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A Survey of Alternative Measures of Macroeconomic Uncertainty: Which Measures Forecast Real Variables and Explain Fluctuations in Asset Volatilities Better?

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Abstract

In the past 20 years, measures of economic uncertainty have been developed that are purely market price based; structural model based, using data on real fundamentals and asset prices; text based; or survey based. We compare the performance of these uncertainty measures in forecasting three real variables with irreversibilities—investment, hiring, and credit creation—as well as in explaining fluctuations in stock market and Treasury bond market volatility. In general, we find that structural model–based measures do better than measures constructed using other approaches, with a model of stock market volatility by David and Veronesi performing the best on several (but not all) dimensions. Their learning-based model's volatility places time-varying weights on inflation, earnings, and consumption news, as agents in the economy assess the impact that inflation has on the stability of real economic growth.

1. INTRODUCTION

It is intuitive that macroeconomic uncertainty impedes decision-making for agents in the economy. Yet, the economics and finance professions are far from reaching a consensus on how to measure economic uncertainty. The most popular methods to measure economic uncertainty are based on pure financial market prices (such as volatility), structural approaches based on macroeconomic fundamental data as well as market prices, textual based, or survey based. In this review, we provide a brief summary of nine different measures of economic uncertainty proposed in the literature, including approaches with exogenous uncertainty and learning-based endogenous uncertainty. We then compare these measures in their ability to forecast real variables affected by economic uncertainty as well as explain the historical fluctuations of asset volatilities.

In past research, stock market volatility has been almost synonymous with economic uncertainty. A highly successful empirical research program in the 1980s and 1990s documented that stock market volatility is persistent and estimated its exogenous dynamic evolution using autoregressive conditional heteroskedasticity models (for a review, see Anderson et al. 2003). In the past two decades, there has been an increased emphasis on distinguishing economic uncertainty from stock market volatility and studying its implication for real economic activity as well as the volatility of assets' returns. For example, in a highly influential paper, Bloom (2009) shows that macroeconomic uncertainty shocks affect real economic activity; however, he uses the volatility of stocks that is implied from the prices of financial options as a measure of uncertainty. In the long-run risk literature pioneered by Bansal & Yaron (2004), economic uncertainty is defined as the time-varying volatility of consumption growth. This perspective has been pursued by the multifactor approach of Jurado, Ludvigson & Ng (2015), who measure the common movement in volatility of several variables. However, even in these papers, uncertainty follows an exogenous process.

In contrast, David (1997) and Veronesi (1999, 2000) develop a Bayesian learning-based framework of economic uncertainty, which they define as agents' standard deviation of the expected growth rate of fundamentals that is endogenously determined by their learning. In addition, asset prices are developed as the expected discounted present value of cash flows in equilibrium, and hence asset volatilities are endogenous functions of agents' beliefs/uncertainty. Intuitively, in periods when investors have low confidence in their estimates of fundamental growth rates, they rationally revise their beliefs about these growth rates more rapidly, causing greater fluctuations in uncertainty and volatility. These authors have developed a structural approach to estimate such models using data on fundamentals as well as asset prices with a view to extracting agents' beliefs about the state of fundamental growth. The approach is flexible so that the set of asset prices and their second moments can be varied according to the question at hand. In particular, this approach has been used to value stocks and Treasury bonds (David & Veronesi 2013), options (David & Veronesi 1999, 2014), and defaultable bonds (David 2008). The parametric specifications of uncertainty enable structural estimation of the underlying parameters of fundamentals and preference parameters of agents in the economy. A key insight from the structural approach is that measures of uncertainty from individual fundamentals (such as earnings or inflation) do not in themselves explain volatility fluctuations, because investors' attention to each fundamental factor evolves over time depending on the conditional joint distribution of inflation and earnings growth.[1]

[1]We find the same property in the beliefs of forecasters: Measures of inflation and earnings uncertainty in themselves do not have a strong relationship with either real variables or asset volatilities, but forecasters' beliefs about recessions do.

There are indeed more direct ways to measure uncertainty either through surveys or from the use of words that mention uncertainty in the media. However, relative to structural approaches, such measures do not precisely tell us how uncertainty affects asset volatilities, the valuation of assets, or derivatives whose payoffs are nonlinear functions of asset prices, although such relationships can be estimated using either regressions or machine learning techniques.

Given the different ways to measure uncertainty, how can we tell which measure is more useful? Uncertainty matters because it affects real decision-making due to the presence of frictions such as real irreversibilities in investment or hiring (e.g., see Bernanke 1983, Jones & Ostroy 1984, Brennan & Schwartz 1985, McDonald & Siegel 1986, or Dixit & Pindyck 1994). Similarly, financial frictions, which impede the ability to borrow for individuals and corporations, make credit creation partially irreversible and undesirable with increases in uncertainty (e.g., see Kiyotaki & Moore 1997, Rampini & Viswanathan 2010). Therefore, one of our main metrics for choosing between alternative uncertainty measures is the forecasting adjusted R^2 for variables with irreversibilities at the 1-year horizon.[2] Given the long-standing symbiotic relationship between uncertainty and asset volatility, another metric for determining the usefulness of uncertainty measures is how useful these measures are in explaining fluctuations in stock market and Treasury bond market volatilities.

The uncertainty measures that we have chosen are all available from the websites of the authors or publicly available.[3] Differences in sample periods make it difficult to compare all nine measures. Hence, we make comparisons for the David & Veronesi (2013) (DV) measure with four others in each of two different samples: a short sample from 1986 to 2020 and a long sample from 1962 to 2020. In each sample, the DV stock volatility has the highest average ranking among five measures, although for explaining stock market volatility fluctuations, the Bekaert, Engstrom & Xu (2021) (BEX) and Jurado, Ludvigson & Ng (2015) (JLN) uncertainty measures are significantly better. Amongst the measures, the structural model–based measures do better than the other approaches, although, notably, the anxiety index, which is the likelihood of a recession from the Survey of Professional Forecasters (SPF), has the joint second-best average ranking along with the JLN uncertainty measure. Finally, we find that the DV stock volatility Granger causes seven of the eight other uncertainty measures, while it is caused by only three of them. An important caveat is that the structural approaches have an in-sample data-fitting aspect that needs to be considered when comparing them to other approaches.

2. ALTERNATIVE APPROACHES TO MEASURE UNCERTAINTY

We compare nine different uncertainty measures in the literature. These measures fall into four major categories: purely market based, structural model based with data on fundamentals and asset prices, text based, and survey based.

[2] Bloom (2014) has pointed out that the effects of uncertainty can depend on the horizon, with positive effects at longer horizons [consistent with the works of Oi (1961), Hartman (1972), and Abel (1983)] offsetting the real options effect. We find results at the 6-month horizon are similar.

[3] All the data used in this review are available on the following websites: David & Veronesi (2013) (**https://people.ucalgary.ca/~adavid/MYPAPERS/beliefsvols_jpe_aug2021.xlsx**); Bekaert, Engstrom & Xu (2021) (**https://www.nancyxu.net/risk-aversion-index**); Jurado, Ludvigson & Ng (2015) (**https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes**); Baker, Bloom & Davis (2015) (**https://fred.stlouisfed.org/series/USEPUINDXD**); Manela & Moreira (2017) (**http://apps.olin.wustl.edu/faculty/manela/data.html**); Azzimonti (2018) (**http://marina-azzimonti.com/datasets/**); and VXO (**https://fred.stlouisfed.org/series/VXOCLS**).

2.1. Market-Based Measures

Bloom (2009) recommends using the volatility of the aggregate stock market as a measure of macroeconomic uncertainty. In fact, he uses the implied volatility from index options. We use the VXO series, which is the implied volatility on the S&P 100 Index, rather than VIX, which is the implied volatility on the S&P 500 Index. The two series have a 0.99 correlation in the common sample, but the former starts in 1986, 4 years earlier than the VIX. Building on the real options literature with irreversibilities, Bloom shows theoretically that shocks to uncertainty in the presence of adjustment costs lead to slowdowns in investment and hiring. His theoretical framework has separate shocks to the first and second moments of productivity, with the latter being a significant addition to macroeconomic models of the business cycle.[4] In a similar spirit to implied volatility, we also use the realized volatility of stock returns, for which we have a longer time series.

2.2. Structural Model–Based Measures

Jurado, Ludvigson & Ng (2015) construct a comprehensive measure of macroeconomic uncertainty by measuring the conditional volatility of 147 series and taking a weighted average of the series. As in the study by Bloom (2009), they model separate shocks to expected growth rates and the volatility of each series. They assume a linear process for the evolution of the variance of each process and, as a first step, must estimate the parameters of each variance process, which they do using Bayesian methods. By using a vast array of series, the authors write,

> Our goal is to provide superior econometric estimates of uncertainty that are as free as possible both from the structure of specific theoretical models, and from dependencies on any single (or small number) of observable economic indicators. (Jurado, Ludvigson & Ng 2015, p. 1182)

It is useful to note that the authors give exogenous weights to the uncertainty of each factor in the construction of macro uncertainty, while in the learning-based models, the weights to alternative macroeconomic factors are determined by the equilibrium conditions.

Bekaert, Engstrom & Xu (2021) use a structural approach that includes both real and financial variables and simultaneously back out both economic uncertainty and the representative investor's risk aversion. Risk aversion follows a dynamic process as in the external habit formation model of Campbell & Cochrane (1999), while second- and higher-order moments of cash flows are driven by two factors. The risk-neutral variance of stocks is one of the moments that is used in their generalized method of moments procedure. Updated time series of both risk aversion and uncertainty of cash flows are made available on the authors' web pages.

As mentioned, another structural approach is the learning-based one, which we discuss separately in Section 2.5.

2.3. Text-Based Measures

Baker, Bloom & Davis (2015) construct a measure of economic policy uncertainty (EPU)—the BBD EPU—from a search of words in ten newspapers. To be added to the count, an article must contain words from three categories: uncertainty, economy, and policy. This measure is now

[4]In contrast, the learning-based framework only has shocks to the first moment, but due to the unobservability of growth rates of productivity, and investors' learning about them, investors' conditional forecasts of future growth rates exhibit time-varying second moments. That is, shocks to first and second moments cannot be easily disentangled. This feature is also present in GARCH models of exogenous autoregressive volatility.

available in several public databases, and the one we analyze is obtained from the FRED database maintained by the Federal Reserve Bank of St. Louis. The paper contributes to a literature on how the effects of investors' and firms' uncertainty about the decisions of policy makers affects their private decisions. In this sense, policy uncertainty is an added propagation mechanism to shocks to both the first and second moments of fundamentals (e.g., see Pastor & Veronesi 2012, Pastor & Veronesi 2013). These authors show that the EPU measure affects firms' hiring and investment decisions.

Another text-based uncertainty measure has been proposed by Manela & Moreira (2017). Like Baker, Bloom & Davis (2015), these authors search newspapers for words that signal uncertainty, but in addition, they use machine learning techniques for training the computer to select words that impact the VIX. Once trained, they use their method to test out of sample the performance of the news-based VIX (NVIX) to predict the VIX. In addition, they provide subcategories of NVIX related to five categories: war, government policy, financial intermediation, the stock market, and natural disasters. They find that 90% of the variation in the VIX is driven by the first two categories. It is useful to keep in mind that this paper seeks to measure the uncertainty of disaster-like events, which are of lower frequency than typical business cycle fluctuations. As such, these authors are more motivated to find an uncertainty measure that predicts stock market returns than one that predicts real decisions, since it has been well established that disasters have a strong influence on the equity premium.

Azzimonti (2018) uses a semantic search method using the Factiva database to measure the frequency of newspaper articles that mention lawmakers' disagreements about policy. Therefore, her measure is one of disagreement rather than of uncertainty. The implications of disagreement on real variables with frictions such as investment are less explored than those of the effect of uncertainty on investment (a notable exception is Baker, Hollifield & Osambela 2016). She finds that her disagreement measure is particularly successful in explaining the decline in investment in the period between 2007 and 2009.

2.4. Survey-Based Measures

We construct a survey-based uncertainty measure that is derived directly from the anxiety index, which is created and disseminated by the Federal Reserve Bank of Philadelphia (FRBP). The FRBP conducts the SPF quarterly, which surveys forecasters working in prominent economic forecasting positions in academia, banks, and other companies. Indeed, surveys are the most intuitive way of measuring uncertainty with the caveat that they measure the uncertainty of a specific group of agents in the economy.[5] The anxiety measure is the average probability of a recession in the following quarter based on the responses of all the forecasters. We take this probability, p_R, and convert it to an uncertainty measure by constructing $p_R(1 - p_R)$.

2.5. The Learning-Based Approach to Measuring Macroeconomic Uncertainty

Learning-based models assume that drifts (growth rates) of fundamentals are hard to observe, so agents in the economy attempt to learn about them from the history of fundamentals as well as other signals. In periods when agents are more uncertain, they revise their beliefs about growth rates more rapidly, and hence their values of financial assets fluctuate more, that is, become more

[5]More recently, the Federal Reserve Bank of New York has started surveying a small sample of consumers directly; however, at this point the time series are too short to compare with the alternative uncertainty measures.

volatile. In this survey, we take the process of economic uncertainty that arises endogenously in David & Veronesi (2013). The model in this paper has two economic fundamentals with time-varying drifts, real earnings growth and inflation; consumption growth is a third fundamental in the model, whose drift is known and constant. Inflation is a signal of future earnings growth. In periods of low inflation (about 2%), earnings growth is stable, but in periods of very high or very low inflation (deflation), earnings growth becomes unstable. Due to this joint distribution, investors' attention to each fundamental factor (inflation versus earnings) evolves over time.

The time series of beliefs of investors is shown in **Figure 1**. The most frequent belief of investors is that of low inflation and high growth (**Figure 1*a***), with the remaining states all reflecting some atypical economic conditions. We see that in the second half of the last century, recessions were typically accompanied by investors' beliefs of high inflation, while in the current century, recessions have been accompanied by beliefs of deflation. This observation includes the COVID-19 pandemic recession of 2020. Since then, the reappearance of inflation for the first time in the current century has raised investors' fears of the stagflation state (**Figure 1*d***). There were also two bouts of good uncertainty before the 2001 and 2008 recessions, when agents seemed optimistic of low inflation accompanied by new economy high earnings growth rates (**Figure 1*e***).

In this approach, asset volatilities are positively related to investors' belief volatilities and have closed-form expressions. The stock return volatility is

$$\sigma^N(\pi_t) = \sigma_Q + \sigma_E + \frac{\sum_{i=1}^{n} G_i \pi_{it} (\nu^i - \overline{\nu}(\pi_t))'(\Sigma')^{-1}}{\sum_{i=1}^{n} G_i \pi_{it}}, \qquad 1.$$

and the Treasury bond return volatility is

$$\sigma^B(\pi_t, \tau) = \frac{\sum_{i=1}^{n} B_i(\tau) \pi_{it} (\nu^i - \overline{\nu}(\pi_t))'(\Sigma')^{-1}}{\sum_{i=1}^{n} B_i(\tau) \pi_{it}}, \qquad 2.$$

where π_{it} is the agent's conditional probability that the composite state of earnings growth and inflation is the vector $\nu_i = (\beta_i, \theta_i, \kappa)$; β_i is the drift rate of inflation, θ_i is the drift rate of earnings growth, and κ is the drift rate of consumption growth; the first two drifts are unobservable, while the consumption drift is known; $\overline{\nu}(\pi_t) = \sum_i \pi_{it} \nu_i$; G_i is the conditional price-earnings ratio (PE) ratio in state i, and $B_i(\tau)$ is the τ period Treasury bond yield in state i; and σ_Q, σ_E, and σ_C are exogenous volatilities of inflation, earnings, and consumption, respectively, and Σ is the matrix with these three vectors as rows.[6] The volatility equations show a compelling relationship between uncertainty and assets' valuations. The term $\pi_{it}(\nu^i - \overline{\nu}(\pi_t))'(\Sigma')^{-1}$ is the volatility of the agent's belief of state i and is composed of the normalized uncertainty of each fundamental drift. However, what matters for stock (bond) volatility is the belief volatility multiplied by the PE (bond yield) weight of that state; that is, asset valuations scale the fundamental uncertainties in each state, so if the asset valuation in a state is very small, uncertainty about that state will not affect the volatility of that asset much. We formally examine the ability of the model to explain volatility fluctuations relative to other uncertainty measures in the next section.

2.6. Survey and Model Probabilities of Inflation and Recessions

In the learning-based model of David & Veronesi (2013), agents learn about the drifts of inflation and earnings growth. **Figure 1** shows the probabilities of composite states of these two variables.

[6] With some abuse of terminology, we refer to the diffusion of a return process as its volatility. Equations 1 and 2 show the diffusion vectors of the return processes. Strictly speaking, the volatility of stock returns, for instance, is the scalar given by $\sqrt{\sigma^N(\pi)\sigma^N(\pi)'}$.

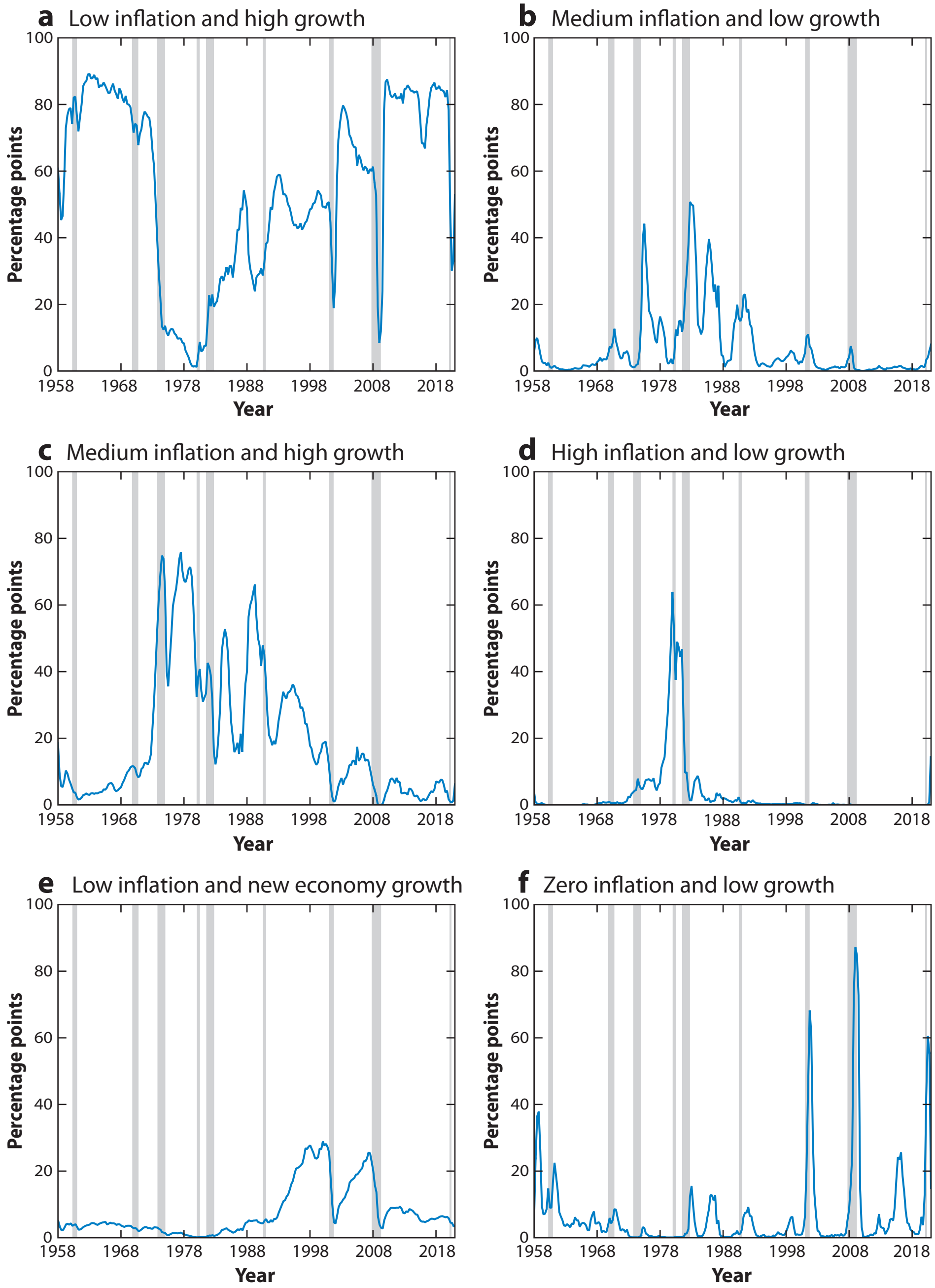


Figure 1

Investors' beliefs about macroeconomic states. Filtered probabilities of six composite states from David & Veronesi (2013) are given here. The beliefs from 2012 to 2020 are based on parameters estimated using data until 2011. Estimated mean real earnings growth rates are −5.18%, 3.26%, and 5.41% at annual rates in the states of low, high, and new economy growth, respectively. Estimated Consumer Price Index mean inflation is at 0.41%, 2.53%, 4.67%, and 10.19% at annual rates in the states of zero, low, medium, and high inflation, respectively.

Here we compare the marginal probabilities of the two state variables with the mean probability assessments of these variables from the SPF. The SPF asks forecasters to provide their probability assessment that the variable of interest (e.g., inflation) will be in given intervals in the following year. The SPF then aggregates the data and provides the average probabilities across forecasters for each interval. **Figure 2*a–d*** shows the SPF probabilities for the next year and the model's analogous probabilities for the four inflation states in our model.[7] For each of the marginals, the correlation between the model probability and the SPF probability is between 50% and 80%. Notably and interestingly, the model probabilities are less volatile than the SPF probabilities. For example, the probability of medium inflation assessed by investors (estimated by our model) remained elevated through the 1990s, while forecasters in the SPF assessed that it declined quite rapidly.

Figure 2*e* shows the SPF probability to be in a recession next quarter together with the marginal probability of low growth from the model. The two series have a high correlation of 52% and display peaks at about the same times.

2.7. Salient Features of Alternative Uncertainty Measures

The time series of all nine uncertainty measures are given in **Figure 3**, and the correlations between them are presented in **Table 1**. With the exception of Azzimonti's (2018) Partisan Conflict Index (PCI), all the measures increase in recessions and are positively correlated with each other (correlations in the range of 0.4–0.7). There are some important differences though, which we note below.

- Most of the measures hit their highest levels during the 2008 financial crisis with the exception of the BBD EPU (**Figure 3*a***), which peaked in 2020.
- The BBD EPU (**Figure 3*a***) measure seems to persist at elevated levels the longest after recessions.
- The PCI (**Figure 3*g***) was very low until the financial crisis and then remained high for several years.
- The SPF recession uncertainty (**Figure 3*h***) is the most volatile among all measures, hitting its highest levels in all the recessions in the sample, while the other measures did not reach peak levels in all recessions.
- The DV stock market volatility measure (**Figure 3*i***) displays similar patterns to the VXO (**Figure 3*e***) and realized volatility (**Figure 3*f***) but has less high-frequency movement than these two measures.
- The BEX uncertainty measure (**Figure 3*c***) was relatively low in the 2001 recession in the sense that it hit about the same level as in 2012 and 2016, when we saw bouts of economic weakness, which were not classified as recessions by the National Bureau of Economic Research.
- The JLN uncertainty measure (**Figure 3*d***) was at its highest levels in the 1960s, when other measures were at relatively benign levels, and was also relatively higher in the 1970s than were the other measures.

[7]There is by necessity some arbitrariness in the definition of the inflation ranges corresponding to high, medium, low, and zero inflation in SPF probabilities. For **Figure 2**, we defined cutoffs for each inflation range as the midpoint between the estimated inflation regimes given by David & Veronesi (2013), resulting in intervals $(-\infty, 1.47)$, $(1.47, 3.59)$, $(3.59, 7.43)$, and $(7.43, \infty)$.

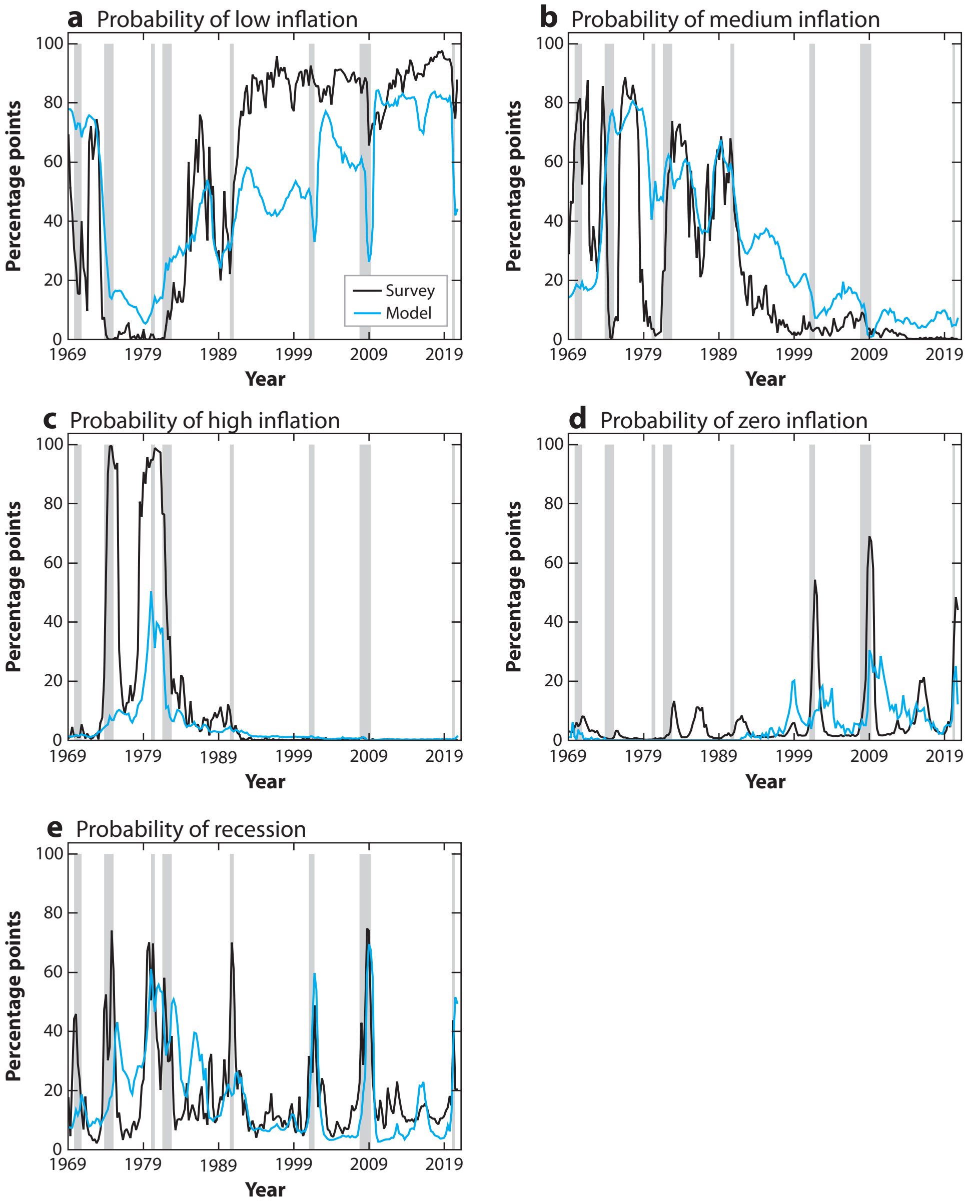


Figure 2

Survey and model probabilities, showing filtered probabilities of six composite states from David & Veronesi (2013). Panels *a–d* show the Survey of Professional Forecasters (SPF) probabilities for the next year (*black lines*) and the model's analogous probabilities (*blue lines*) for the four inflation states in our model. Panel *e* shows the SPF probability to be in a recession next quarter (*blue line*) together with the marginal probability of low growth (LG) from the model (*black line*). The beliefs from 2012 to 2020 are based on parameters estimated using data until 2011. Estimated mean real earnings growth rates are −5.18%, 3.26%, and 5.41% at annual rates in the states of low, high, and new-economy growth, respectively. Estimated Consumer Price Index mean inflation is at 0.41%, 2.53%, 4.67%, and 10.19% at annual rates in the states of zero, low, medium, and high inflation, respectively. The survey probabilities are the average probabilities across forecasters of the variable (earnings growth or inflation) to be in a specified interval. We defined the intervals for each variable to be the midpoints between the estimated means above.

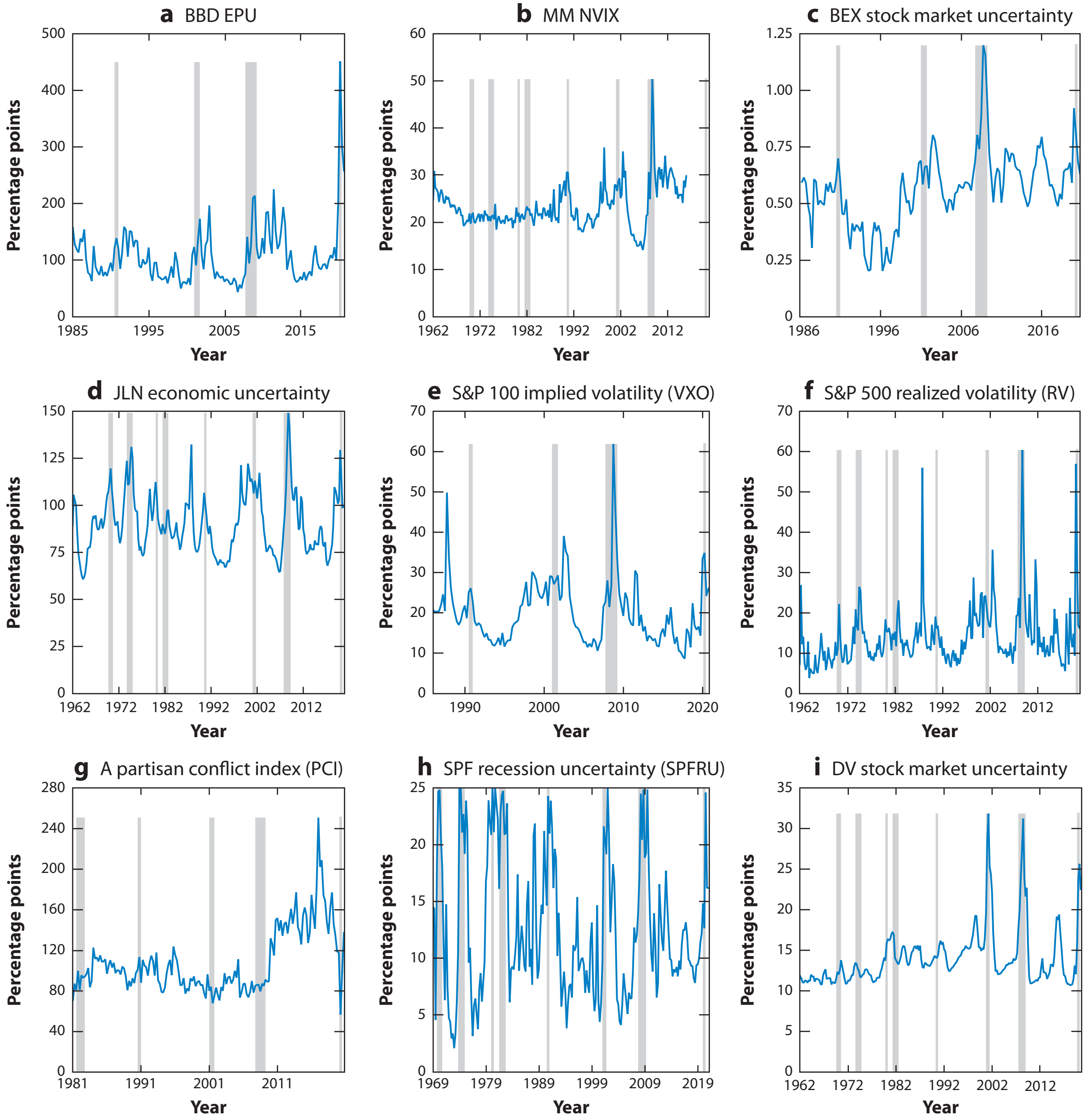


Figure 3

Alternative uncertainty measures. The uncertainty measures are as described in Section 2. BBD EPU stands for the economic policy uncertainty from Baker, Bloom & Davis (2015); MM NVIX stands for the news-based VIX developed by Manela & Moreira (2017); BEX stands for the uncertainty measure from Bekaert, Engstrom & Xu (2021); JLN stands for the financial uncertainty series obtained from the website of Sydney Ludvigson and developed by Jurado, Ludvigson & Ng (2015); VXO stands for the implied volatility on 30-day S&P 100 Index options; RV stands for the realized volatility of the S&P 500 Index; A PCI stands for the Partisan Conflict Index from Azzimonti (2018); SPF stands for the uncertainty measure constructed from the anxiety index published by the Federal Reserve Bank of Philadelphia; and DV stands for the model stock volatility from David & Veronesi (2013).

Table 1 Correlation of uncertainty measures

Short sample: 1986–2020					
	BBD	**BEX**	**VXO**	**A PCI**	**DV**
BBD	1.000	0.418	0.418	0.043	0.315
BEX	0.418	1.000	0.542	0.109	0.414
VXO	0.418	0.542	1.000	−0.365	0.537
A PCI	0.043	0.109	−0.365	1.000	−0.377
DV	0.315	0.414	0.537	−0.376	1.000
Long sample: 1962–2020					
	NVIX	**JLN**	**RV**	**SPF**	**DV**
NVIX	1.000	0.498	0.656	0.281	0.444
JLN	0.498	1.000	0.732	0.487	0.393
RV	0.657	0.732	1.000	0.392	0.477
SPF	0.282	0.487	0.392	1.000	0.352
DV	0.444	0.393	0.477	0.353	1.000

BBD stands for the economic policy uncertainty from Baker, Bloom & Davis (2015); BEX stands for the uncertainty measure developed by Bekaert, Engstrom & Xu (2021); VXO stands for the implied volatility on 30-day S&P 100 Index options; A PCI stands for the Partisan Conflict Index from Azzimonti (2018); DV stands for the model stock volatility from David & Veronesi (2013); NVIX stands for the news-based VIX developed by Manela & Moreira (2017); JLN stands for the financial uncertainty series obtained from the website of Sydney Ludvigson and developed by Jurado, Ludvigson & Ng (2015); RV stands for the realized volatility of the S&P 500 Index; and SPF stands for the uncertainty measure constructed from the anxiety index published by the Federal Reserve Bank of Philadelphia.

2.8. Implementation of Uncertainty Measures: In-Sample and Out-of-Sample Uncertainty

As we evaluate the ability of alternative economic uncertainty measures to forecast real variables or fit asset volatilities, we should keep in mind the sample periods used by the authors to construct these measures. We make the following summary comments:

- David & Veronesi (2013) use data until 2011 to estimate their model. Investors' beliefs from 2012 to 2020 are updated assuming that they would observe incoming fundamental data each quarter using Bayes' law, and the parameters estimated using data until 2011. Therefore, the fits from 2012 to 2020 can be interpreted as out-of-sample implications of their model.
- Jurado, Ludvigson & Ng (2015) provide series of economic uncertainty for a few vintages, based on reestimating their model parameters as new data have become available. We provide results for the latest vintage of their uncertainty measure. We should therefore interpret their results as in sample.
- Manela & Moreira (2017) use a text-based approach to measure uncertainty and in addition incorporate machine learning techniques to pick up appropriate words and phrases that impact stock market volatility. Interestingly, their training and test samples are from 1996–2009 and 1986–1995, respectively. Therefore, we should consider the fits in these periods as in sample and those for the remaining periods as out of sample.
- Bekaert, Engstrom & Xu (2021) have a structural approach to fitting volatility and asset prices over the period from 1986:2 to 2020, so their results should be considered in sample.
- The text-based measures of Baker, Bloom & Davis (2015) and Azzimonti (2018) and the SPF do not have any fitting aspect of the data, so the classification should be neutral to the sample. Similarly, the VXO and realized volatility are pure data constructions without any fitting aspects.

3. FORECASTING REAL VARIABLES WITH IRREVERSIBILITIES

Real options–based models predict that decision-makers delay irreversible decisions when confronted with increased uncertainty (see references in Section 1). The decisions that we consider are aggregate investment, credit creation, and hiring. Real options–based models imply that the future flow of these variables would be adversely affected by the level of uncertainty. Plots of these variables are presented in **Figure 4**, and they show that each of these variables is strongly procyclical, dropping substantially in and around the eight recessions in our sample from 1962 to 2020. In this section, we briefly study the relative performance of the nine alternative uncertainty measures that are described in Section 2 in forecasting real variables subject to complete or partial irreversibilities. As noted, the uncertainty measures are strongly countercyclical, and so we should expect negative relationships between these variables and uncertainty.

Before providing the results, we ask why forecasts of these variables based on current uncertainty are more relevant than fitting their current values? Since we have picked variables with partial irreversibilities, it is reasonable to assume that decision-makers will be unable to impact their current or near-term values significantly. For the sake of brevity, we provide results for one-year-ahead forecasts. We note that we use static four-quarter-ahead forecasts rather than dynamic forecasts using vector autoregressions, since again due to the irreversibilities, the dynamic impact of uncertainty on near-term investment and its consequent impact on the next period's uncertainty will be muted.

3.1. Investment

We start with the specification of our investment forecast equation:

$$\log(\mathrm{ik}(t+4)/\mathrm{ik}(t)) = \alpha + \beta_U\,(U(t) - U(t-1)) + \beta_Q\,Ret(t) + \epsilon(t+4), \qquad 3.$$

where $\mathrm{ik}(t) = I(t)/K(t-1)$ is the investment-capital ratio, $U(t)$ is a measure of uncertainty at t, and Ret is the S&P 500 real return at t. It is useful to note that we include the stock returns to predict investment, consistent with Tobin's Q theory.[8]

It is also useful to note that we forecast log changes in the investment-capital ratio, since it is known to be slow moving (e.g., see Cummins, Hassett & Oliner 2006). The results of the forecasting exercise are given in **Table 2**, which also contains the exact descriptions of the variables. The table contains two sets of results, the first for the uncertainty measures that are available for the shorter sample, which starts in 1986:2, and the second for those available for the longer sample, which starts in 1962.[9]

Looking at the results, it is immediately evident that for the longer sample, the impact of each measure of uncertainty on investment is negative and is strongly statistically significant. For the shorter sample though, the BBD EPU does not have a significant coefficient, while Azzimonti's (2018) PCI has a positive coefficient. As seen in **Figure 3**, her disagreement measure was fairly

[8]Pastor & Veronesi (2003) and David & Veronesi (2013) show that even in the absence of frictions, uncertainty affects the valuation of assets through both cash flow and discount rate channels. Indeed, the cash flow effects of uncertainty may be positive and offset the negative discount rate effect of uncertainty. These effects on valuation can then affect real decisions, such as investment, through channels such as Tobin's Q.

[9]It is relevant to point out that there are three exceptions to these sample specifications. Azzimonti's (2018) PCI started in 1981, but to compare to other measures we restrict the results to start in 1986. The NVIX ended in 2016, and this biases our results in favor of NVIX, since the 2020 recession and the plunge in real variables were largely unpredictable. The SPF recession uncertainty measure starts in 1968, so our results when comparing to the other models are biased in its favor as well. However, we ran our horse races to start in 1968 as well and obtained the same rankings.

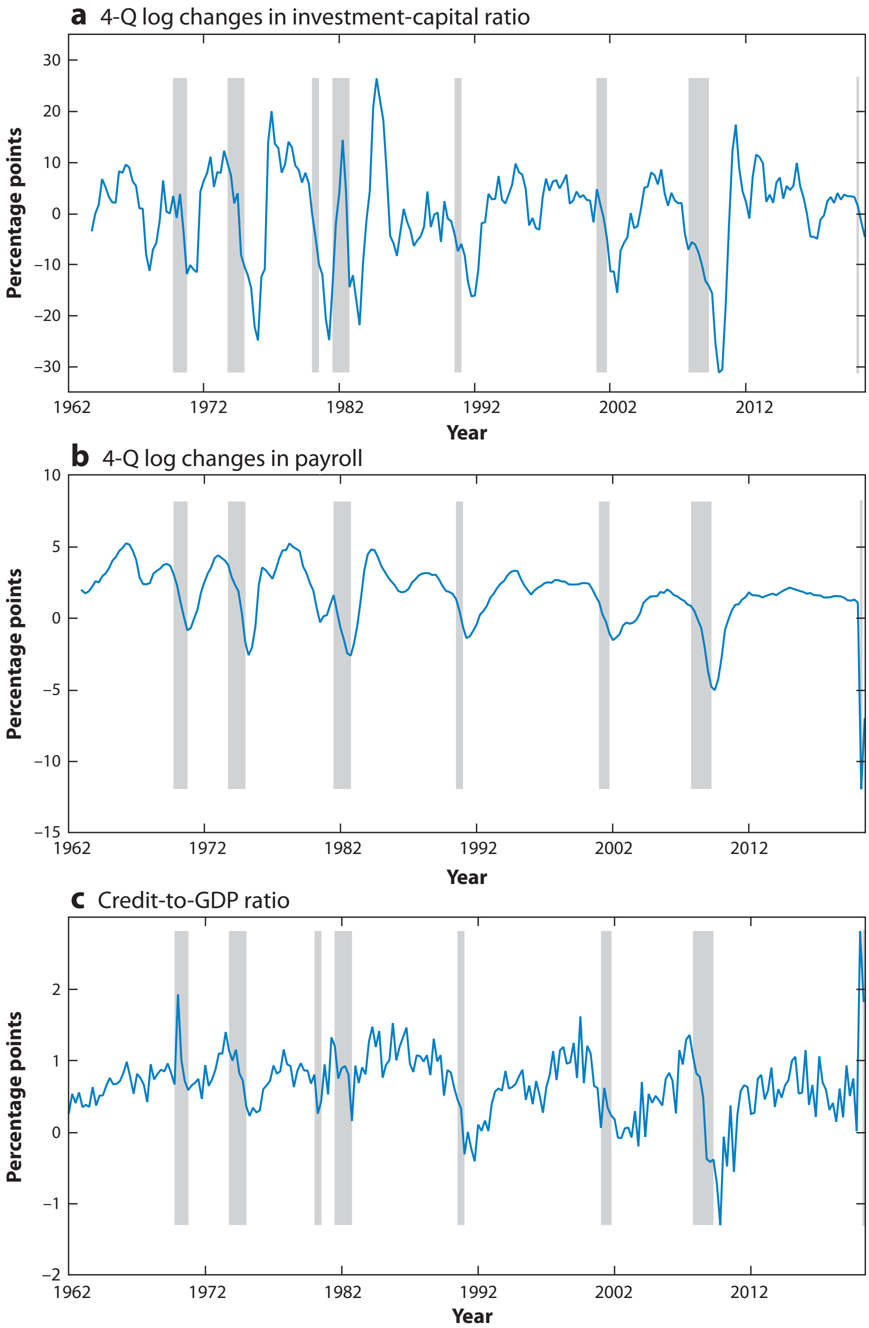


Figure 4

Fundamentals with irreversibilities. **Tables 2–4** provide exact sources of the three data series. (*a*) $ik(t) = I(t)/K(t-1)$ is the investment-capital ratio. Capital stock (in constant prices) is series RKNAN-PUSA666NRUG; investment in nominal dollars is series GPDI and is deflated using the Consumer Price Index. These series are obtained from the Federal Reserve Bank of St. Louis's FRED database. (*b*) Payrolls (*pr*) denote total nonfarm employees, which is the series PAYEMS obtained from the FRED database. (*c*) $cg(t) = \text{creditgrowth}(t)/\text{GDP}(t-1)$ provides the credit-to-GDP ratio. Credit growth at nonfinancial corporate businesses is from the Federal Reserve Board's flow of funds accounts (series FA104104005.Q), and nominal GDP is from the FRED database.

Table 2 Investment and uncertainty

	Sample: 1986–2020:1			Sample: 1962–2020:1		
	Coeff.	SE	*p*-value	Coeff.	SE	*p*-value
	BBD EPU			**MM NVIX****		
$\bar{R}^2$	0.140			0.144		
α	−0.008	0.013	0.507	−0.006	0.010	0.573
β_U	0.000	0.000	0.465	−0.003	0.002	0.194
β_Q	0.383	0.131	0.004	0.420	0.097	0.000
	BEX stock market uncertainty			**JLN multifactor uncertainty**		
$\bar{R}^2$	0.175			0.194		
α	−0.006	0.012	0.623	−0.333	0.010	0.738
β_U	−21.033	8.082	0.010	−0.339	0.137	0.015
β_Q	0.280	0.103	0.008	0.305	0.093	0.001
	VXO			**Realized volatility**		
$\bar{R}^2$	0.138			0.139		
α	−0.009	0.013	0.503	−0.006	0.010	0.559
β_U	0.000	0.001	0.766	0.047	0.102	0.647
β_Q	0.393	0.139	0.006	0.482	0.103	0.000
	A PCI*			**SPF recession uncertainty*****		
$\bar{R}^2$	0.140			0.171		
α	−0.009	0.013	0.487	−0.008	0.011	0.485
β_U	0.000	0.000	0.314	−0.004	0.001	0.009
β_Q	0.414	0.124	0.001	0.443	0.099	0.000
	DV stock volatility			**DV stock volatility**		
$\bar{R}^2$	0.242			0.179		
α	−0.009	0.011	0.433	−0.006	0.010	0.561
β_U	−1.392	0.591	0.020	−1.255	0.571	0.029
β_Q	0.380	0.099	0.000	0.453	0.085	0.000

We report the results of the regression $\log(\mathrm{ik}(t+4)/\mathrm{ik}(t)) = \alpha + \beta_U(U(t) - U(t-1)) + \beta_Q Ret(t) + \epsilon(t+4)$, where $\mathrm{ik}(t) = I(t)/K(t-1)$ is the investment-capital ratio, $U(t)$ is a measure of uncertainty at t, and Ret is the S&P 500 real return at t. Capital stock (in constant prices) is series RKNANPUSA666NRUG; investment in nominal dollars is series GPDI and is deflated using the Consumer Price Index. These series are obtained from the Federal Reserve Bank of St. Louis's FRED database. *, **, and *** denote that the sample for the variable is from 1981 to 2020:1, 1962 to 2016:1, and 1968:4 to 2020:1, respectively. Standard errors are adjusted for heteroskedasticity and autocorrelation using the methodology of Newey & West (1987). BBD EPU stands for the economic policy uncertainty from Baker, Bloom & Davis (2015); BEX stands for the uncertainty measure developed by Bekaert, Engstrom & Xu (2021); VXO stands for the implied volatility on 30-day S&P 100 Index options; A PCI stands for the Partisan Conflict Index from Azzimonti (2018); DV stands for the model stock volatility from David & Veronesi (2013); MM NVIX stands for the news-based VIX developed by Manela & Moreira (2017); JLN stands for the financial uncertainty series obtained from the website of Sydney Ludvigson and developed by Jurado, Ludvigson & Ng (2015); and SPF stands for the uncertainty measure constructed from the anxiety index published by the Federal Reserve Bank of Philadelphia.

low until the 2008 financial crisis and hence is unable to forecast investment in the early part of her sample (1981–2007). Among the remaining measures, in the shorter sample, the DV stock volatility measure has the best forecasting power with an adjusted R^2 of 24.2%, while the BEX stock market uncertainty measure is next best at 17.5%. In the long sample, the JLN measure is the best, with an adjusted R^2 of 19.4%, although the gap in performance among all the models is quite small, and the DV and SPF recession uncertainty measures have adjusted R^2s that are only about 1.5 percentage points smaller.

Table 3 Hiring and uncertainty

	Sample: 1986–2021:2			Sample: 1962–2021:2		
	Coeff.	SE	*p*-value	Coeff.	SE	*p*-value
	BBD EPU			**MM NVIX****		
$\bar{R}^2$	0.092			0.165		
α	0.008	0.007	0.266	0.044	0.011	0.000
β_U	0.000	0.000	0.949	−0.001	0.000	0.008
β_Q	0.098	0.036	0.008	0.060	0.020	0.004
	BEX stock market uncertainty			**JLN multifactor uncertainty**		
$\bar{R}^2$	0.251			0.205		
α	0.042	0.006	0.000	0.064	0.012	0.000
β_U	−5.772	1.227	0.000	−0.053	0.013	0.000
β_Q	0.056	0.029	0.056	0.046	0.022	0.034
	VXO			**Realized volatility**		
$\bar{R}^2$	0.100			0.155		
α	0.015	0.009	0.110	0.029	0.005	0.000
β_U	0.000	0.000	0.485	−0.096	0.033	0.004
β_Q	0.084	0.038	0.029	0.037	0.025	0.138
	A PCI*			**SPF recession uncertainty*****		
$\bar{R}^2$	0.092			0.268		
α	0.008	0.009	0.326	0.033	0.005	0.000
β_U	0.000	0.000	0.984	−0.002	0.000	0.000
β_Q	0.097	0.034	0.005	0.070	0.024	0.004
	DV stock volatility			**DV stock volatility**		
$\bar{R}^2$	0.136			0.187		
α	0.028	0.014	0.059	0.047	0.010	0.000
β_U	−0.124	0.088	0.061	−0.227	0.068	0.001
β_Q	0.081	0.034	0.019	0.069	0.021	0.001

We report the results of the regression $\log(pr(t+4)/\mathrm{pr}(t)) = \alpha + \beta_U U(t) + \beta_Q Ret(t) + \epsilon(t+4)$, where *pr* denotes total nonfarm employees, which is the series PAYEMS obtained from the Federal Reserve Bank of St. Louis's FRED database, and *Ret* is the S&P 500 real return at *t*. *, **, and *** denote that the sample for the variable is from 1981 to 2021:2, 1962 to 2016:1, and 1968:4 to 2021:2, respectively. Standard errors are adjusted for heteroskedasticity and autocorrelation using the methodology of Newey & West (1987). BBD EPU stands for the economic policy uncertainty from Baker, Bloom & Davis (2015); BEX stands for the uncertainty measure developed by Bekaert, Engstrom & Xu (2021); VXO stands for the implied volatility on 30-day S&P 100 Index options; A PCI stands for the Partisan Conflict Index from Azzimonti (2018); DV stands for the model stock volatility from David & Veronesi (2013); MM NVIX stands for the news-based VIX developed by Manela & Moreira (2017); JLN stands for the financial uncertainty series obtained from the website of Sydney Ludvigson and developed by Jurado, Ludvigson & Ng (2015); and SPF stands for the uncertainty measure constructed from the anxiety index published by the Federal Reserve Bank of Philadelphia.

3.2. Hiring

For aggregate hiring decisions, we present in **Table 3** the results of the forecasting equation

$$\log(pr(t+4)/pr(t)) = \alpha + \beta_U\, U(t) + \beta_Q\, Ret(t) + \epsilon(t+4), \qquad 4.$$

where *pr* denotes total nonfarm employees, and *Ret* is the S&P 500 real return at *t*. As for investment, due to the need for specialized employees, hiring is partially irreversible, and hence firms would likely reduce it when confronted with higher uncertainty. Since the growth in payrolls does not appear to have any trends (see **Figure 4*b***), we do not difference it, and hence do not difference uncertainty on the right-hand side of the equation either. In the spirit of Tobin's Q for investment, we also include stock returns as an explanatory variable.

As we see in **Table 3**, the effect of most of the uncertainty measures is negative, and the effect of stock returns is positive. As we see in **Figure 4**, hiring dipped significantly in all the recessions; however, it recovered at different speeds after the recessions. In particular, the recovery in payrolls after the 1991 recession took 3–4 years.[10] For the short sample, once again the differences in the performance of alternative measures of uncertainty are larger. The BEX stock market uncertainty provides the best forecast of hiring growth, with an adjusted R^2 of 25.1%, while the DV model volatility is a distant second at 13.6%. The BBD EPU and Azzimonti's (2018) PCI have insignificant coefficients. For the longer sample, all the uncertainty measures have statistically significant coefficients and similar forecasting power, although the performance of the SPF recession uncertainty measure is the best, with an adjusted R^2 of nearly 27%, while the JLN uncertainty and DV stock volatility are close and come in as the second and third best, respectively.

3.3. Credit

Due to financial frictions, credit creation is also subject to irreversibilities (see references in Section 1) and is likely impacted by uncertainty. As seen in **Figure 4**, credit growth falls during recessions and typically recovers over several years; that is, there is evidence of a credit cycle that lags the real business cycle. In **Table 4** we present the results of the regression

$$cg(t+4) = \alpha + \beta_U\, U(t) + \epsilon(t+4), \qquad 5.$$

where $cg(t) = \text{creditgrowth}(t)/\text{GDP}(t-1)$ and $U(t)$ is a measure of uncertainty at t. This definition of credit growth has been used by several authors (e.g., see Krishnamurthy & Muir 2017). Unlike investment, and hiring, stock returns do not significantly improve the forecasts of credit growth. For each of the samples, the DV stock market volatility provides substantially better forecasts of credit growth than do the alternative uncertainty measures. For the shorter sample, the BEX stock market uncertainty measure is next best, while for the longer sample, the second best is the SPF recession uncertainty. With the exception of Azzimonti's (2018) PCI, all the uncertainty measures have statistically significant negative coefficients.

4. FINANCIAL MARKET VOLATILITY AND ECONOMIC UNCERTAINTY

In the following two subsections, we compare the performance of all the different approaches to explain the fluctuations in stock volatility and Treasury bond market volatility.

4.1. Stock Market Volatility

Since the aggregate stock market is to a large extent efficient, it should react contemporaneously to agents' macroeconomic uncertainty. We hence fit the contemporaneous relationship

$$\text{RV}(t) = \alpha + \beta_U\, U(t) + \epsilon(t), \qquad 6.$$

where RV is the realized volatility of the S&P 500 Index returns computed as the standard deviation of the daily returns realized in the quarter. Results for the regression for alternative uncertainty measures are provided in **Table 5**. In this table, we have two fewer explanatory measures than for the real variables since the dependent variable and the volatility measures are essentially the same. For each of the samples, there is one dominant measure: the BEX stock market

[10]We note that we have hiring and credit data until 2021:2, so our analysis includes the forecast made during the 2020 recession, while for investment, our data ended in 2020:1, so the forecasts in the recession were not included.

Table 4 Credit and uncertainty

	Sample: 1986–2021:2			Sample: 1962–2021:2		
	Coeff.	SE	*p*-value	Coeff.	SE	*p*-value
	BBD EPU			MM NVIX**		
$\bar{R}^2$	0.056			0.065		
α	14.007	2.614	0.000	9.46	0.000	0.903
β_U	−973.514	540.387	0.074	−1.91	0.000	0.012
	BEX stock market uncertainty			JLN multifactor uncertainty		
$\bar{R}^2$	0.149			0.068		
α	12.474	2.092	0.000	13.359	3.164	0.000
β_U	−1, 253.963	410.097	0.003	−7.500	3.776	0.048
	VXO			Realized volatility		
$\bar{R}^2$	0.078			0.089		
α	9.315	1.882	0.000	9.325	0.632	0.000
β_U	−0.192	0.111	0.088	−0.029	−4.843	0.000
	A PCI*			SPF recession uncertainty***		
$\bar{R}^2$	0.002			0.115		
α	4.437	1.513	0.004	0.781	0.721	0.000
β_U	0.015	0.013	0.244	−0.118	0.042	0.006
	DV stock volatility			DV stock volatility		
$\bar{R}^2$	0.198			0.187		
α	14.391	1.586	0.000	14.477	2.122	0.000
β_U	−59.495	10.242	0.000	−56.392	16.018	0.001

We report the results of the regression $cg(t+4) = \alpha + \beta_U\, U(t) + \epsilon(t+4)$, where $cg(t) = \text{creditgrowth}(t)/\text{GDP}(t-1)$ and $U(t)$ is a measure of uncertainty at t. Credit growth at nonfinancial corporate businesses is from the Federal Reserve Board's flow of funds accounts (series FA104104005.Q), and nominal GDP is from the Federal Reserve Bank of St. Louis's FRED database. *, **, and *** denote that the sample for the variable is from 1981 to 2021:2, 1962 to 2016:1, and 1968:4 to 2021:2, respectively. Standard errors are adjusted for heteroskedasticity and autocorrelation using the methodology of Newey & West (1987). BBD EPU stands for the economic policy uncertainty from Baker, Bloom & Davis (2015); BEX stands for the uncertainty measure developed by Bekaert, Engstrom & Xu (2021); VXO stands for the implied volatility on 30-day S&P 100 Index options; A PCI stands for the Partisan Conflict Index from Azzimonti (2018); DV stands for the model stock volatility from David & Veronesi (2013); NVIX stands for the news-based VIX developed by Manela & Moreira (2017); JLN stands for the financial uncertainty series obtained from the website of Sydney Ludvigson and developed by Jurado, Ludvigson & Ng (2015); and SPF stands for the uncertainty measure constructed from the anxiety index published by the Federal Reserve Bank of Philadelphia.

uncertainty for the short sample and the JLN multifactor uncertainty measure for the long sample, with adjusted R^2s of 35.4% and 53.1%, respectively. The DV stock volatility explains about 20% in each sample and is second best. As seen in **Figure 5*a***, the model stock market volatility tracks the realized volatility of the S&P 500 very closely except for the 1987 crash (which was known to be related to microstructure issues rather than macroeconomic issues). In fact, its β_U coefficient is very close to 1, although we recall that realized volatility is one of the overidentifying moments used in the estimation of the model using data until 2011. The fit of the BBD EPU is fairly good as well, with an adjusted R^2 of 14.1%.

4.2. Treasury Bond Market Volatility

An advantage of an equilibrium model for measuring economic uncertainty is that the volatility of different assets can be formulated using the same uncertainty measures. As we see here, some of the alternative uncertainty measures have little explanatory power for Treasury bond market volatility. In **Table 6**, we provide the statistics for the fits of the regression

$$\text{RV}(t) = \alpha + \beta_U\, U(t) + \epsilon(t), \qquad 7.$$

Table 5 Stock market volatility and uncertainty

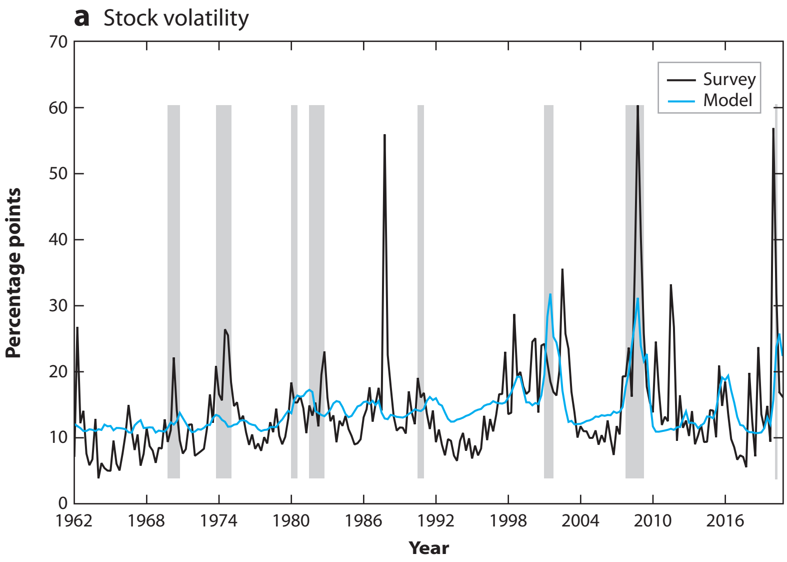
	Sample: 1986–2021:2			Sample: 1962–2021:2		
	Coeff.	SE	*p*-value	Coeff.	SE	*p*-value
	BBD EPU			MM NVIX**		
$\bar{R}^2$	0.141			0.363		
α	0.086	0.019	0.000	−0.081	0.045	0.072
β_U	0.001	0.000	0.002	0.009	0.002	0.000
	BEX stock market uncertainty			JLN multifactor uncertainty		
$\bar{R}^2$	0.354			0.531		
α	−0.025	0.041	0.544	−0.172	0.040	0.000
β_U	32.410	7.259	0.000	0.345	0.0467	0.000
	A PCI*			SPF recession uncertainty***		
$\bar{R}^2$	0.038			0.135		
α	0.216	0.030	0.000	0.087	0.012	0.000
β_U	−0.000	0.000	0.009	0.005	0.001	0.000
	DV stock volatility			DV stock volatility		
$\bar{R}^2$	0.187			0.237		
α	0.013	0.050	0.795	−0.003	0.018	0.849
β_U	0.957	0.344	0.006	1.025	0.126	0.000

We report the results of the regression $\mathrm{RV}(t) = \alpha + \beta_U\, U(t) + \epsilon(t)$, where RV is the realized volatility of the S&P 500 Index returns computed as the standard deviation of the daily returns realized in the quarter. Returns are obtained from the Center for Research in Security Prices. *, **, and *** denote that the sample for the variable is from 1981 to 2020, 1962 to 2020:1, and 1968:4 to 2020, respectively. Standard errors are adjusted for heteroskedasticity and autocorrelation using the methodology of Newey & West (1987). BBD EPU stands for the economic policy uncertainty from Baker, Bloom & Davis (2015); BEX stands for the uncertainty measure developed by Bekaert, Engstrom & Xu (2021); VXO stands for the implied volatility on 30-day S&P 100 Index options; A PCI stands for the Partisan Conflict Index from Azzimonti (2018); DV stands for the model stock volatility from David & Veronesi (2013); MM NVIX stands for the news-based VIX developed by Manela & Moreira (2017); JLN stands for the financial uncertainty series obtained from the website of Sydney Ludvigson and developed by Jurado, Ludvigson & Ng (2015); and SPF stands for the uncertainty measure constructed from the anxiety index published by the Federal Reserve Bank of Philadelphia.

where RV is the realized volatility of 5-year Treasury bonds computed as the standard deviation of the daily returns realized in the quarter and $U(t)$ is a measure of uncertainty at t. For the short sample, the results are a bit confusing. We included VXO as a measure of uncertainty, and it has the highest adjusted R^2 among all the uncertainty measures, although the use of a volatility to explain movements in a volatility may be questionable. The PCI measure of Azzimonti (2018) has a strong $\bar{R}^2$; however, its coefficient is negative. For the longer sample, the DV bond market volatility has an $\bar{R}^2$ of about 40%, although its β_U coefficient is below 1. As seen in **Figure 5*b***, in the sample until 2000, the model volatility is very close to realized volatility; however, in the latter part of the sample, the model volatility is mostly below realized volatility, suggesting that fears in the bond market about the harmful effects of deflation are higher than are estimated by our model. The SPF recession uncertainty is second best in the longer sample, with an adjusted R^2 of 14%. It is also important to note that the BEX stock market uncertainty measure and the JLN multifactor uncertainty measure, each of which is very successful in explaining stock market volatility, have a low ability to explain bond market volatility. The same can be said for the MM NVIX.

5. AGGREGATING THE RESULTS

In this section, we aggregate the results to produce a ranking of the uncertainty measures for forecasting real variables and explaining volatility fluctuations. We also shed light on the rankings using Granger causality tests. To rank the measures, we simply take the average ranking



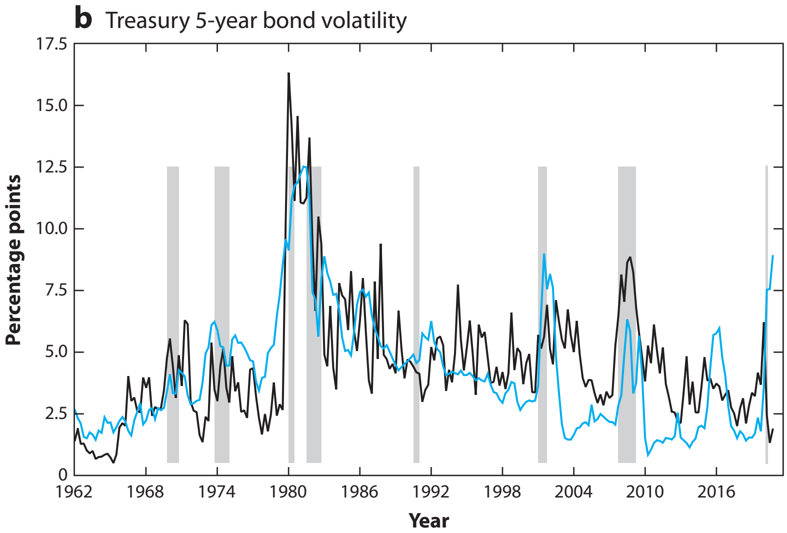


Figure 5

Stock and bond volatilities (data and model). Data volatilities are realized volatilities on the S&P 500 Index and 5-year Treasury bonds constructed from daily returns data obtained from the Center for Research in Security Prices. Model volatilities are obtained by using the closed-form expressions in Equations 1 and 2 and the filtered probabilities of the six composite states in **Figure 1** using the estimated parameters given by David & Veronesi (2013).

of each measure across the three real variables and two volatilities in Sections 3 and 4. The average rankings are provided in **Table 7**. In each of the samples, the DV stock volatility has the highest ranking (lowest number). The other two structural approaches—the BEX stock market uncertainty and the JLN multifactor uncertainty—are second in the two samples, respectively; that is, the measures based on structural approaches do better than uncertainty measures based

Table 6 5-Year Treasury bond market volatility and uncertainty

	Sample: 1986–2020			Sample: 1962–2020		
	Coeff.	SE	*p*-value	Coeff.	SE	*p*-value
	BBD EPU			MM NVIX**		
$\bar{R}^2$	0.056			−0.001		
α	9.283	1.428	0.000	0.0392	0.013	0.005
β_U	−0.035	0.016	0.032	0.000	0.001	0.619
	BEX stock market uncertainty			JLN multifactor uncertainty		
$\bar{R}^2$	0.023			0.068		
α	0.036	0.009	0.000	0.008	0.013	0.507
β_U	1.636	1.783	0.360	0.039	0.014	0.004
	VXO			Realized volatility		
$\bar{R}^2$	0.273			0.089		
α	4.987	0.791	0.000	9.325	0.632	0.000
β_U	0.202	0.036	0.000	−19.653	4.053	0.000
	A PCI*			SPF recession uncertainty***		
$\bar{R}^2$	0.146			0.141		
α	0.076	0.008	0.000	8.781	0.721	0.000
β_U	−0.000	0.000	0.000	−0.118	0.042	0.006
	DV bond volatility			DV bond volatility		
$\bar{R}^2$	0.074			0.404		
α	0.037	0.004	0.000	0.017	0.005	0.001
β_U	0.216	0.118	0.069	0.675	0.126	0.000

We report the results of the regression $\mathrm{RV}(t) = \alpha + \beta_U\, U(t) + \epsilon(t)$, where RV is the realized volatility of 5-year Treasury bonds computed as the standard deviation of the daily returns realized in the quarter. Returns are obtained from the Center for Research in Security Prices. *, **, and *** denote that the sample for the variable is from 1981 to 2020, 1962 to 2020:1, and 1968:4 to 2020, respectively. Standard errors are adjusted for heteroskedasticity and autocorrelation using the methodology of Newey & West (1987). BBD EPU stands for the economic policy uncertainty from Baker, Bloom & Davis (2015); BEX stands for the uncertainty measure developed by Bekaert, Engstrom & Xu (2021); VXO stands for the implied volatility on 30-day S&P 100 Index options; A PCI stands for the Partisan Conflict Index from Azzimonti (2018); DV stands for the model stock volatility from David & Veronesi (2013); MM NVIX stands for the news-based VIX developed by Manela & Moreira (2017); JLN stands for the financial uncertainty series obtained from the website of Sydney Ludvigson and developed by Jurado, Ludvigson & Ng (2015); and SPF stands for the uncertainty measure constructed from the anxiety index published by the Federal Reserve Bank of Philadelphia.

on pure asset prices, texts, or surveys. Notably, though, the SPF recession uncertainty is jointly ranked second in the long sample and is useful particularly for forecasting job growth.

We provide some further evidence on this main result by conducting Granger causality tests, whose results are presented in **Table 8**. In particular, we verify whether the David & Veronesi (2013) stock market volatility Granger causes each of the other uncertainty measures or is Granger caused by them. The top panel shows that the David & Veronesi (2013) measure strongly causes five of the measures (p-values smaller than 0.1) and weakly causes two others (p-values of about 0.12), but it does not Granger cause the SPF recession uncertainty measure. On the reverse side, it is caused only by three of the measures: the JLN, realized volatility, and SPF recession uncertainty. That is, these three measures contain information that is not in the DV stock volatility.

Finally, we shed some light on the reasons underlying the strong performance of the model by David & Veronesi (2013). As discussed in Section 2.5, asset volatilities in this model are related to the beliefs of fundamentals weighed by asset valuation ratios. Over time, the relative volatilities to inflation, earnings, and consumption news fluctuate. We show the relative weight to inflation, earnings, and consumption news in stock and bond volatilities in **Figure 6**. Using the stock and

Table 7 Average ranking

Uncertainty measure	Ranking
Sample: 1986–2020	
BBD EPU	3.4
BEX stock market uncertainty	1.8
VXO	3.7
A PCI	4.2
DV stock volatility	1.6
Sample: 1962–2020	
MM NVIX	4.0
JLN multifactor uncertainty	2.4
Realized uncertainty	4.0
SPF recession uncertainty	2.4
DV stock volatility	2.0

BBD EPU stands for the economic policy uncertainty from Baker, Bloom & Davis (2015); BEX stands for the uncertainty measure developed by Bekaert, Engstrom & Xu (2021); VXO stands for the implied volatility on 30-day S&P 100 Index options; A PCI stands for the Partisan Conflict Index from Azzimonti (2018); DV stands for the model stock volatility from David & Veronesi (2013); MM NVIX stands for the news-based VIX developed by Manela & Moreira (2017); JLN stands for the financial uncertainty series obtained from the website of Sydney Ludvigson and developed by Jurado, Ludvigson & Ng (2015); and SPF stands for the uncertainty measure constructed from the anxiety index published by the Federal Reserve Bank of Philadelphia.

Table 8 Pairwise Granger causality tests (with two lags) of DV stock market volatility and alternative uncertainty measures

Null hypothesis:	*F*-statistic	*p*-value
DV stock market volatility does not Granger cause BBD EPU	2.636	0.075
DV stock market volatility does not Granger cause BEX stock market uncertainty	3.114	0.047
DV stock market volatility does not Granger cause VXO	4.536	0.012
DV stock market volatility does not Granger cause A PCI	2.181	0.116
DV stock market volatility does not Granger cause MM NVIX	9.020	0.000
DV stock market volatility does not Granger cause JLN multifactor uncertainty	2.110	0.123
DV stock market volatility does not Granger cause realized volatility	6.519	0.002
DV stock market volatility does not Granger cause SPF recession uncertainty	0.988	0.373
BBD EPU does not Granger cause DV stock market volatility	0.600	0.546
BEX stock market uncertainty does not Granger cause DV stock market volatility	0.898	0.409
VXO does not Granger cause DV stock market volatility	0.769	0.465
A PCI does not Granger cause DV stock market volatility	1.033	0.358
MM NVIX does not Granger cause DV stock market volatility	0.446	0.640
JLN multifactor uncertainty does not Granger cause DV stock market volatility	2.742	0.066
Realized volatility does not Granger cause DV stock market volatility	4.635	0.011
SPF recession uncertainty does not Granger cause DV stock market volatility	7.475	0.000

DV stands for the model stock volatility from David & Veronesi (2013); BBD EPU stands for the economic policy uncertainty from Baker, Bloom & Davis (2015); BEX stands for the uncertainty measure developed by Bekaert, Engstrom & Xu (2021); VXO stands for the implied volatility on 30-day S&P 100 Index options; A PCI stands for the Partisan Conflict Index from Azzimonti (2018); MM NVIX stands for the news-based VIX developed by Manela & Moreira (2017); JLN stands for the financial uncertainty series obtained from the website of Sydney Ludvigson and developed by Jurado, Ludvigson & Ng (2015); and SPF stands for the uncertainty measure constructed from the anxiety index published by the Federal Reserve Bank of Philadelphia.

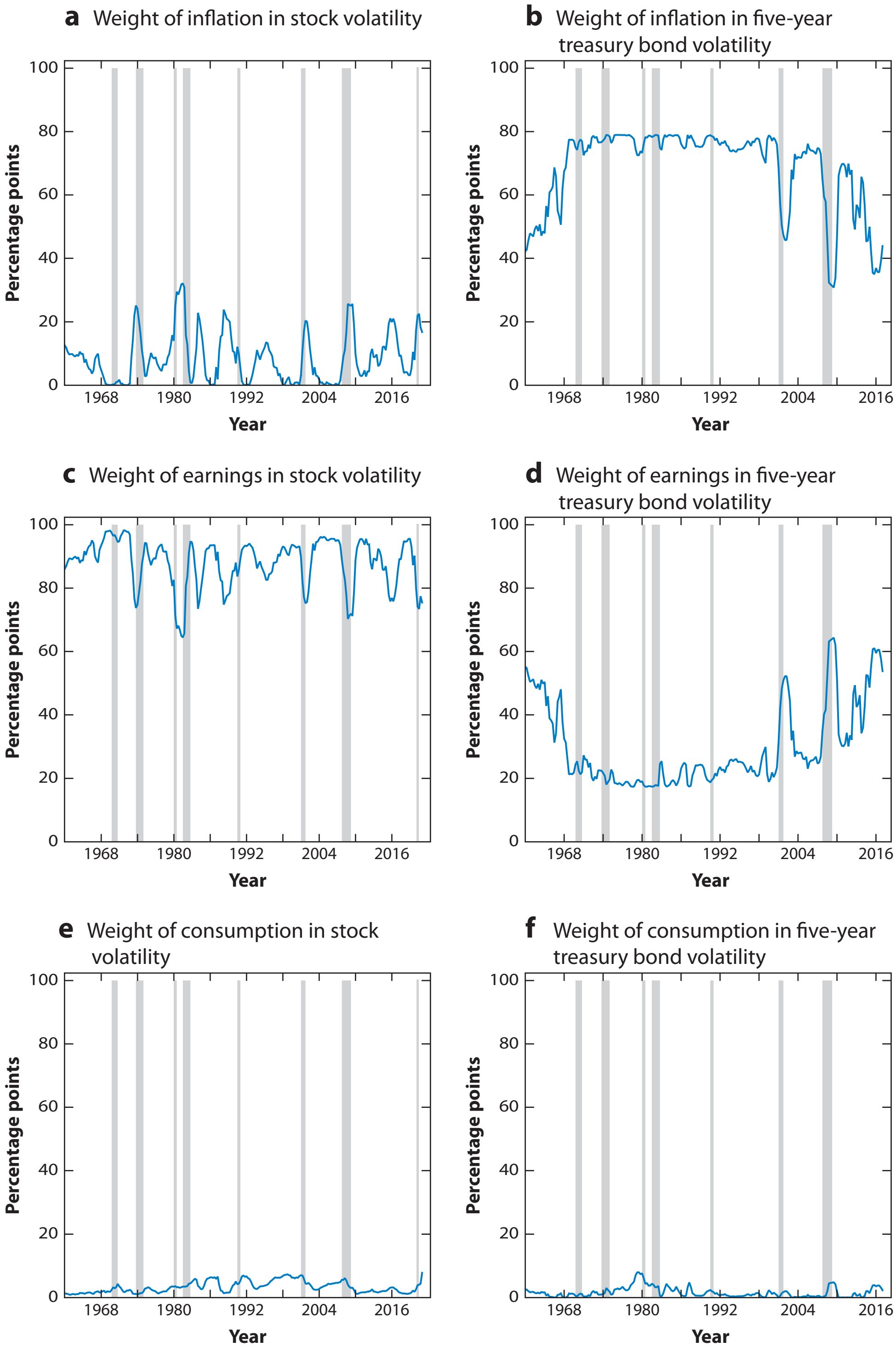


Figure 6

Weights of alternative fundamentals in asset volatilities. The weight of factor i in stock volatility is $\sigma^N(\pi(t))_i^2 / \sum_i \sigma^N(\pi(t))_i^2$. At each date, model volatilities are obtained by using the closed-form expressions in Equations 1 and 2 and the filtered probabilities of the six composite states in **Figure 1** using the estimated parameters given by David & Veronesi (2013). Bond weights are analogously calculated.

bond volatility formulas in Equations 1 and 2, respectively, we calculate the weights as the variance with respect to the shock in question relative to the total variance. In **Figure 6*a*,*c*,*e***, we see that on average about 88% of stock volatility is explained by earnings news in this model, while about 9% and 3% percent of the variation is from inflation and consumption shocks, respectively. However, the weight of inflation shocks is quite volatile; it increases during recessions, reaching a peak of nearly 30% during the 1981 recession. Surprisingly, the share has been very high in the recessions of the current century, as well as in the bout of economic weakness in 2016; however, as seen in **Figure 1**, the uncertainty in this century is about deflation rather than high inflation. **Figure 6*b*,*d*,*f*** shows that for 5-year Treasury bonds, inflation news explains nearly 68% of the fluctuations, while news on earnings and consumption growth accounts for 30% and 2%, respectively. The weight to earnings news for bonds increases during recessions (opposite to that for stocks). The fluctuations of the weights to alternative uncertainties are crucial to the success of the model volatility. If instead we use the individual uncertainties in linear specifications, we explain a very small amount of variations in real variables and volatilities. This is true using uncertainties of inflation and earnings from the SPF as well.

6. UNCERTAINTY AND REAL VARIABLES IN THE PANDEMIC PERIOD

As seen in **Figure 3**, most of the uncertainty measures rose sharply at the onset of the COVID-19 pandemic in the first quarter of 2020. However, the only measure that was above its level in the financial crisis was the BBD EPU. The more puzzling aspects of the pandemic are the fluctuations in the real variables. During the first two quarters of 2020, investment declined modestly, but payrolls declined at double-digit rates, the steepest declines in our 60-year sample. This decline in payrolls was not forecasted based on the uncertainty measures a year earlier as the onset of the pandemic was largely an unanticipated event. Even more surprising, though, was the rapid growth in credit at its fastest rate in the sample, since during past episodes of high uncertainty it had contracted heavily. This puzzling change in the sign of credit growth could likely be explained by making a distinction between inside and outside credit (see Gurley & Shaw 1960), as policy makers proactively provided unprecedented access to credit to counter the loss in jobs and decline in economic activity.

Given these large differences in the fluctuations of the real variables, a natural question arises as to how the absolute and relative forecasting performance of the alternative uncertainty measures would be affected if the pandemic period was excluded from our sample. In short, the answer is that the $\bar{R}^2$s of the investment regression are nearly unchanged; however, the $\bar{R}^2$s of the hiring and credit growth are substantially higher, in the range of 30% to 45%, for most of the measures. Despite the higher levels, the relative ranking among the measures is relatively unchanged.

7. CONCLUSION

In the past 20 years, several authors have constructed measures of economic uncertainty to help understand fluctuations in real variables with irreversibilities and asset volatilities. In this review, we compare the performance of nine of these measures, which are publicly available. The measures are constructed based on one of the four following methodologies: purely market based using asset pricing data, structural model based using data on real fundamentals and asset prices, text based, or survey based. One of the structural model–based measures is the learning-based measure developed in David & Veronesi (2013).

We compare the performance of these uncertainty measures in forecasting three real variables with irreversibilities—investment, hiring, and credit creation—as well as in explaining fluctuations in stock market and Treasury bond market volatility. Due to data availability, we make comparisons for David & Veronesi's (2013) measure with four others in each of two different samples: a short sample from 1986 to 2020 and a long sample from 1962 to 2020. We find that in each group, the DV stock market volatility measure has the highest average ranking of R^2s across the five regressions. We also provide evidence that the DV measure at least weakly (p-value smaller than 0.12) Granger causes seven of the eight measures, while it is only Granger caused by three of them. Among the other measures, the structural model–based measures [specifically the measures created by Bekaert, Engstrom & Xu (2021) and Jurado, Ludvigson & Ng (2015)] do better than measures constructed using the other approaches.

The main reason for the good performance of David & Veronesi's (2013) stock volatility measure is that the learning-based model volatility implies time-varying weights on inflation, earnings, and consumption news, as agents in the economy assess the impact that inflation has on the stability of real economic growth. For stocks, fluctuations in returns are based predominantly on earnings news at most dates, except during recessions, when the weight given to inflation news increases to about 25%. For Treasury bonds, fluctuations in returns are mainly driven by inflation news, but the weight to earnings news has risen as high as 40% in the recessions of the current century, mainly driven by concerns that deflation news will lead to future real slowdowns. Linear specifications using measures of inflation and earnings uncertainty are unable to forecast the real variables or explain fluctuations in asset volatilities. This property is true of measures of uncertainty constructed from the SPF as well. A measure of the uncertainty of a recession in the following quarter based on the SPF's anxiety index has fairly good performance; however, it is more volatile than David & Veronesi's (2013) stock market volatility.

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LITERATURE CITED

Abel AB. 1983. Optimal investment under uncertainty. *Am. Econ. Rev.* 73:228–33

Anderson TG, Bollerslev T, Diebold FX, Labys P. 2003. Modeling and forecasting realized volatility. *Econometrica* 71(2):579–625

Azzimonti M. 2018. Partisan conflict and private investment. *J. Monetary Econ.* 93:114–31

Baker SD, Hollifield B, Osambela E. 2016. Disagreement, speculation, and aggregate investment. *J. Financ. Econ.* 119:210–25

Baker SR, Bloom N, Davis SJ. 2015. *Measuring economic policy uncertainty*. NBER Work. Pap. 21633

Bansal R, Yaron A. 2004. Risks for the long run: a potential resolution of asset pricing puzzles. *J. Finance* 59(4):1481–509

Bekaert G, Engstrom EC, Xu NR. 2021. The time variation in risk appetite and uncertainty. *Manag. Sci.* 68(6):3975–4004

Bernanke BS. 1983. Irreversibility, uncertainty, and cyclical investment. *Q. J. Econ.* 98:85–106

Bloom N. 2009. The impact of uncertainty shocks. *Econometrica* 77:623–89

Bloom N. 2014. Fluctuations in uncertainty. *J. Econ. Perspect.* 28:153–76

Brennan MJ, Schwartz ES. 1985. Evaluating natural resource investments. *J. Bus.* 58:135–57
Campbell JY, Cochrane JH. 1999. By force of habit: a consumption-based explanation of aggregate stock market behavior. *J. Political Econ.* 107:205–51
Cummins J, Hassett K, Oliner SD. 2006. Investment behavior, observable expectations, and internal funds. *Am. Econ. Rev.* 96:796–810
David A. 1997. Fluctuating confidence in stock markets: Implications for returns and volatility. *J. Financ. Quant. Anal.* 32(4):427–62
David A. 2008. Inflation uncertainty, asset valuations, and the credit spreads puzzle. *Rev. Financ. Stud.* 21:2487–34
David A, Veronesi P. 1999. *Option prices with uncertain fundamentals: theory and evidence on the dynamics of implied volatilities*. FEDS Work. Pap. 1999-47, Fed. Reserve Board, Washington, DC
David A, Veronesi P. 2013. What ties return volatilities to price valuations and fundamentals? *J. Political Econ.* 121:682–46
David A, Veronesi P. 2014. Investors' and central bank's uncertainty measures embedded in index options. *Rev. Financ. Stud.* 27:1661–716
Dixit AK, Pindyck RS. 1994. *Investment Under Uncertainty*. Princeton, NJ: Princeton Univ. Press
Gurley JG, Shaw ES. 1960. *Money in a Theory of Finance*. Washington, DC: Brookings Inst.
Hartman R. 1972. The effects of price and cost uncertainty on investment. *J. Econ. Theory* 5:258–66
Jones RA, Ostroy JM. 1984. Flexibility and uncertainty. *Rev. Econ. Stud.* 51:13–32
Jurado K, Ludvigson SC, Ng S. 2015. Measuring uncertainty. *Am. Econ. Rev.* 105:1177–216
Kiyotaki N, Moore J. 1997. Credit cycles. *J. Political Econ.* 105:211–48
Krishnamurthy A, Muir T. 2017. *How credit cycles across a financial crisis*. NBER Work. Pap. 23850
Manela A, Moreira A. 2017. News implied volatility and disaster concerns. *J. Financ. Econ.* 123:137–62
McDonald R, Siegel D. 1986. The value of waiting to invest. *Q. J. Econ.* 101:707–28
Newey WR, West KD. 1987. A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55:703–8
Oi WY. 1961. The desirability of price instability under perfect competition. *Econometrica* 29:58–64
Pastor L, Veronesi P. 2003. Stock valuation and learning about profitability. *J. Financ.* 58(5):1749–90
Pastor L, Veronesi P. 2012. Uncertainty about government policy and stock prices. *J. Finance* 67:1219–64
Pastor L, Veronesi P. 2013. Political uncertainty and risk premia. *J. Financ. Econ.* 110:520–45
Rampini A, Viswanathan S. 2010. Collateral, risk management, and the distribution of debt capacity. *J. Finance* 65:2293–322
Veronesi P. 1999. Stock market overreaction to bad news in good times: a rational expectations equilibrium model. *Rev. Financ. Stud.* 12:975–1007
Veronesi P. 2000. How does information quality affect stock returns? *J. Finance* 55(2):807–39

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