What is Certain about Uncertainty?*

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Abstract

This paper provides a comprehensive survey of existing measures of uncertainty, risk, and volatility, noting their conceptual distinctions. It summarizes how they are constructed, their relative advantages in usage, and their effects on financial market and economic outcomes. The measures are divided into four categories based on the construction methodology: news-based, survey-based, econometric-based, and market-based measures. While heightened uncertainty is typically associated with negative real and financial outcomes, the magnitude of these effects and the interpretation of transmission channels crucially depend on identification considerations.

Keywords: global risk, uncertainty, volatility, crises, economic policy, monetary policy, downside risk, transmission.

JEL codes: E6, G1, G15

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1 Introduction

The past decade has highlighted the challenges faced by households and businesses grappling with uncertainty about, among other issues, future economic growth, inflation, and economic policies. Policymakers consistently reference their own uncertainty stemming from a resurgence of global risks over trade and geopolitical tensions, as well as newer sources of risk such as global climate and health events.\(^1\) Although it is generally accepted that uncertainties and risks affect the way households and businesses make decisions, uncertainty is not directly observable. Researchers have used a variety of approaches to quantify uncertainty, identify shocks to uncertainty, and estimate the transmission effects of uncertainty. As we elaborate upon below, the choices made by researchers on these dimensions are important for understanding and interpreting the mechanisms by which risk and uncertainty arise and propagate through the economy.

In this review article, we summarize a broad set of measures that have been proposed in the literature to characterize uncertainty, risk, and volatility. The existing measures differ along multiple dimensions, including the object over which the uncertainty applies, construction methodology, and frequency, as well as the horizon over which risk, uncertainty or volatility is relevant and the availability (or not) in real time. We divide the measures into four broad categories depending on the methodology used, namely, text-based, survey-based, econometric-based, and market-based measures. These measures are summarized by category in Table 1.\(^2\)

**Newspaper-based measures.** The pioneering work of Baker, Bloom, and Davis (2016) has led to a rapidly growing literature that utilizes textual data, especially news articles, to measure uncertainty and risk. Baker, Bloom, and Davis (2016) develop an index of overall economic policy uncertainty, including fiscal, monetary, trade, healthcare, national security, and regulatory policies, based on the occurrence of certain keywords in newspaper coverage. Also using daily searches of keywords in news articles, Husted, Rogers, and

\(^1\) For instance, following the FOMC’s first inter-meeting action since December of 2008, Fed Chair Jerome Powell noted on March 3, 2020, “The magnitude and persistence of the [virus’] overall effect on the U.S. economy remain highly uncertain and the situation remains a fluid one. In response, we have eased the stance of monetary policy to provide some more support to the economy.”

\(^2\) In most cases, the measures were originally constructed in the papers referenced in Table 1.
Sun (2020); Caldara, Iacoviello, Molligo, Prestipino, and Raffo (2020b); and Caldara and Iacoviello (2018) measure uncertainty about Fed monetary policy, uncertainty about U.S. international trade policy, and geopolitical risks, respectively. These papers find contractionary effects of increases in the measured uncertainty or risk on several economic and financial variables.

Table 1 Uncertainty and Risk Measures

| Variable | Description | Source | Frequency | Figure |
|----------|-------------|--------|-----------|--------|
| **Newspaper-based** | | | | |
| Economic Policy Uncertainty | Share of news articles discussing uncertainty about various aspects of economic policy broadly defined | Baker, Bloom, and Davis (2016) | daily/monthly | Fig. 2 |
| Monetary Policy Uncertainty | Share of news articles discussing U.S. monetary policy actions and their consequences | Husted, Rogers, and Sun (2020) | daily/monthly | Fig. 3 |
| Trade Policy Uncertainty | Share of news articles discussing uncertainty about trade policy | Caldara, Iacoviello, Molligo, Prestipino, and Raffo (2020b) | daily/monthly | Fig. 4 |
| World Uncertainty | Index counting the frequency of the word “uncertainty” in country reports for 145 nations | Ahir, Bloom, and Furceri (2018) using Economist Intelligence Unit reports | quarterly | Fig. 5 |
| Geopolitical Risk | Share of news articles discussing geopolitical events such as wars, political tensions, and terrorist acts | Caldara and Iacoviello (2018) | daily/monthly | Fig. 6 |
| **Survey-based** | | | | |
| Survey of Business Uncertainty | Panel survey of one-year-ahead uncertainty firms have about their own employment and sales | Altig, Barrero, Bloom, Davis, Meyer, and Parker (2020) | monthly | Fig. 7 |
| Consumers' Perceived Uncertainty | Customer reported uncertainty regarding car purchases over the next 12 months | Michigan Survey of Consumers | monthly | Fig. 8 |
| Macroeconomic Uncertainty | Squared deviations of macroeconomic data release surprises | Scotts (2010) using the Bloomberg survey expectations | daily/monthly | Fig. 9 |
| Professional Forecasters Uncertainty | Derived from the tails of the distribution of errors forecasting U.S. GDP growth | Rossi and Schipper (2015) using the Survey of Professional Forecasters | quarterly | Fig. 10 |
| **Econometric-based** | | | | |
| Macroeconomic Uncertainty | Aggregate of the conditional volatility of the unforecastable component of a set of U.S. economic variables | Jurado, Ludvigson, and Ng (2015) | monthly | Fig. 11 |
| Financial Uncertainty | Aggregate of the conditional volatility of the unforecastable component of a set of U.S. financial variables | Ludvigson, Ma, and Ng (2019) | monthly | Fig. 11 |
| **Market-based** | | | | |
| Realized Volatility | Stock market’s actual volatility calculated as sum of squared intra-daily S&P 500 returns | Andersen, Bollerslev, Christoffersen, and Diebold (2006) | continuous/daily | Fig. 12 |
| VIX | Inferred market expected volatility based on S&P 500 index options | Chicago Board Options Exchange (CBOE) | continuous/daily | Fig. 13 |
| Variance Risk Premium | Difference between option-implied and expected realized variance of S&P 500 returns | Bollerslev, Tauchen, and Zhou (2009) | continuous/daily | Fig. 14 |
| Market-based Monetary Policy Uncertainty | 90% confidence interval of the market-implied distribution for the effective Fed Funds rate | Steiner (2006) | continuous/daily | Fig. 15 |

As described further in Section 2, news-based measures are computed from a daily count of the number of articles containing pre-specified search terms that are considered informative about the subject studied, including key words related to uncertainty or risk. The raw count is scaled by the total number of articles in the corresponding newspaper and normalized to have standard deviation one. The final index aggregates across a set of H newspapers and is subsequently scaled to produce the uncertainty index itself (with mean of 100) as

\[
\text{Policy Uncertainty}(t) = \frac{1}{T} \times 100
\]

where \( nn(i,t), i \in \{1, H\} \) is the share of articles containing relevant uncertainty terms,
normalized by its standard deviation $\sigma_i$, in each newspaper

$$nn(i,t) = \left( \frac{\text{policy uncertainty articles}(i,t)}{\text{total articles}(i,t)} \right) / \sigma_i.$$ 

**Survey-based measures.** News-based indices reflect—effectively in real time—the combined uncertainty projected by a large swathe of the society. A different method of computing uncertainty utilizes surveys of individual businesses, households, and market participants. As detailed in Section 3, survey-based measures of uncertainty, in, e.g., Altig, Barrero, Bloom, Davis, Meyer, and Parker (2020) and Leduc and Liu (2016), are useful as direct measures of the uncertainty that these specific entities perceive over sales, expenditure plans, and aggregate economic activity. In addition to survey measures being explicit about the segments of society facing uncertainty, the measures are also relatively precise in pinpointing the horizon over which the uncertainty prevails. Both of these features are more difficult to discern from news-based indices. One downside to the survey measures, compared to alternatives such as news-based and market-based measures, is their potential staleness, especially around fast-breaking important events.

The survey measures take many different forms, depending on the nature of the survey itself. For example, to construct a measure of firms’ uncertainty about their own employment, the Survey of Business Uncertainty (SBU)$^3$ takes as input (1) the firm’s current employment level ($CEmp_t$) as reported by the respondent; (2) the expected employment for the next 12 months ($FEmp_i$) under five different scenarios ($i$), which are explicitly provided to the respondents; and (3) the associated probabilities the firm attaches to these scenarios ($p_i$). Scenario-specific growth rates reflecting the firms responses ($EGr_i$) are constructed as

$$EGr_{i,t} = 2\left(\frac{FEmp_{i,t} - CEmp_t}{FEmp_{i,t} + CEmp_t}\right),$$

and uncertainty is computed from the first and second moments implied by the subjective

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$^3$Calculated and maintained by the Federal Reserve Bank of Atlanta, in partnership with Steven Davis (University of Chicago Booth School of Business) and Nicholas Bloom (Stanford University). Technical details are described in Altig, Barrero, Bloom, Davis, Meyer, and Parker (2020).
growth distribution as

\[
Mean(EGr)_t = \sum_{i=1}^{5} p_i EGr_{i,t}
\]

\[
Std.Dev.(EGr)_t = \left( \sum_{i=1}^{5} p_i (EGr_{i,t} - Mean(EGr)_t)^2 \right)^{1/2}
\].

**Econometric-based measures.** Several authors have measured uncertainty through the (lack of) econometric predictability. Environments in which firm and household expenditures, or aggregate activity, are less forecastable are characterized as featuring high uncertainty. Prominent measures of this type of uncertainty include Jurado, Ludvigson, and Ng (2015) macroeconomic uncertainty (MU) and Ludvigson, Ma, and Ng (2019) financial uncertainty (FU). Compared to alternative measures of uncertainty, econometric-based measures have the advantage of being directly grounded in—and guided by—statistical inference, and they reflect the “big picture” in the same sense as news-based measures. However, econometric-based measures are available at lower frequencies and may be significantly different when estimated on ex-post revised data versus real-time data (Rogers and Xu, 2019).

Arguably the most prominent example of an econometric-based measure of uncertainty is from Jurado, Ludvigson, and Ng (2015). They compute the uncertainty associated with a generic variable \( y_{jt} \), whose value in some future period is determined by the following factor augmented forecasting model:

\[
y_{j,t+1} = \phi_j y(L)y_{jt} + \Gamma_j F(L)\hat{F}_t + \gamma_j^W(L)W_t + \nu_{j,t+1}^y,
\]

where \( F \) denotes a vector of unobserved factors, \( L \) is the lag operator, and the vector \( W_t \) represents additional predictors. Jurado, Ludvigson, and Ng (2015) assume that the variable \( y_t \) is represented by a factor augmented vector autoregression, whose first-order companion form can be compactly represented as

\[
Y_{jt} = \Phi_j^Y Y_{j,t-1} + V_{j,t},
\]

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and whose forecast error variance at time $t$ can be written as

$$
\Phi_{j,t}(h) = E_t[(Y_{j,t+h} - E_tY_{j,t+h})(Y_{j,t+h} - E_tY_{j,t+h})'].
$$

The expected forecast uncertainty associated with series $y_{j,t+h}$ at horizon $h$, denoted $U^Y_j(h)$, is the square-root of the appropriate entry of the forecast error variance $\Phi_{j,t}(h)$. The final measure of macroeconomic uncertainty is a weighted average of the uncertainty estimates of the individual series $j$. We provide further analysis of econometric-based measures in Section 4.

**Asset-based measures.** As we review in Section 5, a wide set of uncertainty measures emerges from financial markets, reflecting volatility in equity returns and interest rates, among other financial variables. One widely used uncertainty measure is the VIX, the Chicago Board of Options Exchange’s Volatility Index, an index calculated using equity index options and measuring market participants’ expectations for the volatility of the S&P 500 index over the coming 30 days. The VIX index has the advantage of being available in real time and at intraday frequency.

The VIX index estimates the expected volatility by averaging the weighted out-of-the-money S&P 500 put and call options over a wide range of strike prices. Specifically, the formula used in the VIX index calculation is as follows:\footnote{See Bakshi and Madan (2000); Demeterfi, Derman, Kamal, and Zou (1999); Britten-Jones and Neuberger (2000); and Carr and Wu (2009).}

$$
\tilde{V}_{t,T} = \frac{2}{T-t} \sum_i \frac{O_t(K_i, T)}{B_t(T)} \frac{\Delta K_i}{K_i^2},
$$

where $O_t(K_i, T)$ is the current price of an out-of-the-money put or call option on the S&P 500 index with strike $K_i$ and expiration $T$ (one month maturity in case of VIX); $B_t(T)$ is the time–$t$ price of a bond paying 1 dollar at $T$; $\Delta K_i = K_i - K_{i-1}$, and the summation in the above formula is over all available strike levels. While the VIX index is designed to measure expected volatility of the S&P 500 index over a 30-day horizon, option-implied volatility indices at horizons other than 30 days can also be constructed via Equation 7.
by using options with the corresponding horizons (maturities). For example, CBOE also provides the S&P 500 3-Month Volatility Index, which is an index designed to measure 3-month expected volatility.

These measures, constructed using different approaches, in principle reflect uncertainty or risks perceived by different segments of the population. For example, the news-based measures directly reflect the perception of editorship at major media press, which in turn reflects and influences readership; on the other hand, market-based measures tend to reflect the view of market participants actively trading in one particular asset market. Relatedly, measures constructed differently have their comparative advantages. For example, survey-based measures allow precision concerning the sector in which the uncertainty is located (e.g., firms, households, or traders), the economic measure (e.g., employment, expenditures, policy), and the horizon over which the uncertainty prevails. However, these measures tend to be available at a lower frequency and hence possibly stale relative to, say, news-based or market-based measures.

It is important to note the conceptual distinctions that exist among risk, uncertainty, and volatility, although they are sometimes studied without explicit differentiation in research. As proposed by Knight (1921), risk applies to situations in which the outcome is unknown to decision makers, but the probability distribution governing the outcome is known. Volatility, often used synonymously with risk, is a statistical measure of the variation in observed outcomes. In contrast, uncertainty is characterized by both an unknown outcome and an unknown probability distribution. The paramount importance of such distinction has been made salient by the market response at the onset of the COVID-19 pandemic: a fundamental shock is compounded by panic, by turning risk into uncertainty. When agents realize that their assumptions about risk are no longer valid and conditions of uncertainty apply, their fear about unexpected losses can ravage financial markets.⁵

⁵There is also an extensive related literature on “Knightian uncertainty” (Knight, 1921) and ambiguity aversion. In contemporary usage, Knightian uncertainty concerns cases where the support of a random variable is known, but the probability measure associated with the support is not. This can occur because the agent does not have a prior and so cannot compute a posterior. Alternatively, it can derive from failure of identification. In such cases, expected utility maximization cannot be the basis of
Figure 1 displays some of the measures listed in Table 1, all normalized over the period January 1985 to December 2019, and marks their temporal association with key events. Macroeconomic, financial, and economic policy uncertainty spiked around the 2008 global financial crisis and again with COVID-19. However, only some measures increase around other crises. For instance, financial uncertainty is the only measure capturing the dot-com bubble of the late 90’s, and trade policy uncertainty only surges around the trade tensions between the U.S. and China from 2018 onward. Such differences foreshadow some of the messages from our review, as we take up below.

Figure 1 Select Measures of Uncertainty

![Figure 1 Select Measures of Uncertainty](image)

Notes: This figure plots macroeconomic uncertainty calculated by Jurado, Ludvigson, and Ng (2015), economic policy uncertainty calculated by Baker, Bloom, and Davis (2016), trade policy uncertainty calculated by Caldara, Iacoviello, Molligo, Prestipino, and Raffo (2020b) and the CBOE S&P 500 VIX. All variables are normalized for the period Jan/85 to Dec/19. Time series for trade and economic policy uncertainty are 12-month moving averages. Sources: sydneyludvigson.com (Macro uncertainty), policyuncertainty.com (Economic policy uncertainty), matteoiacoviello.com (Trade policy uncertainty), and fred.stlouisfed.org (VIX).

Two broad lessons emerge from our review. First, given the conceptual differences between risk and uncertainty, it is of critical importance to draw a clear distinction in measurement. Carefully defining the nature of uncertainty or risk is also important. This has become particularly relevant with the emergence of new sources of risk, such as trade and geopolitical tensions, and global health risks, such as the outbreak of COVID-decision making, and, instead, agents may use a MinMax approach, trying to minimize the possible loss for a worst case (maximum loss) scenario. Ambiguity aversion, in contrast, refers to weighting the worst case scenario beyond what is justified in an expected utility context.
19. The available measures are, by construction, limited to characterize particular types of uncertainty at particular horizons. For instance, although the VIX is a widely used measure of financial uncertainty, it is designed to capture near-term risk assessments related to the U.S. stock market. This might in part explain the divergence between the low levels of VIX in the three years after the 2016 U.S. presidential election when economic policy uncertainties appeared elevated.

A second lesson is that although heightened uncertainty appears to be generally associated with worse economic and financial outcomes, the nature and magnitude of such effects critically depend on the type of uncertainty and the identification strategy used to estimate its effects. For example, Ludvigson, Ma, and Ng (2019) and Carriero, Clark, and Marcellino (2018) show that uncertainty has different effects depending on whether it is of macro or of financial origin. Two important recent contributions demonstrate that conclusions concerning the transmission of uncertainty shocks hinge on careful identification. Ludvigson, Ma, and Ng (2019) find that elevated macroeconomic uncertainty in recessions is often an endogenous response to output shocks, while uncertainty about financial markets is a significant driver of business cycles. Berger, Dew-Becker, and Giglio (2020) analyze the real effects of volatility and uncertainty and argue that it is key to distinguish between realized volatility (RV) and expected volatility (a measure of uncertainty). They present a wide set of results showing that it is the realized part of volatility that has robust negative effects on real activity. Changes in expected volatility—uncertainty shocks—have no statistically significant negative effects. According to Berger, Dew-Becker, and Giglio (2020), it is the RV component that drives previous results in the literature showing significant negative effects of uncertainty, rather than second-moment uncertainty shocks.\footnote{In addition, Baley, Veldkamp, and Waugh (2021) note the large rise in U.S. exports-to-GDP from 2016-19, a time of sharply rising trade policy uncertainty. They show that global uncertainty can increase or decrease international trade in a general equilibrium model with information frictions, and note other mechanisms by which reduced uncertainty limits risk-sharing. Trade offers a mechanism for risk sharing, and risk sharing is most effective when both parties are uninformed. In their model, higher uncertainty leads to increases in trade because agents receive improved terms of trade, particularly in states of nature in which consumption is most valuable.}
2 News-based Indicators of Uncertainty and Risk

As recently highlighted by Gentzkow, Kelly, and Taddy (2019), digital text provides a treasure trove of recorded information on communications, and has been widely used as an input to economic research. Newspapers are one prime example. As described in the following subsections of this review, many influential measures of uncertainty and risk have been constructed using word counts from newspaper articles. Such measures have the benefit of reflecting the perceptions of a wide swathe of society and of being effectively available in real time. News-based indices of policy-related economic uncertainty reflect concerns about who will make policy decisions, what policies will be undertaken, when decisions will be enacted and have impacts, as well as what the economic effects will be (Baker, Bloom, and Davis, 2016). Such measures of uncertainty thus capture a broader sense of uncertainty than, say, market-based or survey-based measures.

2.1 Economic Policy Uncertainty

One of the most widely used indicators of uncertainty is the economic policy uncertainty (EPU) index developed by Baker, Bloom, and Davis (2016). For the United States, the EPU index is constructed from three components. The first component quantifies policy-related uncertainty by searching the archives of 10 major U.S. newspapers for articles that contain terms related to EPU. The second component gauges uncertainty regarding the federal tax code, by counting the number of federal tax code provisions set to expire in future years. The third component measures disagreement among economic forecasters as an indicator of uncertainty. EPU indexes are constructed for almost 20 other countries or country aggregates, based on only the first component, newspaper articles regarding policy uncertainty.\footnote{EPU indexes are available for the following countries and country aggregates: the global aggregate, Australia, Brazil, Canada, Chile, China, Colombia, Europe, France, Germany, India, Ireland, Italy, Japan, Korea, Mexico, the Netherlands, Russia, Singapore, Spain, Sweden, and the United Kingdom.}

For the United States, the news component of the EPU index is constructed by counting the number of articles in 10 leading U.S. newspapers that contain the words “economic” or “economy;” “uncertain” or “uncertainty;” and one or more of “Congress,”
“deficit,” “Federal Reserve,” “legislation,” “regulation,” or “White House.” Analogous searches are performed for the other countries.

An obvious difficulty with these raw counts is that the overall volume of articles varies across newspapers and time. Thus, Baker, Bloom, and Davis (2016) scale the raw monthly counts for each newspaper by the total number of articles in that newspaper and in that month to produce a monthly EPU series for each newspaper. They scale each newspaper-level series to ensure that each has a unit standard deviation for the 1985 to 2009 period, and then take the average of these 10 monthly series. Finally, they normalize the 10-paper average series to a mean of 100 over the sample. The series for all countries are standardized similarly.\(^8\)

Figure 2 shows the monthly time series for the U.S. EPU index constructed based on newspaper coverage since 1985. The index shows clear spikes around events such as the Gulf wars, presidential elections, the terrorist attacks on September 11, 2001, the stimulus debate in early 2008, the Lehman Brothers bankruptcy and the subsequent Troubled Asset Relief Program (TARP), legislation in late 2008, the summer 2011 debt ceiling dispute, and the battle over the “fiscal cliff” in late 2012.

**Figure 2 Economic Policy Uncertainty (EPU)**

![Figure 2: Economic Policy Uncertainty (EPU)](image)

*Notes: This figure depicts the Baker, Bloom, and Davis (2016) EPU index for the United States. Index is calculated as the share of news articles discussing uncertainty about various economic policies broadly defined. Jan. 1985 to Dec. 2009 = 100. Source: policyuncertainty.com.*

\(^8\)The indexes are updated regularly on the policyuncertainty.com website.
Baker, Bloom, and Davis (2016) also develop subindexes for policy categories by counting the number of articles in over 2,000 U.S. newspapers that not only meet the criteria for inclusion in the EPU index but also contain terms relevant to the specific category in question. For example, they construct a health care EPU index by searching for articles that discuss rising EPU as well as terms such as “health care,” “Medicaid,” “Medicare,” “health insurance,” “affordable care act,” and “medical insurance reform.” Similarly, they create a trade policy index by searching for words including “import tariffs,” “world trade organization,” and “trade policy” in addition to their baseline trio of search terms.9

Researchers have used EPU indexes to show that policy uncertainty can affect the economy and asset prices. For example, using firm-level data, researchers have shown that policy uncertainty seems to reduce investment and employment, especially in firms that are more dependent on government spending (Gulen and Ion, 2016; Baker, Bloom, and Davis, 2016). At the macro level, researchers have shown that higher policy uncertainty can lead to lower investment, output, and employment (Bachmann, Elstner, and Sims, 2013; Baker, Bloom, and Davis, 2016) as well as reduced monetary policy effectiveness (Aastveit, Natvik, and Sola, 2017). Financial research has also shown that policy uncertainty can increase stock volatility, stock co-movement, and equity premiums (Pástor and Veronesi, 2012; Pástor and Veronesi, 2013; Brogaard and Detzel, 2015) as well as financial intermediation costs (Francis, Hasan, and Zhu, 2014).

There are two recent streams in the literature on news-based uncertainty that seem highly promising. The first stream links news-based and asset market indicators. Baker, Bloom, Davis, and Kost (2019a) rely on equity market volatility-related articles to construct a newspaper measure that closely tracks the VIX, parsing the forces driving stock market volatility. Baker, Bloom, Davis, and Sammon (2019b) do a narrative identification of the triggers of large daily stock market movements in several countries, by analysing

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9Other category-specific indexes for the United States include monetary policy, taxes, fiscal policy and government spending, national security, entitlement programs, regulation, financial regulation, and sovereign debt and currency crises. In related work, Arbatli, Davis, Ito, Mihako, and Saito (2017) developed category-specific EPU indexes for Japan covering monetary policy, fiscal policy, trade policy, and exchange rate policy. Similarly, Hardouvelis, Karalas, Karanastasis, and Samartzis (2018) created category-specific EPU indices for Greece.
newspaper articles the day after these jumps. Based on these two methodologies, Baker, Bloom, Davis, Kost, Sammon, and Viratyosin (2020) evaluate the impact of COVID-19 on U.S. stock market performance. The second stream incorporates computational linguistics. Larsen (2021), for example, uses unsupervised machine learning methods to classify news, constructing several uncertainty components for Norway. Novelly, Hassan, Hollander, Lent, and Tahoun (2019) apply computational linguistics and construct a measure of political risk faced by individual U.S. firms, using the share of their quarterly earnings conference calls devoted to political risks.

2.2 Monetary Policy Uncertainty

To capture uncertainty related to central bank policies, Husted, Rogers, and Sun (2020) construct an index of monetary policy uncertainty (MPU) by tracking the frequency of newspaper articles discussing uncertainty about Fed monetary policy. The U.S. MPU index measures the perceived uncertainty surrounding the Federal Reserve Board’s policy decisions and their consequences.

Using ProQuest Newsstand as a primary source, Husted, Rogers, and Sun (2020) construct their index by searching for keywords related to monetary policy from the following three sets: (i) “uncertainty” or “uncertain;” (ii) “monetary policy(ies),” “interest rate(s),” “federal fund(s) rate,” or “fed fund(s) rate;” and (iii) “Federal Reserve,” “the Fed,” “Federal Open Market Committee;” or “FOMC.” The raw count of identified articles is scaled by the total number of newspaper articles that meet their search criteria (iii), in order to address issues related to time-varying popularity and increased coverage of the Fed due to improved transparency in its communication strategy. The share of articles is subsequently normalized to have a unit standard deviation for each newspaper over the sample period. The resulting series are aggregated across newspapers and normalized to have a mean of 100 over the sample. With the MPU index, Husted, Rogers, and Sun (2020) show that heightened uncertainty about Fed policy can have negative

Kalamara, Turrell, Redl, Kapetanios, and Kapadia (2020) show that U.K. newspaper indicators constructed with machine learning algorithms contain signals of economic sentiment and uncertainty, which can improve economic forecasts.
transmission effects at both the aggregate and firm levels.

Figure 3 shows the Husted, Rogers, and Sun (2020) U.S. MPU index since 1985. Notably, the index spikes during the taper tantrum in 2013 and right before liftoff of the Fed Funds rate in 2015. The index declines in the immediate aftermath of the FOMC’s 100 basis point cut in the Fed Funds rate and quantitative easing measures to support market functioning in the extraordinary meeting of 15 March 2020. The timing of these spikes relative to policy decisions shows the ability of the index to capture the ex-post and ex-ante uncertainty of different FOMC decisions. Major macroeconomic events with the capacity to affect monetary policy, like the invasion of Iraq in 2003, also move the index. As emphasized in Husted, Rogers, and Sun (2020) and reiterated in Section 5 below, news-based MPU differs in important ways from measures derived from asset markets both conceptually and in practice, especially in its ability to capture episodes such as Taper Tantrum and liftoff uncertainty during periods of unconventional monetary policy when the market-based measures fell close to zero.\(^{11}\)

**Figure 3 Monetary Policy Uncertainty (MPU)**

![Image of Figure 3](https://ssrn.com/abstract=3894581)

*Notes: This figure depicts the Husted, Rogers, and Sun (2020) MPU index for the United States. Index calculated as the share of articles discussing uncertainty about U.S. monetary policy actions and their consequences. Jan. 1985 to Dec. 2018 = 100. Source: sites.google.com/site/lucasfhusted.*

\(^{11}\)For regular updates of the series, visit sites.google.com/site/lucasfhusted. MPU indexes for the euro area, the United Kingdom, Japan, and Canada are also constructed by the authors.
2.3 Trade Policy Uncertainty

Caldara, Iacoviello, Molligo, Prestipino, and Raffo (2020b) develop two measures of uncertainty related to trade policies (TPU). The first is based on searches of newspaper articles that discuss trade policy uncertainty. To calculate this index, Caldara et al. (2020b) run text searches of the electronic archives of seven U.S. newspapers and select articles that discuss TPU by searching for terms such as “risk,” “threat,” and “uncertainty,” that appear in the same article as a term related to trade policy, such as “tariff,” “import duty,” “import barrier,” and “anti-dumping.” The TPU index is the monthly share of articles discussing trade policy uncertainty rescaled to equal 100 for an article share of 1 percent.

The second measure is constructed by aggregating firm-level TPU obtained from automated text search of the quarterly earnings call transcripts of U.S.-listed corporations. Figure 4 shows that the news-based TPU reached initial highs in the first half of 2018 and, after subsiding, reached a new peak in the first half of 2019. Using bivariate VAR models, Caldara, Iacoviello, Molligo, Prestipino, and Raffo (2020b) further find that one-standard deviation increases in both measures of TPU reduce business investment between 1 to 2 percent for about a year. This effect is stronger using the news-based measure.

Figure 4 Trade Policy Uncertainty (TPU)
2.4 World Uncertainty Index

Ahir, Bloom, and Furceri (2018) construct a panel of uncertainty measures for 143 developed and developing countries based on a word count of “uncertainty” and its variants from Economist Intelligence Unit country reports. These reports cover specific topics related to political and economic developments and have a standardized structure across countries. More importantly, because these reports are all produced by the same source, the possibility of ideological bias between countries is mitigated. The World Uncertainty Index (WUI) is a GDP-weighted average of country-level uncertainty indexes, and is calculated using quarterly data spanning from 1996. The index is designed to capture global uncertainty co-movement, as heightened local uncertainty may spread across borders through economic and financial linkages.

Figure 5 World Uncertainty Index (WUI)

![Figure 5](image)

Notes: This figure depicts the World Uncertainty Index from Ahir, Bloom, and Furceri (2018). Index calculated as the frequency of the word “uncertainty” in Economist Intelligence Unit country reports for 143 nations. The index is normalized by the total number of words and aggregated as a GDP-weighted average. The figure shows some of the main significant historical events that triggered global uncertainty. Average 1996q1 to 2010q4 = 100.

Source: policyuncertainty.com.

Figure 5 shows the WUI index time series. As seen in the figure, global uncertainty seems to have increased substantially in recent years in part due to a cluster of recent events in systemic large economies (such as the United States, the Euro area, the United Kingdom, and China) and increased global spillovers from such economies. Uncertainty spiked in high-profile episodes such as the 9/11 attacks, the Iraq war, the sovereign debt

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crisis in Europe, Brexit, and several U.S trade policy developments. Interestingly, the dynamics of the index around the global financial crisis is more muted. At the country level, Ahir, Bloom, and Furceri (2018) discuss several stylized facts of uncertainty. In particular, (i) uncertainty is, on average, higher in developing economies, (ii) uncertainty is more synchronized among advanced economies, and (iii) there is significant heterogeneity across countries driven by country-specific events. The United Kingdom, for example, displays a notable spike in uncertainty related to the Brexit referendum that is not necessarily reflected in other countries’ uncertainty. A quantitative analysis of a panel of 46 countries shows that global uncertainty has real effects. In particular, a one-standard deviation increase in the WUI index generates a statistically significant decrease in output, which peaks at around 1.4 percent 10 quarters after the shock.

2.5 Geopolitical Risk

Caldara and Iacoviello (2018) construct an index that measures geopolitical risk (GPR) based on a tally of newspaper stories that contain a fairly broad set of terms related to geopolitical tensions. The GPR index measures the risk associated with geopolitical events, such as wars, political tensions, and terrorist acts, that affect the normal course of domestic politics and international relations. Caldara and Iacoviello (2018) also propose two indexes that distinguish between geopolitical acts and geopolitical threats.\textsuperscript{12} The GPR index is constructed by counting the occurrence of words related to geopolitical tensions in leading international newspapers. In particular, the GPR index reflects automated text searches in the electronic archives of 11 national and international newspapers for articles that contain words associated with (1) Geopolitical Threats, (2) Nuclear Threats, (3) War Threats, (4) Terrorist Threats, (5) War Acts, and (6) Terrorist Acts.\textsuperscript{13}

Figure 6 shows the GPR index since 1990. The GPR index spikes during the Gulf War, the 2003 invasion of Iraq, and on 9/11, as well as in periods of increased bilateral tensions. Moreover, the index has remained heightened since the beginning of 2017, a

\textsuperscript{12}Country-specific GPR indexes are also available for the following countries: the United States, Argentina, Brazil, China, Colombia, India, Indonesia, Israel, Korea, Malaysia, Mexico, the Philippines, Russia, Saudi Arabia, South Africa, Thailand, Turkey, and Venezuela.

\textsuperscript{13}For the specific set of keywords, please refer to Caldara and Iacoviello (2018).

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sign of mounting tensions between the U.S. administration at the time and their global partners, as well as growing instability in the Levant. Caldara and Iacoviello (2018) show that increased geopolitical risk leads to declines in real activity and is associated with increases in the VIX, lower oil prices, and higher corporate credit spreads.

Figure 6 Geopolitical Risk Index (GPR)

![Geopolitical Risk Index](image)

*Notes: This figure depicts the GPR index from Caldara and Iacoviello (2018). Index calculated as the share of news articles discussing geopolitical events such as wars, political tensions, and terrorist acts. Sample mean = 100. Source: matteiiaacoviello.com.*

3 Survey-based Indicators

As noted above, news-based measures of uncertainty reflect the views of a large swathe of society (readers and writers) concerning their outlook over some unspecified horizon. Economic surveys provide an alternative measure of uncertainty that is more specific on both fronts, agents and future horizons. These measures can be summarized as *ex-ante*, reflecting expectations about future outcomes, or *ex-post*, combining expectations with realizations.

3.1 Ex-Ante Survey-based Indicators

Useful information emerges from survey participants’ probabilistic assessments of future economic outcomes. These surveys typically ask each individual respondent about point
predictions (that is, mean or mode expectation) of future events, such as inflation or GDP growth for the next year. Aggregating individual responses allows for the estimation of a measure of the dispersion across respondents regarding the point prediction. However, this aggregation across individuals does not provide meaningful information regarding the uncertainty that each individual may attach to their point forecast. Therefore, some surveys also ask individual respondents about the uncertainty surrounding the point forecasts. Such surveys allow for the estimation of both the dispersion across individuals and the uncertainty of each individual regarding his or her own forecast. For example, the Survey of Professional Forecasters, a quarterly publication produced by the Federal Reserve Bank of Philadelphia, asks respondents to provide both point estimates and probabilistic assessments of the outlook for U.S. inflation and 10-year interest rates, from which aggregate proxies for both dispersion and uncertainty can be constructed.

Altig, Barrero, Bloom, Davis, Meyer, and Parker (2020) describe the Survey of Business Uncertainty (SBU), recently-constructed in partnership with the the Federal Reserve Bank of Atlanta. The SBU measures uncertainty from respondents, providing a 5-point probability distribution over 12-month-ahead sales and employment for each firm. It also asks respondents for the current values of these quantities. Thus, the Survey allows the calculation of each firm’s expected growth rate over the next year and its degree of uncertainty about that expectation. Figure 7 presents the SBU for expected sales revenue growth and employment growth, showing that subjective uncertainty increased quite substantially due to the COVID-19 crisis.

Leduc and Liu (2016) construct a measure of consumers’ perceived uncertainty based on a question regarding future expected car purchases from the monthly University of Michigan Survey of Consumers. Specifically, the authors focus on the questions: “Speaking now of the automobile market–do you think the next 12 months or so will be a good

14Both the dispersion across individuals and the uncertainty that each individual perceives are relevant for studying market surprises and the effects of realized future events. For a detailed discussion of this issue, see the speech by the Federal Reserve Board’s Vice Chairman Stanley Fischer on April 17, 2017, “Monetary Policy Expectations and Surprises,” www.federalreserve.gov/newsevents/speech/fischer20170417a.htm.

15In addition to the core survey questions on sales and employment, the Survey also asks at least one special question each month. The SBU is released by 11 a.m. ET on the last Wednesday of the month.
time or a bad time to buy a vehicle, such as a car, pickup, van or sport utility vehicle?" and the follow-up “Why do you say so?” The consumers’ perceived uncertainty measure is the fraction of respondents who report “uncertain future” as a reason why it will be a bad time. Figure 8 shows that the consumers’ perceived uncertainty regarding car purchases markedly increased during the 2008 Global Financial Crisis, and persisted in a higher level until around 2014. The COVID-19 crisis caused an unprecedented jump in the consumer uncertainty, up three to five times its pre-pandemic level.

3.2 Ex-Post Survey-based Indicators

Scotti (2016) uses macroeconomic news and survey forecasts to construct an ex-post realized measure of uncertainty about the state of the economy. The macroeconomic uncertainty index in Scotti (2016) is calculated based on weighted averages of the square of economic data surprises, which are measured by examining deviations of recent economic data releases from consensus expectations from Bloomberg forecasts an hour before the data release. A dynamic factor model is employed to estimate monthly business condition indexes and compute the weights representing the contribution of the economic indicators.
Figure 8 Consumers’ Perceived Uncertainty (Car Purchases)

Notes: This figure depicts the consumers’ perceived uncertainty from the University of Michigan Survey of Consumers in the U.S. The index is calculated as the fraction of respondents who report “uncertain future” as a reason why it will be a bad time to buy a car over the next 12 months; in percentage points.
Source: Leduc and Liu (2016).

to these business condition indexes. Those weights are then used to average the squared surprises to construct the uncertainty index. Figure 9 shows Scotti’s uncertainty index since 1990, which rises leading up to and after the global financial crisis and Brexit. The surge in early 2020 gives a sense of the unprecedented effects of the COVID-19 crisis. Scotti (2016) shows that higher uncertainty is associated with lower real activity.

Figure 9 Scotti’s Uncertainty Index

Notes: This figure depicts Scotti’s uncertainty index about the state of the macroeconomy from Scotti (2016). The index is calculated as the squared deviations of macroeconomic data release surprises from the Bloomberg survey expectations. Sample mean = 1.0.
Source: sites.google.com/site/chiarascottifrb.

Electronic copy available at: https://ssrn.com/abstract=3894581
Rossi and Sekhposyan (2015) construct uncertainty based on the realization of, e.g., GDP growth, relative to the unconditional forecast error distribution from nowcasts and forecasts of the Survey of Professional Forecasters.\footnote{Other papers that study survey-based macroeconomic uncertainty and ex-post forecast errors include Giordani and Söderlind (2003); Lahiri and Sheng (2010); Bachmann, Elstner, and Sims (2013); Arslan, Atabek, Hulagu, and Şahinöz (2015); Binder (2017); Ozturk and Sheng (2018); Jo and Sekkel (2019); and Dahlhaus and Sekhposyan (2020). Bachmann, Elstner, and Hristov (2017) show how surveys that combine expectations with outcome data can be used to refine uncertainty measurement. See also Grishchenko, Mouabbi, and Renne (2019), who use a range of inflation forecasts in the surveys of professional forecasters to construct an inflation uncertainty measure.} Figure 10 presents the Survey of Professional Forecasters uncertainty index related to the GDP nowcast. The index seems to spike after historic uncertainty events, such as the Iraq crisis, the 9/11 attacks, and the COVID-19 shocks, and to remain high during prolonged recessionary periods, such as the 2008 Global Financial Crisis.

4 Econometric-based Indicators

Another way to measure uncertainty and risk takes an objective econometric-based approach, rather than relying on the sentiment reflected in news, surveys, or analysts’ forecasts. Uncertainty is equated with lack of predictability of aggregate activity under
this approach. Related to this, researchers have used quantile regressions to estimate the value of aggregate economic activity that is “at risk.” Like the survey-based measures, those based on the econometric approach are well defined in terms of the horizon over which the uncertainty or risk is purported to prevail.

4.1 Macro and Financial Uncertainty

Jurado et al. (2015) (JLN) and Ludvigson et al. (2019) (LMN) construct indexes of macroeconomic and financial uncertainty as an aggregate of the volatility of statistical forecasts for hundreds of economic series. To calculate their measure, JLN and LMN use monthly datasets comprising information from hundreds of macroeconomic and financial indicators, and construct direct econometric estimates of uncertainty for each indicator. Formally, JLN and LMN define the \( h \)-period ahead uncertainty in a single variable as the conditional volatility of the unforecastable component of the future value of the variable; that is, the difference between the future value of the variable and its expectation based on the information available at time \( t \). The aggregate uncertainty at the macro (financial) level is the average of the uncertainty measures across all macro (financial) variables.

The uncertainty indexes in JLN and LMN differentiate uncertainty from traditionally used measures of volatility, such as conditional volatility. Conditional volatility (see stock volatility in section 5.1) does not necessarily remove the forecastable component of a time series, while the JLN index does so by incorporating a large number of indicators into the forecasting model for each individual time series. Figure 11 compares the macroeconomic and financial uncertainty indexes derived from JLN and LMN. As can be seen from the figure, the financial uncertainty index exhibits more sharp moves than the macro uncertainty index, and although both spike at the outset of the global financial crisis, the two series often rise and fall at different times.

JLN find that increases in macroeconomic uncertainty are associated with large declines in U.S. real economic activity. In the further investigation of LMN, the authors trace the source of transmission of uncertainty to real activity to financial uncertainty shocks, and find little evidence of reverse causality in this relationship. In addition, LMN
find that higher macroeconomic uncertainty and EPU (Baker, Bloom, and Davis, 2016) in recessions are an endogenous response to real economic activity, rather than positive shocks to macro or policy uncertainty causing lower economic activity. Instead, macro uncertainty is argued to be an amplifier of recessions rather than a cause of them. Bali, Brown, and Tang (2017) find that exposure to JLN uncertainty measures predicts a significant proportion of the cross-sectional dispersion in future stock returns.

Macroeconomic and financial uncertainty can also be obtained using econometric techniques from the estimated latent stochastic volatility process of macroeconomic and financial variables. This approach is used, for example, for interest rate uncertainty (Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe, 2011), financial uncertainty (Alessandri and Mumtaz, 2019 and Shin and Zhong, 2020), uncertainty about fiscal policy (Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez, 2015), inflation uncertainty (Chan, 2017) and regional-specific uncertainty (Mumtaz and Musso, 2017). In many of their estimates, exogenous positive shocks to the JLN’s macroeconomic uncertainty and EPU initially raise real activity.

Redl (2020) constructs macro uncertainty indexes for 11 advanced countries based on the JLN framework and finds that macro uncertainty shocks matter for the vast majority of countries and that the real effects of macro uncertainty shocks are generally larger conditioning on close elections.
Carriero et al. (2018) propose a model in which the common factors of the stochastic volatilities of macro and financial variables are allowed to interact.¹⁹

4.2 Quantile-Regression Risk Measures

The value-at-risk (VaR) is defined in the finance literature as a threshold such that the probability of a specific outcome not exceeding this threshold is equal to a desired level. This threshold is equivalent to the corresponding quantile of the desired level. The VaR has recently been used to construct measures of risk to U.S. macroeconomic aggregates drawing from quantile regressions. Unlike standard OLS regressions, quantile regressions look beyond the conditional mean and allow the study of the conditional quantiles of a given variable. Thus, this technique makes it possible to analyze how economic conditions influence not only the modal outlook but also the tail dynamics of economic time series.

Using the VaR methodology, Adrian, Boyarchenko, and Giannone (2019) compute the downside risk to the annualized average growth rate of U.S. GDP over the next quarter/year by constructing a conditional distribution using quantile regressions. Their conditioning variables are macroeconomic activity, as summarized by GDP growth, and financial conditions, characterized by the National Financial Conditions Index (NFCI) constructed by the Chicago Fed. They find that, while the relationship between average future GDP growth and economic conditions is fairly symmetric across quantiles, financial conditions have explanatory power for the left tail (e.g., its 10th quantile) of GDP growth but no information content for its right tail (e.g., its 90th quantile). In this sense, the downside vulnerability of GDP growth seems to be informed by financial health and/or by amplification mechanisms in the financial sector.²⁰

¹⁹Following a similar setup, Cascaldi-Garcia (2019) constructs quarterly macro and financial uncertainties for the United States. Some periods are characterized by high macro and financial uncertainties, such as the global financial crisis, but some are characterized mostly by macro uncertainty (as in the Great Moderation of the mid-1980s) or by financial uncertainty (as in the dot-com crisis of 1999-2001).

²⁰Adrian, Grinberg, Liang, and Malik (2021) find similar results in an international context by looking at a panel of 11 advanced and 11 emerging market economies. Furthermore, Caldara, Cascaldi-Garcia, Cuba-Borda, and Loria (2020a) quantify risks to the economic outlook using a Markov-Switching model that alternates normal times and crisis times. In their model, growth-at-risk emerges when the probability of switching from the normal to the crisis regime increases due to a deterioration in economic and financial indicators. Also using the quantile regression methodology, Lopez-Salido and Loria (2019) study risks to the inflation outlook.

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5 Asset-Market Indicators

A wide set of risk and uncertainty measures are derived from financial markets. These are typically computed as some measures of volatility or other higher-order moments of returns in a particular market over a particular time period. Asset-based measures have the advantage of being available in real time, essentially continuously. As such, policymakers, the press, and other decision makers may be inclined to rely on them during crises when important developments occur rapidly. Research using asset-based measures must be careful to separate uncertainty from risk, and as emphasized by Berger, Dew-Becker, and Giglio (2020), expected volatility from realized volatility.

5.1 Realized Volatility

Realized volatility (RV), defined as the scaled sum of squared daily returns, was pioneered by Andersen, Bollerslev, Diebold, and Labys (2001, 2003). Additional research on RV harnesses the information content of intraday returns (rather than daily returns). RV measures have been shown to improve on traditional measures like generalized autoregressive conditional heteroskedasticity (GARCH) precisely by exploiting the additional information content of intraday returns.\footnote{Liu, Patton, and Sheppard (2015) provide an overview of the different classes of RV estimators.} Liu, Patton, and Sheppard (2015) provide an overview of the different classes of RV estimators. The properties of RV-style estimators are well documented in the literature, and they are routinely used for forecasting volatility (see Alizadeh, Brandt, and Diebold, 2002; Corsi, 2009; and Patton and Sheppard, 2015, among many others) and for predicting returns (e.g., Bollerslev and Zhou, 2006).

Figure 12 shows the time series of RV for the S&P500 in the United States calculated using intradaily returns. RV is particularly high around episodes that were associated with unexpected news or events. Not surprisingly, the most notable spikes occurred around the collapse of Lehman Brothers in 2008 and in March 2020 during the COVID-19 pandemic, when RV reached values over 92 percent.\footnote{Cascaldi-Garcia and Galvao (2018) argue that prolonged periods of low realized volatility, rather...}
(2019), among others, show that financial uncertainty shocks (proxied by shocks to RV) cause temporary recessionary effects, depressing output, consumption, investment, hours worked, and stock prices.

**Figure 12 Realized Volatility (RV)**

![Figure 12 Realized Volatility (RV)](image)

*Notes: This figure depicts the realized variance values for the S&P500, expressed in annualized percents. Realized volatility is calculated as the square root of the sum of intraday squared returns over the last 22 trading days.*

*Source: Federal Reserve Board staff calculations from Bloomberg Finance LP.*

### 5.2 Derivative-Implied Risk and Uncertainty Measures

Derivative prices reflect investor preferences as well as investor beliefs about the likelihood of future price realizations of the underlying asset. For instance, buying a put option is a profitable strategy only if the price of the underlying asset falls below the strike price of the option. The price of a put option will increase with the probability an investor assigns to an outcome in which the price of the asset will drop below its strike price, and will also increase with the value an investor places on a positive return in the event of a price drop. Thus, at any point in time, the prices of derivatives at different strikes contain commingled information about the probabilities assigned to each possible market outcome as well as investor preferences.

than realized volatility itself, have predictive power for the incidence of banking crises and can be used as a reliable crisis indicator. Moreover, low volatility increases banking sector leverage and aggregate credit. They interpret these results as stemming from increased risk appetite and risk taking, which presage stress events such as in the late 1920s before the Great Depression, the mid-1990s before the Asian crisis, and the mid-2000s before the 2008 crisis.
Derivative-implied distributions can be used to calculate derivative-implied moments, such as the derivative-implied volatility or skewness, as well as the cost of insurance against any potential outcome, e.g., a price drop of a certain magnitude. The derivative-implied distribution used to generate these moments is often referred to as the risk-neutral distribution because, by construction, this is the probability measure that makes the expected return on a risky investment equal to the risk-free rate. Comparing the estimated actual (often referred as physical) distribution—the one that yields moments such as the RV—with the derivative-implied distribution can provide information about investor risk preferences, such as their preference for having positive returns in one state of the economy, e.g., a large drop in asset prices, versus another. For example, if the risk-neutral distribution systematically has wider tails than the physical distribution (that is, more probability assigned to extreme market outcomes under the risk-neutral measure), we can infer that either investors systematically overestimate the probability of tail events or that their estimations are correct but they particularly value positive returns in those tail events.

The VIX and other Option-Implied Volatilities for Equities

As highlighted in Table 1, the VIX—the U.S. option-implied volatility index—is the most popular derivative-implied risk measure. It is frequently used by researchers and market participants to gauge fear or uncertainty with respect to the U.S. equity market. Although there has been extensive research on the usefulness of the VIX as a tool to monitor equity and other financial asset markets, its informational content is often misunderstood. Option-implied volatility for the U.S. equity index is calculated using the methodology first introduced by Britten-Jones and Neuberger (2000). In particular, it is calculated as a weighted average of the price of out-of-the-money S&P 500 put and call options that expire in more than 23 days but less than 37 days. The weight assigned to each option depends on its strike and its maturity, and is intended to generate a portfolio of options that isolates the expected volatility of the underlying equity index at the 30-day horizon. Therefore, option-implied volatility is formally defined as the risk-neutral
expectation of the volatility of the equity index over the next 30 days.\footnote{Option-implied volatilities are also available at horizons other than 30 days. For example, the S&P 500 VIX Short-Term Futures Exchange Traded has a 9-day horizon. Still, the 30-day measure is the most widely used because of the relatively high liquidity for the options around this horizon. Also note that related measures for other countries are also available for: Germany (DAX 30), Japan (Nikkei 225), the United Kingdom (FTSE 100), Switzerland (SMI), the Netherlands (AEX 25), France (CAC 100), and the euro area (Euro Stoxx 50). Option-implied volatility indexes are highly correlated across countries and tend to spike simultaneously (Londono, 2013).}

Figure 13 shows the time series for the VIX between January 2000 and May 2020. The index is particularly high around episodes of high market uncertainty, usually associated with unexpected news or events, which is why the VIX is commonly known as the “investor fear gauge” (e.g., Whaley, 2000). Not surprisingly, the most notorious VIX spikes in this sample occurred around the collapse of Lehman Brothers in 2008 and in March 2020 during the COVID-19 pandemic, when the VIX reached almost 90 percent.

The informational content of option-implied volatilities, especially the VIX, has been extensively explored in the literature. In particular, the VIX has been shown to be a useful predictor of future RV (see, for example, Jiang and Tian, 2005). However, it can be difficult to disentangle whether movements in the VIX reflect changes in expected volatility or changes in preferences. Under some assumptions, for example stationarity, we can extract the component of the VIX related to investor attitudes or preferences.
toward volatility. This concept, known as the variance risk premium, is usually linked to risk aversion (see, for example Bollerslev et al., 2009 and Bekaert, Hoerova, and Lo Duca, 2013). Variance swap contracts with maturities ranging from one month to two years are traded as over-the-counter assets.\textsuperscript{25} We elaborate in greater detail on variance risk premia below.

\textbf{Variance Risk Premia and Higher-Order Moments}

The variance risk premium is a measure of the compensation that investors demand for bearing volatility risk or, in other words, a measure of investors' preference for volatility. Formally, the variance risk premium is defined as the difference between a risk-neutral measure of expected variance, for example, the squared value of VIX, and a physical measure of expected realized variance (Bollerslev et al., 2009). The variance risk premium is often used as a time-varying and state-dependent measure of risk aversion (Rosenberg and Engle, 2002). This measure is also used as a gauge of macroeconomic risk compensation (Bollerslev et al., 2009; Drechsler and Yaron, 2011). Empirically, it has been shown that the variance risk premium is one of the most successful short-term (between one-month and one-quarter ahead) predictors of returns across a broad range of U.S. and international financial assets (Bollerslev et al., 2009; Bollerslev, Gibson, and Zhou, 2011; Dew-Becker, Giglio, Le, and Rodriguez, 2017; Londono and Zhou, 2017; and Londono, 2013).

Figure 14 shows the variance risk premium for the United States between January 2000 and May 2020. The magnitude of this premium increases around key episodes generally associated with high macroeconomic uncertainty, such as the collapse of Lehman Brothers, the European debt crisis, and, more recently, during the COVID-19 pandemic.

Feunou, Jahan-Parvar, and Okou (2018) and Kilic and Shaliastovich (2019) decompose the variance risk premium into upside and downside variance risk premiums. The former represents market participants’ interest in being exposed to upside risk and the higher gains it generates, while the latter represents the premium that market participants

\textsuperscript{25}Variance swaps are contracts in which one party pays a fixed amount at maturity, which we refer to as the price of the variance swap, in exchange for a payment equal to the sum of squared daily log returns of the underlying asset (in this case, S&P 500 returns) occurring until maturity.
Figure 14 Variance Risk Premiums for Headline Equity Indexes

Notes: This figure depicts the variance risk premium calculated as the difference between the square of the option-implied volatility and the expected realized variance. The expected realized variance is calculated as an in-sample forecast of realized variance using the one-month-lagged realized variance, the square of the VIX, and two measures of RV that rely heavily on recent stock returns. The variance risk premium is expressed in (annualized) squared percents. Source: Federal Reserve Board’s staff calculations from Bloomberg Finance LP.

demand as compensation to bear downside risk and the possible losses it may generate. These studies show that the downside component of the variance risk premium explains most of the dynamics and predictability of the total variance risk premium.26

Built on earlier work by Kim and White (2004) as well as more recent studies by Feunou, Jahan-Parvar, and Tédongap (2013) Feunou, Jahan-Parvar, and Tédongap (2016) and Patton and Sheppard (2015), Feunou, Jahan-Parvar, and Okou (2018) show that the difference between upside and downside variance risk premiums, also known as the signed-jump premium, is a measure of the skewness risk premium. This measure, which shares many similarities with the Bollerslev and Todorov (2011) “fear index,” has the potential of capturing the degree of market participant concerns about tail risks.

Other recent contributions to the literature on higher-order moments include work on tail indexes by Torben Andersen and Viktor Todorov, who provide a wealth of regularly updated measures.27 Datta, Londono, and Ross (2017) broaden the applications of higher-

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26 Londono and Xu (2019) show that downside and upside variance risk premiums also play a role in explaining the global component of international equity risk premiums.

27 Data available at tailindex.com/index.html. See Andersen, Fusari, and Todorov (2015, 2020), Bollerslev and Todorov (2011), and Bollerslev, Todorov, and Xu (2015).
order moment estimation to commodities markets using oil options prices. Almeida, Ardison, Garcia, and Vicente (2017) pioneered a non-parametric approach to measuring tail risk that employs return series alone—without any derivatives data—and is therefore suitable for constructing tail risk series going considerably longer back in time.\(^{28}\)

Parallel to the finance literature studying the pricing of uncertainty and jumps in financial markets, Berger, Dew-Becker, and Giglio (2020) take a macroeconomic approach, and utilize methods from the news shocks literature to analyze the effects of uncertainty and volatility shocks on the economy. They argue that it is critical to distinguish between realized and expected volatility (forward-looking uncertainty) to understand the effects of uncertainty shocks. They estimate a structural VAR, as is common in the macroeconomics literature, and find that it is the realized stock market volatility that is associated with downturns, while changes in expected volatility—shocks to forward looking uncertainty—appear to have no significant negative effects. Evidence from asset prices and risk premia is consistent with these findings.\(^{29}\)

**Moments from Firm-Specific Data**

Additional measures of volatility can be computed by exploiting the distribution of stock returns across firms at each point in time (for example, all stocks in the S&P 500). Bloom (2009) and Christiano, Motto, and Rostagno (2014) use the variance across individual stock returns at each point in time as a measure of cross-sectional uncertainty and show that exogenous shocks to these measures are important sources of business cycle fluctuations. Dew-Becker and Giglio (2020) provide a measure of forward-looking cross-sectional uncertainty by using individual stock options. They document that cross-sectional uncertainty has a mixed relationship with the real activity, and it is rather the aggregate uncertainty that is a more powerful driver of the aggregate economy.

**Monetary Policy Uncertainty Redux**

Several papers derive measures of uncertainty about the path of monetary policy from policy-sensitive interest rate derivatives. These measures represent a distinct alternative

\(^{28}\)For more detailed reflections on the advantages of this non-parametric approach to measuring tail risk and its asset pricing theory underpinnings along with empirical comparisons to several other often-applied uncertainty measures, see Dobrev and Schaumburg (2017).

\(^{29}\)See Dew-Becker, Giglio, Le, and Rodriguez (2017).
to news-based measures of monetary policy uncertainty which reflect the uncertainty of a broader segment of society, as emphasized by Husted, Rogers, and Sun (2020). Swanson (2006) developed a measure of monetary policy uncertainty based on the width of the probability distribution of the federal funds rate one-year ahead, as implied by market prices on interest rate derivatives. Figure 15 shows the 90%-confidence interval of the market-implied distribution for the effective federal funds rate at the one-year horizon, computed from at-the-money eurodollar futures options and adjusted for the level difference in volatility between the federal funds rate and eurodollar rates. According to this measure, U.S. monetary policy uncertainty fluctuated notably in the early 1990s, declined in the 2000s, reached a trough during the zero lower bound (ZLB) period, and moved up again in recent years after the FOMC began to lift interest rates away from the ZLB. More recently, this measure declined drastically as the Federal Reserve slashed interest rates again to the ZLB following the COVID-19 pandemic outbreak.

Several papers study the effect of market-based monetary policy uncertainty on various market prices. For example, Swanson (2006) uses the derivative-based measure from eurodollar futures and options, similar to the one shown on figure 15, to find that increased transparency in Federal Reserve communications, associated with a decline in monetary policy uncertainty, has led to improved private sector interest rates forecasts. De Pooter, Favara, Modugno, and Wu (2020) document that the level of market monetary policy uncertainty matters for the reaction of medium- and long-term yields on nominal and real U.S. Treasury securities to monetary policy surprises. Bauer, Lakdawala, and Mueller (2019) show that changes in uncertainty have pronounced effects on asset prices, distinct from the effects of changes in expected policy rates: when uncertainty is low, monetary policy surprises have stronger effects on asset prices.³⁰

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³⁰See also Tillmann (2020), Istrefi and Mouabbi (2018), and on the modeling side Bundick, Herriford, and Smith (2017).
6 Conclusion

Research measuring economic and financial uncertainty and estimating their effects has been ubiquitous over the last decade. Private forecasters, central banks, and other policy institutions routinely produce outlooks (and policies) that are influenced by these measures of uncertainty. Research on uncertainty is devoted to macroeconomic phenomena such as inflation and GDP growth, microeconomic issues concerning firm-level investment, health care, and export market entry and exit, and finance topics such as corporate strategy and equity returns. There are a range of theoretical predictions about the relationship between uncertainty and economic activity. The traditional mechanism builds on irreversible investment, emphasizing the importance of delaying investment until uncertainty is resolved (e.g., Bernanke, 1983; Rodrik, 1991; Bertola and Caballero, 1994; Bloom, 2009). In addition, the financial frictions theory stipulates that a rise in credit spreads to compensate bondholders for heightened uncertainty induces protracted declines in investment (e.g., Gilchrist, Sim, and Zakrajšek, 2014; Arellano, Bai, and Keehoe, 2019; Christiano, Motto, and Rostagno, 2014). Dixit, Eberly, and Pindyck (1996) show that rather than facing costly reversibility, which causes caution about undertaking

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new investment, firms may instead face costly preemption or costly expansion in some aspects of their business. This alternative real option—options to expand—might be especially valuable during times of disruptions, reversing the typical response to uncertainty. Given the lack of theoretical consensus, the question of the transmission effects of uncertainty is an empirical one.

As noted in Jurado, Ludvigson, and Ng (2015), a major challenge in empirically examining the behavior and impact of uncertainty is that no objective measure of uncertainty exists; the empirical literature has proposed a growing number of proxies of uncertainty that correlates with the latent stochastic process. In this paper, we review a broad set of measures of uncertainty, risk, and volatility to help broaden knowledge about the calculation and usefulness of these measures. We highlight their differences and comparative advantages. For example, survey-based measures allow precision concerning the sector in which the uncertainty is located (e.g., firms, households, or traders), the economic measure (e.g., employment, expenditures, policy), and the horizon over which the uncertainty prevails. However, these measures tend to be available at lower frequency and hence possibly be stale relative to, say, news-based or market-based measures.

Finally, we note that several research topics remain somewhat thinly investigated, including exploration of the channels through which uncertainty affects real and financial outcomes; a more structured understanding of the interconnection among uncertainty measures; the endogeneity and causality between macroeconomic and financial uncertainty; the spillover effects of uncertainty across countries; and whether uncertainty modifies how other economic shocks are transmitted.
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