future economic declines. Chang, d'Avernas & Eisfeldt (2024) attribute this result [along with its analog in the cross-section by Gilchrist, Sim & Zakrajsek (2014)] to credit spreads capturing debt overhang, as opposed to uncertainty, which they find is expansionary. The literature on structural credit risk also studies the relationship between uncertainty and credit spreads; for a recent analysis, see Du, Elkamhi & Ericsson (2019), and for an earlier analysis, see Campbell & Taksler (2003), among many others.

3. THE DECLINE IN THE VARIANCE RISK PREMIUM

Most of the existing literature on the pricing of realized volatility and uncertainty has focused on estimating—and explaining with theoretical models—the unconditional risk premia associated with them (starting with Fleming 1998, Coval & Shumway 2001, Bakshi & Kapadia 2003). Studying conditional moments is relatively harder in these markets given the short time series available. Recent work, however, explores the time variation in the VRP and asks which theoretical models can explain the observed patterns.

3.1. Business-Cycle and High-Frequency Variation in the Variance Risk Premium

Two approaches have been taken in the literature to explore time variation in the VRP. The first is based on reduced-form predictive regressions of returns to variance-related derivatives (option portfolios, variance swaps) using a variety of predictors. A second approach estimates no-arbitrage models, which model directly the pricing kernel and its dynamics as a function of observable variables or latent factors; the time variation in the VRP in these models arises from changes in the quantity and/or price of volatility risk. Among these papers, Todorov (2010) shows how the VRP is higher following jumps in the market. Corradi, Distaso & Mele (2013) use a no-arbitrage model to document variation in the VRP with macroeconomic factors. Barras & Malkhozov (2016) document that the VRP depends on volatility itself, various financial and macroeconomic indicators,

[9]See also Binder, McElroy & Sheng (2022); Clark, Ganics & Mertens (2022).

and the financial health of intermediaries. Finally, Johnson (2017) shows that the slope of the term structure of the VIX predicts variation in the VRP.

A subset of papers in this literature specifically exploits information in the term structure of variance derivatives to estimate its physical and risk-neutral dynamics; implicitly or explicitly, these models also have implications about the dynamics of the conditional VRP (see Egloff, Leippold & Wu 2010; Feunou et al. 2014; Filipović, Gourier & Mancini 2016; Dew-Becker et al. 2017; Aït-Sahalia, Karaman & Mancini 2020).

3.2. Longer-Term Trends in the Variance Risk Premium

Dew-Becker & Giglio (2023b) point out that beyond the higher-frequency variation in the VRP discussed so far, there also appear to be longer-term trends likely due to changes in the markets where variance risks are traded. The starting point of their analysis is that the VRP can be studied, rather than in options markets, by using synthetic options, which are dynamic portfolios of the underlying asset that replicate the payoff of the option (Black & Scholes 1973, Merton 1973). While replication is always imperfect in practice, it works surprisingly well, with an R^2 for options of more than 85% at a monthly maturity using daily rebalancing. Dew-Becker & Giglio (2023b) apply the replication to the CRSP total market return since 1926 and study the long-term trends in the premium associated with synthetic options, comparing it with trends in the option-based VRP over the last decades.

The focus of the paper is on the alpha of options and synthetic options (as in Heston, Jacobs & Kim 2023; Coval & Shumway 2001, and many others) in order to control for the leverage effect, the fact that innovations in S&P 500 volatility are very strongly negatively correlated with S&P 500 returns and hence have a large negative beta. Obviously, vanilla options do not give direct exposure to variance risk. However, since their payoffs are convex functions of the market return, they have volatility exposure—higher ex post volatility is generally associated with higher option returns, which is also easy to confirm with the synthetic options.

Dew-Becker & Giglio (2023b) obtain two main results. First, the alpha of synthetic options was never significantly negative at any time since 1926: The market downturns and high-volatility states hedged by synthetic options were priced essentially in line with the capital asset pricing model (CAPM) for the last century. Second, they replicate the negative alpha of traded options since 1987 that earlier literature has found, but they also show that this premium has trended down significantly in the last two decades. In addition, other measures of the VRP, such as the gap between the VIX and realized volatility, have also trended to or even passed across zero.

These patterns are clearly visible in **Figure 3*a***, which replicates results in Dew-Becker & Giglio (2023b), showing cumulative CAPM alphas from traded and synthetic put options. The cumulative alphas for traded options show a clear flattening around 2010. Bates (2022) finds generally similar results (though with different methods). As noted by Heston & Todorov (2023) (who find zero alpha for S&P 500 variance since 2006), the market crash associated with COVID-19 in March 2020 has a major impact on the overall mean returns, but the cumulative returns reveal that, even before COVID-19, the premium had flattened out substantially compared to what was observed previously. Naturally, given the data in **Figure 3**, studies that use more recent data samples will tend to find weaker evidence of a VRP—Heston & Todorov (2023) and Heston, Jacobs & Kim (2023) being two recent examples.

Figure 3*b* plots rolling 10-year information ratios for traded options and various other investments exposed to the VRP–delta-hedged puts, delta-hedged straddles, and RV minus the VIX. In all four cases, the premium is trended significantly toward zero, and in many cases has now switched signs.

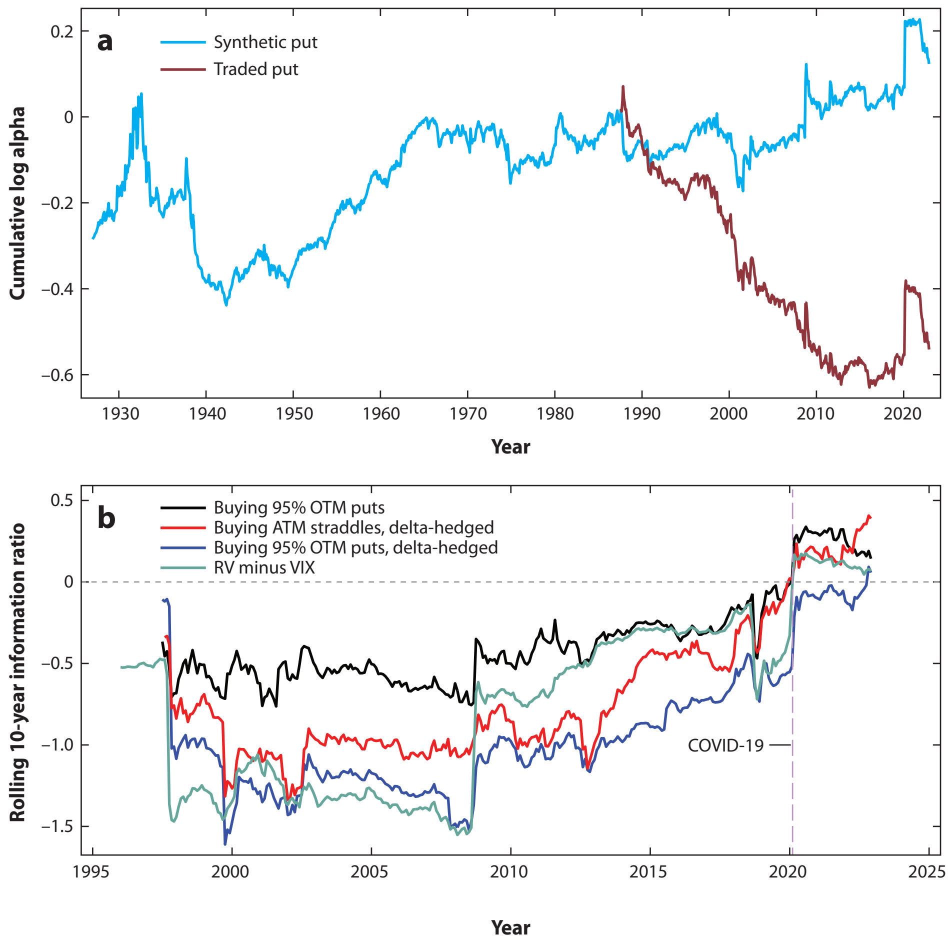

Figure 3

Cumulative CAPM alphas from put options. Panel *a* plots cumulative CAPM alphas from traded (*brown*) and synthetic (*blue*) put options since 1926. Panel *b* plots 10-year rolling information ratios for 95% OTM puts (*black*), delta-hedged ATM straddles (*red*), delta-hedged 95% OTM puts (*blue*), and RV minus VIX (*green*). Abbreviations: ATM, at-the-money; CAPM, capital asset pricing model; OTM, out-of-the-money; RV, realized volatility. Data from Optionmetrics.

3.3. Models

Consumption-based asset pricing models have strong implications for the VRP and option prices more generally, and several specifically target their moments. While a number of mechanisms can explain the unconditional VRP [e.g., correlation of realized variance with long-run shocks in Drechsler & Yaron (2011) or disaster-risk exposure as in Seo & Wachter (2019)], matching the time variation in the VRP documented in the data is harder. The empirical studies reviewed above show that conditional risk premia depend in a rich way on financial variables, macroeconomic conditions, as well as intermediation frictions, and these relations are hard to match for typically stylized models, though some models can match some of them. For example, the VRP varies with the aggregate jump intensity in Drechsler & Yaron (2011), with the skewness of consumption shocks in the habit formation model of Bekaert & Engstrom (2017), with beliefs about the dynamics of volatility (Lochstoer & Muir 2022), and with cyclical changes in hedging demand in Cheng (2019).

Longer-term trends like the secular decline in the VRP documented by Dew-Becker & Giglio (2023b) are even harder to generate for structural models simply because such models are typically stationary by construction. Dew-Becker & Giglio (2023b) propose, consistent with the demand-driven work of Garleanu, Pedersen & Poteshman (2008), Cheng (2019), Constantinides & Lian (2021), and others, that shifts in the VRP and on option returns more generally might be driven by changes in the cost intermediaries face when hedging options exposure. The basic economic mechanism comes from a long line of work (see Bates 2003) and operates as follows [in that article, it is derived as an extension of Garleanu, Pedersen & Poteshman (2008)]. The market for options sees the participation of some retail investors who want to buy S&P 500 options, even at relatively high prices. Due to preferences or constraints, that demand is not satisfied by other retail investors but rather by a relatively small number of intermediaries. Those intermediaries then charge a premium for bearing the risk associated with being short options, causing the options to be overpriced, consistent with the data. This explains the large negative CAPM alpha in traded options and hence the VRP. At the same time, the average equity investor does not have particularly strong aversion to market downturns and has no preference for buying (overpriced) options; this average investor's preferences are reflected in the market price and, therefore, indirectly in the premia associated with synthetic options. As reported above, synthetic options are priced consistently with the CAPM.

In this model, therefore, the discrepancy between the zero alpha of synthetic options and the large negative alpha of traded options is due to intermediation frictions and demand pressures in the options market. The model has one important additional prediction: The degree of overpricing of traded options should be related to the costs and risks to the intermediaries of holding the short options positions. Those costs and risks, in standard models (e.g., Garleanu, Pedersen & Poteshman 2008), depend on the cost of trading and the degree to which the returns on options can be replicated by dynamically trading futures. Past work has provided evidence on the importance of these hedging costs empirically.[10] Dew-Becker & Giglio (2023b) show that the downward trend in the traded-option premium lines up well with the decline in these hedging costs of intermediaries as measured by bid-ask spreads and basis risk in the futures market.

In addition to those factors, over time the demand asymmetry that must be borne by dealers alone may have also shrunk. It is well-known that hedge fund investment strategies produce returns that are very similar to a short options position (Jurek & Stafford 2015). As the hedge fund sector has grown over time, then, there is effectively an increased supply of option-like exposures, which offsets the retail demand. Similarly, the rise of exchange-traded products (ETPs) giving exposure to the VIX (such as short-volatility ETPs) also provides a source of supply of these exposures. Overall, then, a range of factors have trended over time toward shrinkage of the VRP, as observed empirically.

4. THE IMPORTANCE OF SKEWNESS

Skewness—typically negative skewness—is pervasive in returns on financial assets, and so finance has a long history of studying it. Negative skewness is also pervasive in the macroeconomy, though it gets somewhat less attention. Both the finance and macroeconomic literatures have made significant advances in measuring and modeling skewness, aimed at understanding skewness both as

[10]See also Jackwerth (2000), Bollen & Whaley (2004), Han (2008), Jurek & Stafford (2015), and Frazzini & Pedersen (2022).

a source of risk and fluctuations and as an endogenous variable that depends on the state of the economy. Interestingly, the macroeconomic and finance models interact on both of those topics. In terms of causation, finance gives a way of measuring conditional skewness—again, using option prices—that can be used to evaluate whether it is a driver of the business cycle. And in terms of the source of skewness, macroeconomic models provide new tools that help to model its dependence on other variables. We review these recent advances separately in finance and in macroeconomics.

4.1. Recent Work on Skewness in Finance

There are two main channels through which skewness in returns can arise: jump/tail risk and stochastic volatility (with volatility increasing when returns are more negative). The two are theoretically distinct concepts in a continuous-time setting, though in discrete time they cannot be fully distinguished from each other (because the part that is originated from within-period variation is not observable). A large literature in asset pricing has proposed measurement and models of jumps and tail risk, as well as stochastic volatility, in equity and option markets. This literature has been extensively reviewed (e.g., Aït-Sahalia & Hansen 2010; Embrechts, Klüppelberg & Mikosch 1997). Another strand of the literature has focused on forecasting various moments, including skewness, and again it has been reviewed extensively (see, e.g., Christoffersen, Jacobs & Chang 2013).

There have been a number of improvements in measurement of both realized and implied skewness, tail risk, and volatility asymmetry over the past decade. Some papers have focused directly on the measurement and pricing of realized skewness; most notably, Neuberger (2012) shows how measurement of realized skewness can be improved relative to just using the sample third moment, and Amaya et al. (2015) study the pricing of realized skewness in equity markets.

Other studies have separately focused on the two potential sources of skewness: asymmetric volatility and tail risk. Starting from the former (i.e., the idea that volatility is higher in bad compared to good times), the asset pricing literature has made some progress incorporating it in standard consumption models. For example, Segal, Shaliastovich & Yaron (2015) study a version of the long-run risk model of Bansal & Yaron (2004) that allows for differential upside and downside volatility, and Bekaert & Engstrom (2017) allow for differential upside and downside volatility in a model with external habit formation. Several studies have focused on the econometric properties of upward and downward volatility, like those by Bekaert, Engstrom & Ermolov (2015), Patton & Sheppard (2015), and Baruník, Kočenda & Vácha (2016) (see also the recent review by Bollerslev 2022). Pricing in equity markets has been studied, among others, by Bollerslev, Li & Zhao (2020), and pricing in option markets (decomposing the VRP into an upward component and a downward component) has been explored by Feunou, Jahan-Parvar & Okou (2018) and Kilic & Shaliastovich (2019) (see also Muravyev & Ni 2020).

A second possible source of skewness is price jumps. Whereas an earlier literature in asset pricing focused on very large but rare tail events [e.g., as a consequence of economic disasters, as in Rietz (1988); Barro (2006); Martin (2013)], the recent literature has focused on smaller but more frequent jumps that appear to be more aligned with observed return behavior (see the discussion by Backus, Chernov & Martin 2011). The most important innovation in measuring and studying the pricing of tail risks has come from exploiting information in high-frequency data and options, especially short-dated ones (see Bollerslev & Todorov 2011, 2014; Andersen, Fusari & Todorov 2015; Bollerslev, Todorov & Xu 2015). In general, option markets are especially informative about skewness and its pricing because of the asymmetric nature of option payoffs. One point to keep in mind, which parallels the distinction between realized variance and uncertainty from above, is that given a certain maturity (say, a month), option prices do not allow researchers to distinguish across the different sources of skewness in returns (volatility asymmetry and jumps occurring within the month). That said, just like studying the term structure of options can help disentangle the pricing of realized variance and that of uncertainty risk, looking at options with different maturities can help disentangle jump risk from asymmetric volatility risk. In particular, as the time to maturity shrinks to zero, out-of-the-money option prices will be especially informative about the jump risk.

4.2. Tail Risk Expectations from Cliquet Options

Plain-vanilla equity options provide protection against a drop in the underlying price of a certain size over a fixed horizon. That drop can come cumulatively over the course of many days or via a single large decline. As discussed above, we might be interested in separating the two and understand the relative pricing. Here, we introduce some novel evidence from a derivative, the cliquet option, whose payoff relates directly to a single large drop in the underlying price.

Specifically, we obtained data from a participant in the interdealer broker market on crash cliquets on the S&P 500. While we have a few different specifications available, the best data appear to be for put spreads that protect against a 10–20% decline in the index in a day. That is, their payout on a given day t is

$$X_t^{cliquet} = \max\left\{-10\% - r_{s\&p500,t}, 0\right\} - \max\left\{-20\% - r_{s\&p500,t}, 0\right\}. \qquad 2.$$

So, if in a day t the return of the S&P 500 is above -10%, the payoff is zero. It provides linear protection up to -20% (again, of the return in that day) and then pays no more for declines larger than 20%. The cliquet options in our data set have 6-month maturity and are knockout options. That means that the cliquet will pay the payoff $X_t^{cliquet}$ every day until $X_t^{cliquet} > 0$ (i.e., the option is triggered), and then the contract terminates. The price of the option therefore technically reflects the risk-neutral expectation of the first jump over the next 6 months. Assuming that a single-day decline of more than 10% happening twice in a given 6-month period is vanishingly unlikely (which might actually be too strong, but we can assume it just for simplicity), the price of the cliquets we are studying will be the risk-neutral expectation of $X_t^{cliquet}$ conditional on a drop of at least 10%, multiplied by the risk-neutral probability of such an event.

Figure 4 plots prices of the cliquets between August 2013 and December 2016 against (panel *a*) the VIX and (panel *b*) a measure of left-tail probability [probability of a 10% drop in the S&P 500 over the next week under the risk-neutral probability (Bollerslev, Todorov & Xu 2015)]. Panel *c* shows cliquets on the Europe STOXX Index against the VSTOXX (the analogues of VIX for the STOXX Index).

All three panels in **Figure 4** show high correlation between the series for most of the period. **Figure 4*a*,*c*** suggest that a very large part of the variation in the implied volatility indexes is due to jump risk. **Figure 4*b*** indicates that the (risk-neutral) expectation of jumps over the following 6 months is also highly correlated with the short-term (1-week) jump risk estimated using short-maturity options.

These contracts provide a novel and interesting measure of financial risk. While our sample is short, future work that expands the series to a longer time period can use these data to study the market's perceptions on the quantity and prices of tail risk in financial markets.

4.3. Time-Varying Skewness in Macroeconomics

Skewness, for both aggregate time series and in the cross-section, has received growing attention in macroeconomics. As in finance, there is a relatively long literature trying to understand unconditional skewness (e.g., Sichel 1993), but the literature on time variation in skewness is relatively more recent and active. This section first reviews recent empirical advances and then describes some theoretical work on the topic.

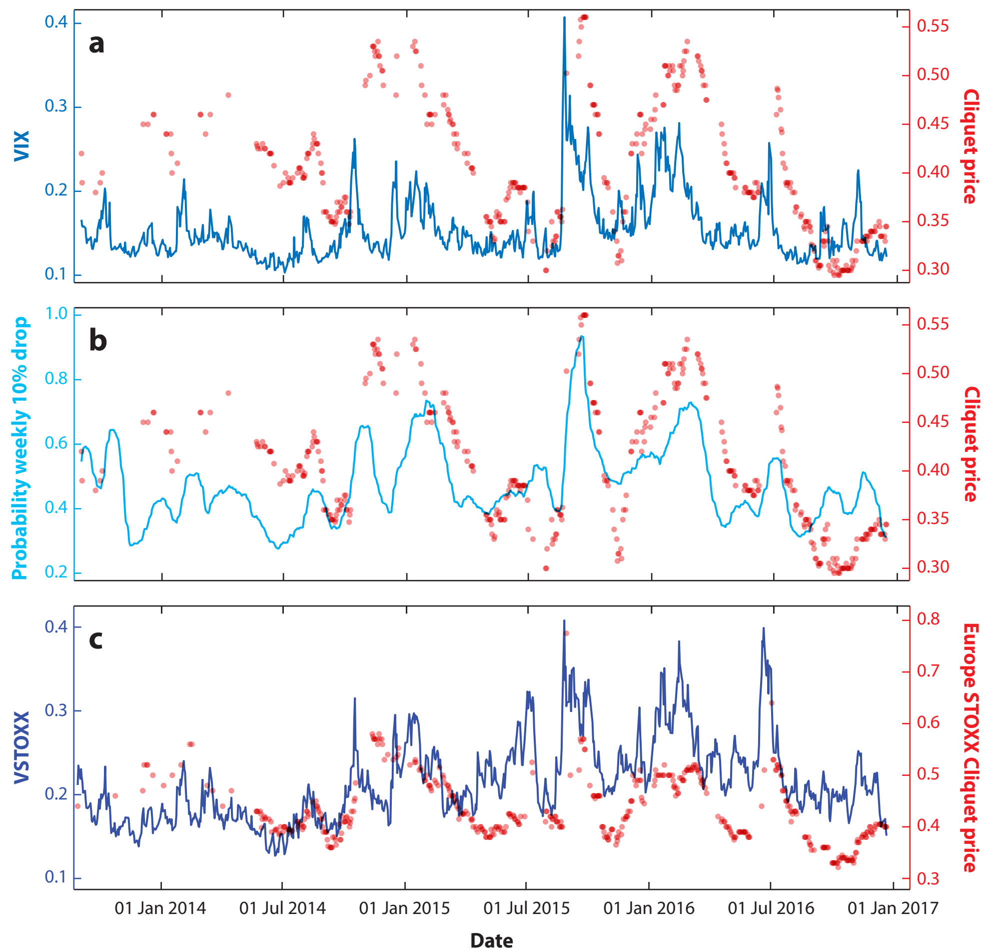

Figure 4

Plots of the cliquet price between August 2013 and December 2016 (*a*) against the VIX, (*b*) against a measure of left-tail probability, and (*c*) on the Europe STOXX against the VSTOXX. Inter-dealer broker market data obtained by the authors.

4.3.1. Measurement. At the micro level, Guvenen, Ozkan & Song (2014) and Guvenen et al. (2021) study income data from the US Social Security Administration and find significant procyclicality in cross-sectional skewness in individual income growth [Schmidt (2022) links this risk back to asset prices]. Salgado, Guvenen & Bloom (2019) show that a wide range of economic variables are not just skewed but that the skewness varies procyclically: Skewness is more negative in bad times.

Dew-Becker (2022) studies the link between financial measures of skewness, like those discussed in the previous section, and the macroeconomy. Consistent with the work on labor income, he finds that option-implied skewness for individual firms—measuring idiosyncratic risk—is significantly procyclical, becoming clearly more negative in recessions. In contrast, though, option-implied skewness for the S&P 500—measuring aggregate risk—is actually countercyclical: It becomes less negative during recessions. That is true even though overall volatility seems to rise. One simple intuition is that, in bad times, the Gaussian risks become relatively larger, while non-Gaussian jump risks do not grow by as much, with the overall result that asymmetry in the shape of the option-implied distribution shrinks toward zero. Gormsen & Jensen (2022) show that countercyclical skewness holds more generally across a sample of stock markets in 17 different countries.

In contrast to Dew-Becker (2022), and more in line with the micro skewness evidence, Iseringhausen, Petrella & Theodoridis (2023) study conditional skewness in the macroeconomy based on the McCracken & Ng (2016) panel data set of macro indicators. They find much stronger evidence for procyclicality in skewness. Their findings again highlight that financial markets and the macroeconomy are in general relatively weakly linked. While financial risk—whether measured by volatility or skewness—is in some recessions and by some measures higher, the link is very much mixed. As we discuss below, understanding when macroeconomic and financial risks are linked and when they are not is an important area of work moving forward.

4.3.2. Models. Salgado, Guvenen & Bloom (2019) present a model in which time-varying skewness is an exogenous driver of the business cycle. Kozlowski, Veldkamp & Venkateswaran (2020) try to understand where agents' beliefs about conditional skewness come from. They develop a model in which agents learn about the distribution of shocks over time, with their conditional distributions varying as they learn. After a particularly negative shock, agents will believe such shocks to be more likely going forward, which naturally means that skewness becomes more negative following bad shocks and, hence, during bad times. Orlik & Veldkamp (2022) make a similar point in the context of countercyclical uncertainty.[11]

Ilut, Kehrig & Schneider (2018) study a model in which firms respond to shocks in a concave manner. They give conditions under which such concave responses can lead to procyclical skewness. The paper is not meant to endogenize those concave responses but rather to show their consequences.

Dew-Becker & Vedolin (2021) endogenize that concavity. They study a production network in which sectors produce output from inputs purchased from other sectors. The sector production functions display complementarity across inputs, causing them to respond in a concave manner to shocks. The effect of concavity is that when shocks are more dispersed or skewed to the left, aggregate output is lower. This is in many ways highly similar to the work by Ilut, Kehrig & Schneider (2018), except with an endogenous mechanism for concave responses to shocks that relies on the network structure of the economy. Additionally, though, the concavity is not part of a given firm or sector's decision function. Rather, it arises out of interactions across economic units. Dew-Becker & Vedolin (2021) emphasize that those interactions are critical for matching the empirical fact that skewness is much more negative at the aggregate than at the firm level. Finally, Jovanovic & Ma (2022) develop a model in which uncertainty and skewness vary together endogenously due to the adoption of new technologies.

5. CONCLUSIONS AND AVENUES FOR FUTURE RESEARCH

The last decade has seen many advances in understanding the relationship between financial uncertainty and the real economy. This review highlights progress in three specific areas: the term structure of uncertainty (both its pricing and the relation with the macroeconomy); variation of the VRP over time, both at high frequency and in its longer-term trends; and the dynamics of conditional skewness.

[11]Earlier work, such as Chalkley & Lee (1998), Veldkamp (2005), and Fajgelbaum, Schaal & Taschereau-Dumouchel (2017), also study skewness via learning but more in order to get unconditional rather than conditional skewness.

The review suggests a number of avenues for future research. First, as to volatility and the business cycle, the relationship is clearly mixed. While some recessions are associated with very high aggregate and cross-sectional uncertainty, others are not. Why? Does the comovement depend on observable state variables? As an example, Chang, d'Avernas & Eisfeldt (2024) suggest that the comovement might be mediated by average distance to default—when it is high, uncertainty is positively related to investment, but when it is low, that effect is overcome by debt overhang, which reverses the relationship (they provide cross-sectional evidence supporting this view).

Second, as to the term structure, there are clearly different shocks to conditional moments at different horizons. Realized volatility, which is either contemporaneous or even backward-looking, is most strongly associated with recessions and most strongly priced. In addition, much of the trade in derivatives markets has shifted to very short maturities, emphasizing their importance. What makes these highly transitory shocks more important than more persistent shocks?

Third, all of the results here are fundamentally about nonlinear processes. These are not simple autoregressive moving average models. Volatility changes over time, both in the aggregate and the cross-section, and does so (sometimes) cyclically. That time variation can itself be a source of unconditional skewness, and additionally evidence has been found of variation in conditional skewness in the economy. The vast majority of research is about linear or linearized models, but understanding the data discussed in this review—which represents a major aspect of the business cycle itself—fundamentally requires a nonlinear approach. While work on nonlinear models has been done, very little of it has made its way into the canonical models analyzed in the literature and for policy. Being able to tractably incorporate nonlinearity and in a way that captures the most important features would make a valuable contribution.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

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