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ABSTRACT

This paper exploits a data rich environment to provide direct econometric estimates of time-varying macroeconomic uncertainty, defined as the common variation in the unforecastable component of a large number of economic indicators. Our estimates display significant independent variations from popular uncertainty proxies, suggesting that much of the variation in the proxies is not driven by uncertainty. Quantitatively important uncertainty episodes appear far more infrequently than indicated by popular uncertainty proxies, but when they do occur, they are larger, more persistent, and are more correlated with real activity. Our estimates provide a benchmark to evaluate theories for which uncertainty shocks play a role in business cycles.

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An online appendix is available at:
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1 Introduction

How important is time-varying economic uncertainty and what role does it play in macroeconomic fluctuations? A large and growing body of literature has concerned itself with this question.[1] At a general level, uncertainty is typically defined as the conditional volatility of a disturbance that is unforecastable from the perspective of economic agents. In partial equilibrium settings, increases in uncertainty can depress hiring, investment, or consumption if agents are subject to fixed costs or partial irreversibilities (a "real options" effect), if agents are risk averse (a "precautionary savings" effect), or if financial constraints tighten in response to higher uncertainty (a "financial frictions" effect). In general equilibrium settings, many of these mechanisms continue to imply a role for time-varying uncertainty, although some may also require additional frictions to generate the same effects.

A challenge in empirically examining the behavior of uncertainty, and its relation to macroeconomic activity, is that no objective measure of uncertainty exists. So far, the empirical literature has relied primarily on proxies or indicators of uncertainty, such as the implied or realized volatility of stock market returns, the cross-sectional dispersion of firm profits, stock returns, or productivity, the cross-sectional dispersion of subjective (survey-based) forecasts, or the appearance of certain "uncertainty-related" key words in news publications. While most of these measures have the advantage of being directly observable, their adequacy as proxies for uncertainty depends on how strongly they are correlated with this latent stochastic process.

Unfortunately, the conditions under which common proxies are likely to be tightly linked to the typical theoretical notion of uncertainty may be quite special. For example, stock market volatility can change over time even if there is no change in uncertainty about economic fundamentals, if leverage changes, or if movements in risk aversion or sentiment are important drivers of asset market fluctuations. Cross-sectional dispersion in individual stock returns can fluctuate without any change in uncertainty if there is heterogeneity in the loadings on common risk factors. Similarly, cross-sectional dispersion in firm-level profits, sales, and productivity can fluctuate over the business cycle merely because there is heterogeneity in the cyclicality of firms' business activity.[2]

This paper provides new measures of uncertainty and relates them to macroeconomic activity. 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

[1]See for example, Bloom (2009); Arellano, Bai, and Kehoe (2011); Bloom, Floetotto, and Jaimovich (2010); Bachmann, Elstner, and Sims (2013); Gilchrist, Sim, and Zakrajsek (2010); Schaal (2012) Bachmann and Bayer (2011); Baker, Bloom, and Davis (2011); Basu and Bundick (2011); Knotek and Khan (2011) Fernández-Villaverde, Pablo Guerrón-Quintana, and Uribe (2011); Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012); Leduc and Liu (2012); Nakamura, Sergeyev, and Steinsson (2012); Orlik and Veldkamp (2013).

[2]Abraham and Katz (1986) also suggested that cross-section variation in employment could vary over the business cycle because of heterogeneity across firms.

single (or small number) of observable economic indicators. We start from the premise that what matters for economic decision making is not whether particular economic indicators have become more or less variable or disperse *per se*, but rather whether the economy has become more or less *predictable*; that is, less or more uncertain.

To formalize our notion of uncertainty, let us define h-period ahead uncertainty in the variable $y_{jt} \in Y_t = (y_{1t}, \ldots, y_{N_y t})'$, denoted by $\mathcal{U}^y_{jt}(h)$, to be the conditional volatility of the purely unforecastable component of the future value of the series. Specifically,

$$\mathcal{U}^y_{jt}(h) \equiv \sqrt{E\left[(y_{jt+h} - E[y_{jt+h}|I_t])^2|I_t\right]} \tag{1}$$

where the expectation $E(\cdot|I_t)$ is taken with respect to information I_t available to economic agents at time t.[3] If the expectation today (conditional on all available information) of the squared error in forecasting y_{jt+h} rises, uncertainty in the variable increases. A measure, or index, of *macroeconomic uncertainty* can then be constructed by aggregating individual uncertainty at each date using aggregation weights w_j :

$$\mathcal{U}^y_t(h) \equiv \text{plim}_{N_y \to \infty} \sum_{j=1}^{N_y} w_j \mathcal{U}^y_{jt}(h) \equiv E_w[\mathcal{U}^y_{jt}(h)]. \tag{2}$$

We use the terms macro and aggregate uncertainty interchangeably.

We emphasize two features of these definitions. First, we distinguish between uncertainty in a series y_{jt} and its conditional volatility. The proper measurement of uncertainty requires removing the forecastable component $E[y_{jt+h}|I_t]$ before computing conditional volatility. Failure to do so will lead to estimates that erroneously categorize forecastable variations as "uncertain." Thus, uncertainty in a series is *not* the same as the conditional volatility of the raw series: it is important to first remove the forecastable component. While this point may seem fairly straightforward, it is worth noting that almost all measures of stock market volatility (realized or implied) or cross-sectional dispersion currently used in the literature do not take this into account.[4] We show below that this matters empirically for a large number of series, including the stock market.

Second, macroeconomic uncertainty is not equal to the uncertainty in any single series y_{jt}. Instead, it is a measure of the common variation in uncertainty across many series. This is

[3] A concept that is often related to uncertainty is risk. In a finance context, risk is often measured by conditional covariance of returns with the stochastic discount factor in equilibrium models. This covariance can in turn be driven by conditional volatility in stock returns. Andersen, Bollerslev, Christoffersen, and Diebold (2012) provide a comprehensive review of the statistical measurement of the conditional variance of financial returns. Uncertainty as defined here is (see discussion below) distinct from conditional volatility but could be one of several reasons why the conditional variances and covariances of returns vary.

[4] Two exceptions are Gilchrist, Sim, and Zakrajsek (2010), who use the financial factors developed by Fama and French (1992) to control for common forecastable variation in their measure of realized volatility, and Bachmann, Elstner, and Sims (2013), who use subjective forecasts of analysts.

important because uncertainty-based theories of the business cycle typically require the existence of common (often countercyclical) variation in uncertainty across large numbers of series. Indeed, in many models of the literature cited above, macroeconomic uncertainty is either directly presumed by introducing stochastic volatility into aggregate shocks (e.g., shocks to aggregate technology, representative-agent preferences, monetary or fiscal policy), or indirectly imposed by way of a presumed countercyclical component in the volatilities of individual firm- or household-level disturbances.[5] This common variation is critical for the study of business cycles because if the variability of the idiosyncratic shock were entirely idiosyncratic, it would have no influence on macroeconomic variables. If these assumptions are correct, we would expect to find evidence of an aggregate uncertainty factor, a common component in uncertainty fluctuations that affects many series, sectors, markets, and geographical regions at the same time.

The objective of our paper is therefore to obtain estimates of (1) and (2). To make these measures of uncertainty operational, we require three key ingredients. First, we require an estimate of the forecast $E[y_{jt+h}|I_t]$. For this, we form factors from a large set of predictors $\{X_{it}\}$, $i = 1, 2, \ldots, N$, whose span is as close to I_t as possible. Using these factors, we then approximate $E[y_{jt+h}|I_t]$ by a diffusion index forecast ideal for data-rich environments. An important aspect of this data-rich approach is that the diffusion indices (or common factors) can be treated as known in the subsequent analysis. Second, defining the h-step-ahead forecast error to be $V^y_{jt+h} \equiv y_{jt+h} - E[y_{jt+h}|I_t]$, we require an estimate of the conditional (on time t information) volatility of this error, $E[(V^y_{t+h})^2|I_t]$. For this, we specify a parametric stochastic volatility model for both the one-step-ahead prediction errors in y_{jt} and the analogous forecast errors for the factors. These volatility estimates are used to recursively compute the values of $E[(V^y_{t+h})^2|I_t]$ for $h > 1$. As we show below, this procedure takes into account an important property of multistep-ahead forecasts, namely that time-varying volatility in the errors of the predictor variables creates additional unforecastable variation in y_{jt+h} (above and beyond that created by stochastic volatility in the one-step-ahead prediction error), and contributes to its uncertainty. The third and final ingredient is an estimate of macroeconomic uncertainty $\mathcal{U}^y_t(h)$ constructed from the individual uncertainty measures $\mathcal{U}^y_{jt}(h)$. Our base-case estimate of $\mathcal{U}^y_t(h)$ is the equally-weighted average of individual uncertainties. It is also possible to let the weights be constructed so that macroeconomic uncertainty is interpreted as the common (latent) factor in the individual measures of uncertainty.

We estimate measures of macroeconomic uncertainty from two post-war datasets of economic activity. The first *macro* dataset is monthly and uses the information in hundreds of macroeconomic and financial indicators. The second *firm level* dataset is quarterly and consists

[5] See, e.g., Bloom (2009), Arellano, Bai, and Kehoe (2011), Bloom, Floetotto, and Jaimovich (2010), Gilchrist, Sim, and Zakrajsek (2010), Schaal (2012), Bachmann and Bayer (2011)).

of 155 firm-level observations on profit growth normalized by sales. We will refer to estimates of macro uncertainty based on the monthly series as *common macro uncertainty* whereas estimates of macro uncertainty based on the quarterly firm-level dataset will be referred to as *common firm-level uncertainty.*

Our main results may be summarized as follows. We find significant independent variation in our estimates of uncertainty as compared to commonly used proxies for uncertainty. An important finding is that our estimates imply far fewer large uncertainty episodes than what is inferred from all of the commonly used proxies we study. For example, consider the 17 uncertainty dates defined in Bloom (2009) as events associated with stock market volatility in excess of 1.65 standard deviations above its trend. By contrast, in a sample extending from 1959:01 to 2011:12, our measure of macro uncertainty exceeds (or come close to exceeding) 1.65 standard deviations from its mean a total of only four (out of 636) months, each of which occur during the three deep recession episodes discussed below. Moreover, our estimate of macroeconomic uncertainty is far more persistent than stock market volatility: the response of macro uncertainty to its own innovation from an autoregression has a half life of 53 months; the comparable figure for stock market volatility is 4 months. Qualitatively, these results are similar for our measures of common firm-level uncertainty in profit growth rates. Taken together, the findings imply that most movements in common uncertainty proxies, such as stock market volatility (the most common), and measures of cross-sectional dispersion, are not associated with a broad-based movement in economic uncertainty as defined in (2). This is important because it suggests that much of the variation in common uncertainty proxies is not driven by uncertainty.

So how important is time-varying economic uncertainty, and to what extent is it dynamically correlated with macroeconomic fluctuations? Our estimates of macro uncertainty reveal three big episodes of uncertainty in the post-war period: the months surrounding the 1973-74 and 1981-82 recessions and the Great Recession of 2007-09. Averaged across all uncertainty forecast horizons, the 2007-09 recession represents the most striking episode of heightened uncertainty since 1960, with the 1981-82 recession a close second. Large positive innovations to macro uncertainty lead to a sizable and protracted decline in real activity (production, hours, employment). These effects are larger and far more persistent and do not exhibit the "overshooting" pattern found previously when stock market volatility is used to proxy for uncertainty. Using an eleven variable monthly macro vector autoregression (VAR) and a recursive identification procedure with uncertainty placed last, we find that common macro uncertainty shocks account for up to 29% of the forecast error variance in industrial production, depending on the VAR forecast horizon. By contrast, stock market volatility explains at most 7%. To form another basis for comparison, shocks to the federal funds rate (a common proxy for unanticipated shifts in monetary policy) explain (at most) the same amount of forecast error variance in production as does macroeconomic uncertainty, despite uncertainty being placed last in the VAR. Finally, we ask how much each series' time-varying *individual* uncertainty is explained by time-varying *macro* uncertainty and find that the role of the latter is strongly countercyclical, roughly doubling in importance during recessions.

These results underscore the importance of considering how aggregate uncertainty is measured when assessing its relationship with the macroeconomy. In particular, our estimates imply that quantitatively important uncertainty episodes occur far more infrequently than what is indicated from common uncertainty proxies, but that when they *do* occur, they display larger and more persistent correlations with real activity. Indeed, the deepest, most protracted recessions in our sample are associated with large increases in estimated uncertainty, while more modest reductions in real activity are not. By contrast, common uncertainty proxies are less persistent and spike far more frequently, often in non-recession periods, or in periods of relative macroeconomic quiescence. Thus many observed spikes in common proxies are at odds with the predictions of uncertainty theories, which imply that high uncertainty leads to a contraction in real activity.

While we find that increases in uncertainty are associated with large declines in real activity, we caution that our results are silent on whether uncertainty is the cause or effect of such declines. Our goal is to develop a defensible measure of time-varying macro uncertainty that can be tracked over time and related to fluctuations in real activity and asset markets. Our estimates do, however, imply that the economy is objectively less predictable in recessions than it is in normal times. This result is not a statement about changing subjective perceptions of uncertainty in recessions as compared to booms. Any theory for which uncertainty is entirely the effect of recessions would need to be consistent with these basic findings.

In this way, our estimates provide a benchmark with which to evaluate theories where uncertainty plays a role in business cycles. Uncertainty as defined in this paper only requires evaluation of the h step ahead conditional expectation and conditional volatility of the variable in question and so can be computed for any number of endogenous variables in a dynamic, stochastic, general equilibrium (DSGE) model. Moreover, these statistics can be computed from within the model regardless of whether the theory implies that uncertainty is the cause or effect of recessions. A comparison of the uncertainty implied by the model and the data can be used to evaluate DSGE models that feature uncertainty.

The rest of this paper is organized as follows. Section 2 reviews related empirical literature on uncertainty in more detail. Section 3 outlines the econometric framework employed in our study, and describes how our measures of uncertainty are constructed. Section 4 describes the data and empirical implementation. Section 5 presents our common macro uncertainty estimates, compares our measure to other proxies of uncertainty used in the literature, and considers the dynamic relationship between macro uncertainty and variables such as production and employment. Section 6 performs a similar analysis for our estimates of common firm-level uncertainty. Section 7 summarizes and concludes.

To conserve space, a large amount of supplementary material for this paper appears in Jurado, Ludvigson, and Ng (2013). This document has two parts. The first part provides results from a large number of robustness exercises designed to check the sensitivity of our results to various assumptions (see description below). The second part is a data appendix that contains details on the construction of all data used in this study, including data sources. The complete dataset used in this study, as well as the uncertainty estimates, are available for download from the authors' website: `http://www.econ.nyu.edu/user/ludvigsons/data.htm`.

2 Related Empirical Literature

The literature on measuring uncertainty is still in its infancy. Existing research has primarily relied on measures of volatility and dispersion as proxies of uncertainty. In his seminal work, Bloom (2009) found a strong countercyclical relationship between real activity and uncertainty as proxied by stock market volatility. His VAR estimates suggest that uncertainty has an impact on output and employment in the six months after an innovation in these measures, with a rise in volatility at first depressing real activity and then increasing it, leading to an over-shoot of its long-run level, consistent with the predictions of models with uncertainty as a driving force of macroeconomic fluctuations. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) also documented a relation between real activity and uncertainty as proxied by dispersion in firm-level earnings, industry-level earnings, total factor productivity, and the predictions of forecasters. A recurring feature of these studies is that the uncertainty proxies are strongly countercyclical.

While these analyses are sensible starting places and important cases to understand, we emphasize here that the measures of dispersion and stock market volatility studied may or may not be tightly linked to true economic uncertainty. Indeed, one of the most popular proxies for uncertainty is closely related to financial market volatility as measured by the VIX, which has a large component that appears driven by factors associated with time-varying risk-aversion rather than economic uncertainty (Bekaert, Hoerova, and Duca (2012)).

A separate strand of the literature focuses on cross-sectional dispersion in N_A analysts' or firms' subjective expectations as a measure of uncertainty:

$$\mathcal{D}^A_{jt}(h) = \sqrt{\sum_{k=1}^{N_{A_t}} w^A_k \left[(y_{jt+h} - E(y_{jt+h}|I_{A_k,t}))^2 | I_{A_k,t} \right]^2}$$

where $I_{A_k,t}$ is the information of agent k at time t, and w^A_k is the weight applied to agent k. One potential advantage of using $\mathcal{D}^A_{jt}(h)$ as a proxy for uncertainty is that it treats the conditional forecast of y_{jt+h} as an observable variable, and therefore does not require estimation of $E[y_{t+h}|I_{A_k,t}]$. Bachmann, Elstner, and Sims (2013) follow this approach using a survey of German firms and argue that uncertainty appears to be more an outcome of recessions than a cause, contrary to the predictions of theoretical models such as Bloom (2009) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012). While analysts' forecasts are interesting in their own right, there are several known drawbacks in using them to measure uncertainty. First, subjective expectations are only available for a limited number of series. For example, of the 132 monthly macroeconomic series we will consider in this paper, not even one-fifth have corresponding expectations series. Second, it is not clear that the responses elicited from these surveys accurately capture the conditional expectations of the economy as a whole. The respondents typically sampled are practitioner forecasters; some analysts' forecasts are known to display systematic biases and omit relevant forecasting information (So (2012)), and analysts may have pecuniary incentives to bias their forecasts in a way that economic agents would not. Third, disagreement in survey forecasts could be more reflective of differences in opinion than of uncertainty (e.g., Diether, Malloy, and Scherbina (2002); Mankiw, Reis, and Wolfers (2003)). As discussed above, it could also reflect differences in firm's loadings on aggregate shocks in the absence of aggregate or idiosyncratic time-varying volatility. Fourth, Lahiri and Sheng (2010) show that, even if forecasts are unbiased, disagreement in analysts' point forecasts does not equal (average across analysts) forecast error uncertainty unless the variance of accumulated aggregate shocks over the forecast horizon is zero. They show empirically using the Survey of Professional Forecasters that the variance of the accumulated aggregate shocks can drive a large wedge between uncertainty and disagreement in times of important economic change, or whenever the forecast horizon is not extremely short. Bachmann, Elstner, and Sims (2013) acknowledge these problems and are careful to address them by using additional proxies for uncertainty, such as an ex-post measure of forecast error variance based on the survey expectations. A similar approach is taken in Scotti (2012) who studies series for which real-time data are available. Whereas these studies focus on variation in outcomes around subjective survey expectations of relatively few variables, we focus on uncertainty around objective statistical forecasts for hundreds of economic series.

Our uncertainty measure is also different from proxies based on the unconditional cross-section dispersion of a particular variable:

$$\mathcal{D}_{jt}^{B} = \sqrt{\frac{1}{N_B}\sum_{k=1}^{N_B}\left[(y_{jkt} \square \frac{1}{N_B}\sum_{i} y_{jit})^2\right]} \tag{3}$$

where y_{jkt} is a variable indexed by j (e.g., firm-level profits studied in Bloom (2009)) for firm k, and N_B is the sample size of firms reporting profits. Notably, this dispersion has no forward looking component; it is the same for all horizons. This measure suffers from the same drawback as $\mathcal{D}^{A}_{jt}(h)$, namely that it can fluctuate without any change in uncertainty if there is heterogeneity in the cyclicality of firms business activity.

Carriero, Clark, and Marcellino (2012) consider common sources of variation in the residual volatilities of a Bayesian Vector Autoregression (VAR). This investigation differs from ours in several ways: their focus is on small-order VARs (e.g., 4 or 8 variables) and residual volatility, which corresponds to our definition of uncertainty only when $h = 1$; our interest is in measuring the prevalence of uncertainty across the entire macroeconomy. Their estimation procedure presumes that individual volatilities only have common shocks, and it is not possible for some series to have homoskedastic shocks while others have heteroskedastic ones. We find a large idiosyncratic component in individual volatilities, the magnitude of which varies across series.

An important unresolved issue for empirical analysis of uncertainty concerns the persistence of uncertainty shocks. In models studied by Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), for example, recessions are caused by an increase in uncertainty, which in turn causes a drop in productivity growth. But other researchers who have studied models where uncertainty plays a key role (e.g., Schaal (2012)) have argued that empirical proxies for uncertainty, such as the cross-sectional dispersion in firms' sales growth, are not persistent enough to explain the prolonged levels of unemployment that have occurred during and after some recessions, notably the 2007-2009 recession and its aftermath. Here we provide new measures of uncertainty and its persistence, finding that they are considerably more persistent than popular proxies such as stock market volatility and measures of dispersion.

3 Econometric Framework

We now turn to a description of our econometric framework. A crucial first step in our analysis is to replace the conditional expectation in (1) by a forecast, from which we construct the forecast error that forms the basis of our uncertainty measures. In order to identify a true forecast error, it is important that our predictive model be as rich as possible, so that our measured forecast error is purged of predictive content. A standard approach is to select a set of K predetermined conditioning variables given by the $K \times 1$ vector W_t, and then estimate

$$y_{t+1} = \beta' W_t + \epsilon_{t+1} \tag{4}$$

by least squares. The one period forecast is $\widehat{y}_{t+1|t} = \hat{\beta}' W_t$ where $\hat{\beta}$ is the least squares estimate of β. An omitted-information bias may arise if economic agents such as financial market participants have more information than that in the conditioning variables. Indeed, recent work finds that forecasts of both real activity and financial returns are substantially improved by augmenting best-fitting conventional forecasting equations with common factors estimated from large datasets.[6] This problem is especially important in our exercise since relevant information not used to form forecasts will lead to spurious estimates of uncertainty and its dynamics.

To address this problem, we use the method of diffusion index forecasting whereby a relatively small number of factors estimated from a large number of economic time series are augmented to an otherwise standard forecasting model. The omitted information problem is remedied by including estimated factors, and possibly non-linear functions of these factors or factors formed from non-linear transformations of the raw data, in the forecasting model. This eliminates the arbitrary reliance on a small number of exogenous predictors and enables the use of information in a vast set of economic variables that are more likely to span the unobservable information sets of economic agents. Diffusion index forecasts are increasingly used in data rich environments. Thus we only generically highlight the forecasting step and focus instead on construction of uncertainty, leaving details about estimation of the factors to the on-line supplementary file.

3.1 Construction of Forecast Uncertainty

Let $X_t = (X_{1t}, \ldots, X_{Nt})'$ generically denote the predictors available for analysis. It is assumed that X_t has been suitably transformed (such as by taking logs and differencing) so as to render the series stationary. We assume that X_{it} has an approximate factor structure taking the form

$$X_{it} = \Lambda_i^{F\prime} F_t + e_{it}^X, \tag{5}$$

where F_t is an $r_F \times 1$ vector of latent common factors, Λ_i^F is a corresponding $r_F \times 1$ vector of latent factor loadings, and e_{it}^X is a vector of idiosyncratic errors. In an *approximate* dynamic factor structure, the idiosyncratic errors e_{it}^X are permitted to have a limited amount of cross-sectional correlation. Importantly, the number of factors r_F is significantly smaller than the number of series, N.

Let y_{jt} generically denote a series that we wish to compute uncertainty in and whose value in period $h \geq 1$ is estimated from a factor augmented forecasting model

$$y_{jt+1} = \phi_j^y(L) y_{jt} + {}_j^F(L)\hat{F}_t + {}_j^W(L) W_t + v_{jt+1}^y \tag{6}$$

where $\phi_j^y(L)$, ${}_j^F(L)$, and ${}_j^W(L)$ are finite-order polynomials in the lag operator L of orders p_y, p_F, and p_W, respectively, the elements of the vector $\hat{F}_t$ are consistent estimates of a rotation of F_t, and the r_w dimensional vector W_t contains additional predictors that are non-linear functions of $\hat{F}_t$ or factors formed from non-linear functions of the X_{it}. An important feature of our analysis is that the one-step-ahead prediction error of y_{jt+1} and of each factor $F_{k,t+1}$ and additional predictor $W_{h,t+1}$ are permitted to have time-varying volatility σ_{jt+1}^y, σ_{kt+1}^F, σ_{ht+1}^W respectively. This feature generates time-varying uncertainty in the series y_{jt}.

[6] See, for example, Stock and Watson (2002b, 2004), , and Ludvigson and Ng (2007, 2009).

When the factors have autoregressive dynamics, a more compact representation of the system above is the *factor augmented vector autoregression* (FAVAR). Let $Z_t \equiv (\hat{F}_t', W_t')'$ be a $r = r_F + r_W$ vector which collects the r_F estimated factors and r_W additional predictors, and define $\mathcal{Z}_t \equiv (Z_t', \ldots, Z_{t-q+1}')'$. Also let $Y_{jt} = (y_{jt}, y_{jt-1}, \ldots, y_{jt-q+1})'$. Then forecasts for any $h > 1$ can be obtained from the FAVAR system, stacked in first-order companion form:

$$\begin{aligned}\underbrace{\begin{pmatrix}\mathcal{Z}_t\\ Y_{jt}\end{pmatrix}}_{(r+1)q\times 1} &= \begin{pmatrix}\underbrace{\Phi^{\mathcal{Z}}}_{qr\times qr} & \underbrace{0}_{qr\times q}\\ \underbrace{\Lambda_j'}_{q\times qr} & \underbrace{\Phi_j^Y}_{q\times q}\end{pmatrix}\begin{pmatrix}\mathcal{Z}_{t-1}\\ Y_{jt-1}\end{pmatrix} + \begin{pmatrix}\mathcal{V}_t^{\mathcal{Z}}\\ \mathcal{V}_{jt}^Y\end{pmatrix} \qquad (7)\\ \mathcal{Y}_{jt} &= \Phi_j^{\mathcal{Y}}\mathcal{Y}_{jt-1} + \mathcal{V}_{jt}^{\mathcal{Y}},\end{aligned}$$

where Λ_j' and Φ_j^Y are functions of the coefficients in the lag polynomials in (6), $\Phi^{\mathcal{Z}}$ stacks the autoregressive coefficients of the components of $\mathcal{Z}_t$.[7] By the assumption of stationarity, the largest eigenvalue of $\Phi_j^{\mathcal{Y}}$ is less than one and, under quadratic loss, the optimal h-period forecast is the conditional mean:

$$E_t\mathcal{Y}_{jt+h} = (\Phi_j^{\mathcal{Y}})^h\mathcal{Y}_{jt}.$$

The forecast error variance at t is

$$\Omega_{jt}^{\mathcal{Y}}(h) \equiv E_t\left[(\mathcal{Y}_{jt+h} - E_t\mathcal{Y}_{jt+h})(\mathcal{Y}_{jt+h} - E_t\mathcal{Y}_{jt+h})'\right].$$

Time variation in the mean squared forecast error in general arises from the fact that shocks to *both* y_{jt} and the predictors Z_t may have time-varying variances. We now turn to these implications. Note first that when $h = 1$,

$$\Omega_{jt}^{\mathcal{Y}}(1) = E_t(\mathcal{V}_{jt+1}^{\mathcal{Y}}\mathcal{V}_{jt+1}^{\mathcal{Y}\prime}). \tag{8}$$

For $h > 1$, the forecast error variance of $\mathcal{Y}_{jt+h}$ evolves according to

$$\Omega_{jt}^{\mathcal{Y}}(h) = \Phi_j^{\mathcal{Y}}\Omega_{jt}^{\mathcal{Y}}(h-1)\Phi_j^{\mathcal{Y}\prime} + E_t(\mathcal{V}_{jt+h}^{\mathcal{Y}}\mathcal{V}_{jt+h}^{\mathcal{Y}\prime}). \tag{9}$$

As $h \to \infty$ the forecast is the unconditional mean and the forecast error variance is the unconditional variance of $\mathcal{Y}_{jt}$. This implies that $\Omega_{jt}^{\mathcal{Y}}(h)$ is less variable as h increases.

We are interested in the expected forecast uncertainty of the scalar series y_{jt+h} given information at time t, denoted $\mathcal{U}_{jt}^y(h)$. This is the square-root of the appropriate entry of the forecast error variance $\Omega_{jt}^{\mathcal{Y}}(h)$. With 1_j being a selection vector,

$$\mathcal{U}_{jt}^y(h) = \sqrt{1_j'\Omega_{jt}^{\mathcal{Y}}(h)1_j}. \tag{10}$$

[7] The above specification assumes that the coefficients are time-invariant. Cogley and Sargent (2005) among others have found important variation in VAR coefficients. Dynamic factor models are somewhat more robustness against temporal parameter instability than small forecasting models (Stock and Watson (2002a)). The reason is that such instabilities can "average out"in the construction of common factors if the instability is sufficiently dissimilar from one series to the next. Nonetheless, as a robustness check, an uncertainty measure is also constructed using recursive out-of-sample forecasts errors and will be discussed below.

To estimate macro (economy-wide) uncertainty $\mathcal{U}_t^y(h)$, we form weighted averages of individual uncertainty estimates:

$$\mathcal{U}_t^y(h) = \sum_{j=1}^{N_y} w_j \mathcal{U}_{jt}^y(h).$$

A simple weighting scheme is to give every series the equal weight of $1/N_y$. If individual uncertainty has a factor structure, the weights can be defined by the eigenvector corresponding to the largest eigenvalue of the $N_y \times N_y$ covariance matrix of the matrix of individual uncertainty.

3.2 Time-varying Uncertainty: A Statistical Decomposition

In this subsection, we show how stochastic volatility in the predictors Z and in y_j contribute to its h period ahead uncertainty. Consider first the factors F_t (the argument for W_t is similar). Suppose that each F_t is serially correlated and well represented by a univariate AR(1) model (dropping the subscript that indexes the factor in question for simplicity):

$$F_t = \Phi^F F_{t-1} + v_t^F.$$

If v_t^F was a martingale difference with constant variance $(\sigma^F)^2$, the forecast error variance $\Omega^F(h) = \Omega^F(h-1) + (\Phi^F)^{2(h-1)}(\sigma^F)^2$ increases with h but is the same for all t. We allow the shocks to F to exhibit time-varying stochastic volatility, ie $v_t^F = \sigma_t^F \varepsilon_t^F$ where log volatility has an autoregressive structure:

$$\log(\sigma_t^F)^2 = \alpha^F + \beta^F \log(\sigma_{t-1}^F)^2 + \tau^F \eta_t^F, \qquad \eta_t^F \overset{iid}{\sim} N(0,1).$$

The stochastic volatility model allows for a shock to the second moment that is independent of the first moment, consistent with theoretical models of uncertainty. The model implies

$$E_t(\sigma_{t+h}^F)^2 = \exp\left[\alpha^F \sum_{s=0}^{h-1} (\beta^F)^s + \frac{(\tau^F)^2}{2} \sum_{s=0}^{h-1} (\beta^F)^{2(s)} + (\beta^F)^h \log(\sigma_t^F)^2\right].$$

Since $\epsilon_t^F \overset{iid}{\sim} (0,1)$ by assumption, $E_t(v_{t+h}^F)^2 = E_t(\sigma_{t+h}^F)^2$. This allows us to compute the $h > 1$ forecast error variance for F using the recursion

$$\Omega_t^F(h) = (\Phi^F)\Omega_t^F(h-1)\Phi^{F\prime} + E_t(v_{t+h}^F v_{t+h}^{F\prime})$$

with $\Omega_t^F(1) = E_t(v_{t+h}^F)^2$. The h period ahead *predictor uncertainty* at time t is the square root of the h-step forecast error variance of the predictor:

$$\mathcal{U}_t^F(h) = \sqrt{1_F' \Omega_t^F(h) 1_F}$$

where 1_F is an appropriate selection vector. It follows from the determinants of $E(\sigma_{t+h}^F)^2$ that h-period-ahead uncertainty of F_t has a level-effect attributable to α^F (the homoskedastic variation in v_{Ft}), a scale effect attributable to τ^F, with persistence determined by β^F.

To understand how uncertainty in the predictors affect uncertainty in the variable of interest y_j, suppose that the forecasting model for y_j only has a single predictor F_t and is given by:

$$y_{jt+1} = \phi_j^y y_{jt} + \ {}_j^F \hat{F}_t + v_{jt+1}^y$$

where $v_{jt+1}^y = \sigma_{jt+1}^y \varepsilon_{jt+1}^y$ with $\varepsilon_{jt+1}^y \overset{iid}{\sim} N(0,1)$ and

$$\log(\sigma_{jt+1}^y)^2 = \alpha_j^y + \beta_j^y \log(\sigma_{jt}^y)^2 + \tau_j^y \eta_{jt+1}, \qquad \eta_{jt+1} \overset{iid}{\sim} N(0,1).$$

When $h = 1$, V_{jt+1}^y coincides with the innovation v_{jt+1}^y which is uncorrelated with the one-step-ahead error in forecasting F_{t+1}, given by $V_{t+1}^F = v_{t+1}^F$. When $h = 2$, the forecast error for the factor is $V_{t+2}^F = \Phi^F V_{t+1}^F + v_{t+2}^F$. The corresponding forecast error for y_{jt} is:

$$V_{jt+2}^y = v_{jt+2}^y + \phi_j^y V_{jt+1}^y + \ {}_j^F V_{t+1}^F$$

which evidently depends on the one-step-ahead forecasting errors made at time t, but V_{t+1}^y and V_{t+1}^F are uncorrelated. When $h = 3$, the forecast error is

$$V_{jt+3}^y = v_{jt+3}^y + \phi_j^y V_{jt+2}^y + \ {}_j^F V_{t+2}^F$$

which evidently depends on V_{jt+2}^y and V_{t+2}^F. But unlike the $h = 2$ case, the two components V_{jt+2}^y and V_{t+2}^F are now correlated because both depend on V_{t+1}^F.

Therefore, returning to the general case when the predictors are $Z_t = (F_t', W_t')'$ and its lags, h-step-ahead forecast error variance for Y_{jt+h} admits the decomposition:

$$\Omega_{jt}^Y(h) = \underbrace{\Phi_j^Y \Omega_{jt}^Y(h \square 1) \Phi_j^{Y\prime}}_{\text{autoregressive}} + \underbrace{\Omega_{jt}^{\mathcal{Z}}(h \square 1)}_{\text{Predictor}} + \underbrace{E_t(\mathcal{V}_{jt+h}^Y \mathcal{V}_{jt+h}^{Y\prime})}_{\text{stochastic volatility } Y} + \underbrace{2\Phi_j^Y \Omega_{jt}^{Y\mathcal{Z}}(h \square 1)}_{\text{covariance}} \tag{11}$$

where $\Omega_{jt}^{Y\mathcal{Z}}(h) = \text{cov}_t(\mathcal{V}_{jt+h}^Y, \mathcal{V}_{jt+h}^{\mathcal{Z}})$. The terms in $E(\mathcal{V}_{j,t+h}^Y \mathcal{V}_{j,t+h}^{Y\prime})$ are computed using the fact that $E_t(v_{jt+h}^y)^2 = E_t(\sigma_{jt+h}^y)^2$, $E_t(v_{t+h}^F)^2 = E_t(\sigma_{t+h}^F)^2$ and $E_t(v_{t+h}^W)^2 = E_t(\sigma_{t+h}^W)^2$.

Time variation in uncertainty can thus be mathematically decomposed into four sources: an autoregressive component, a common factor (predictor) component, a stochastic volatility component, and a covariance term. Representation (11), which is equivalent to (9) for the subvector Y_t, makes clear that predictor uncertainty plays an important role via the second term $\Omega_{jt}^{\mathcal{Z}}(h \square 1)$. It is time-varying because of stochastic volatility in the innovations to the factors and is in general non-zero for multi-step-ahead forecasts, i.e., $h > 1$. The role of stochastic volatility in the series y_j comes through the third term, with the role of the covariance between the forecast errors of the series and the predictors coming through the last term. Computing the left-hand-side therefore requires estimates of stochastic volatility in the residuals of every series y_j, and in every predictor variable Z_j.

4 Empirical Implementation and Macro Data

Our empirical analysis forms forecasts and common uncertainty from two datasets spanning the period 1959:01-2011:12. The first dataset, denoted X^m, is an updated version of the 132 mostly macroeconomic series used in Ludvigson and Ng (2010). The 132 macro series in X^m are selected to represent broad categories of macroeconomic time series: real output and income, employment and hours, real retail, manufacturing and trade sales, consumer spending, housing starts, inventories and inventory sales ratios, orders and unfilled orders, compensation and labor costs, capacity utilization measures, price indexes, bond and stock market indexes, and foreign exchange measures. The second dataset, denoted X^f, is an updated monthly version of the of 147 financial time series used in Ludvigson and Ng (2007). The data include valuation ratios such as the dividend-price ratio and earnings-price ratio, growth rates of aggregate dividends and prices, default and term spreads, yields on corporate bonds of different ratings grades, yields on Treasuries and yield spreads, and a broad cross-section of industry, size, book-market, and momentum portfolio equity returns. A detailed description of the series is given in the Data Appendix of the online supplementary file.

We combine the macro and financial monthly datasets together into one large "macroeconomic dataset" (X) to estimate forecasting factors in these 132+147=279 series. However, we estimate macroeconomic uncertainty $\mathcal{U}_t^y(h)$ from the individual uncertainties in the 132 macro series only. Uncertainties in the 147 financial series are not computed because X^m already includes a number of financial indicators. To obtain a broad-based measure of uncertainty, it is desirable not to over-represent the financial series, which are far more volatile than the macro series and can easily dominate the aggregate uncertainty index.[8]

The stochastic volatility parameters $\alpha_j, \beta_j, \tau_j$ are estimated from the least square residuals of the forecasting models using Markov chain Monte Carlo (MCMC) methods.[9] In the base-case, the average of these model parameters over the MCMC draws are used to estimate $\mathcal{U}_{jt}^y(h)$. Simple averaging is used to obtain an estimate of h period macro uncertainty denoted

$$\overline{\mathcal{U}}_t^y(h) = \frac{1}{N^y} \sum_{j=1}^{N^y} \widehat{\mathcal{U}}_{jt}^y(h). \tag{12}$$

This measure of average uncertainty does not impose any structure on the individual uncertainties above and beyond the assumed assumptions on the latent volatility process.

[8]The macro dataset already contains some 25 financial indicators. If we include the additional 147 indicators in our uncertainty index, their greater volatility will dominate the uncertainty measure and we will get back a aggregate financial market volatility variable as uncertainty.

[9]We use the STOCHVOL package in R, which implements the ancillarity-sufficiency interweaving strategy as discussed in Kastner and Fruhwirth-Schnatter (2013) which is less sensitive to whether the mean of the volatility process is in the observation or the state equation. Earlier versions of this paper implements the algorithm of Kim, Shephard, and Chib (1998) using our own MATLAB code.

As an alternative weighting scheme for constructing macro uncertainty, we also construct a latent common factor estimate of macro uncertainty as the first principal component of the covariance matrix of individual uncertainties, denoted $\overline{\mathbb{U}}_t(h)$. To ensure that the latent uncertainty factor is positive, the method of principal components is applied to the logarithm of the individual uncertainty estimates and then rescaled. Its construction is detailed in the on-line supplementary file.

Throughout, the factors in the forecasting equation are estimated by the method of static principal components (PCA). Bai and Ng (2006) show that if $\sqrt{T}/N \to 0$, the estimates $\hat{F}_t$ can be treated as though they were observed in the subsequent forecasting regression. The defining feature of a model with r_F factors is that the r_F largest population eigenvalues should increase as N increases, while the $N - r_F$ eigenvalues should be bounded. The criterion of Bai and Ng (2002) suggests $r_F = 12$ forecasting factors F_t for the combined datasets X^m and X^f explaining about 54% of the variation in the 279 series, with the first three factors accounting for 37%, 8%, 3%, respectively. The first factor loads heavily on stock market portfolio returns (such as size and book-market portfolio returns), the excess stock market return, and the log dividend-price ratio. The second factor loads heavily on measures of real activity, such as manufacturing production, employment, total production and employment, and capacity utilization. The third factor loads heavily on risk and term spreads in the bond market.

The potential predictors in the forecasting model are $\hat{F}_t = (\hat{F}_{1t}, \ldots \hat{F}_{r_F t})'$ and W_t, where W_t consists of squares of the first component of $\hat{F}_t$, and factors in X_{it}^2 collected into the $N_G \times 1$ vector $\hat{G}_t$. These quadratic terms in W_t are used to capture possible non-linearities and any effect that conditional volatility might have on the conditional mean function. Following Bai and Ng (2008), the predictors ultimately used are selected so as to insure that only those likely to have significant incremental predictive power are included. To do so, we apply a hard thresholding rule using a conservative t test to retain those F_t and W_t that are statistically significant.[10] The most frequently selected predictors are $\hat{F}_{2t}$, a "real" factor highly correlated with measures of industrial production and employment, $\hat{F}_{12t-1}$, highly correlated with lagged hours, $\hat{F}_{4t}$, highly correlated with measures of inflation, and $\hat{F}_{10t}$, highly correlated with exchange rates. Four lags of the dependent variable are always included in the predictive regressions.

Before describing the results, we comment briefly on the question of whether it is desirable for our objective to use so-called "real-time" data, which would restrict the forecasting information set to observations on X_{it} that coincide with the estimated value for this series available at time t from data collection agencies. Such a dataset differs from the final "historical" data on X_{it}

[10] Specifically, we begin with a set of candidate predictors that includes all the estimated factors in X_{it} (the $\hat{F}_t$), the first estimated factor in X_{it}^2 ($\hat{G}_{1t}$), and the square of the first factor in X_{it} ($\hat{F}_{1t}^2$). We then chose subsets from these by running a regression of y_{it+1} on a constant, four lags of the dependent variable, $\hat{F}_t$, $\hat{F}_{1t}^2$, and $\hat{G}_{1t}$ (no lags). Regressors are retained if they have a marginal t statistic greater than 2.575 in the multivariate forecasting regression of y_{it+1} on the candidate predictors known at time t.

because initial estimates of a series are available only with a (typically one month) delay, and earlier available estimates of many series are revised in subsequent months as better estimates become available. In this paper we use the final revised, or historical, data in our estimation, for two reasons. The first is a practical one: our approach calls for a summary statistic of forecasts and therefore uncertainty across many series, requiring far more series than what is in practice available on a real-time data basis.

Second, and more fundamentally, we are interested in forming the most historically accurate estimates of uncertainty at any given point in time in our sample. Restricting information to real-time data is not ideal for this objective because it is likely to be overly restrictive, underestimating the amount of information agents actually had at the time of the forecast. Economic modeling is replete with examples of why this could be so. In representative-agent models, agents typically observe the current aggregate economic state as it occurs. In practice, individuals know their own consumption, incomes, the prices they pay for consumption goods, and probably a good deal about the output of the firm and industries they work in, long before data collection agencies report on these. Even forecasting practitioners can predict a large fraction of a future data release based on current information. In this sense, except for data from asset markets, many of what is called real-time data is not really real-time news, but instead represents newly released information on events that had occurred. Even in heterogeneous-agent models where individuals directly observe only their own economic state variables, the aggregate state upon which their optimization problems depend can typically be well summarized by a few financial market returns that are observable on a timely basis. Partly for this reason, our forecasting equations always include a large number of financial indicators as conditioning variables. The 147 financial data series include many empirical risk-factors for stocks and bonds that we expect to be immediately responsive to any genuine news contained in data releases. These financial indicators can also be expected to respond in real time to disaster-like events (wars, political shocks, natural disasters) that invariably increase uncertainty.[11]

5 Estimates of Macro Uncertainty

We present estimates of macro uncertainty for three horizons: $h = 1$, 3, and 12 months. Figure 1 plots $\overline{\mathcal{U}}_t^y(h)$ over time for $h = 1$, 3, and 12, along with the NBER recession dates. The matching horizontal bars correspond to 1.65 standard deviations above the mean for each series. Figure 1 shows that macro uncertainty is clearly countercyclical: the correlation of $\overline{\mathcal{U}}_t^y(h)$ with industrial production growth is -0.62, -0.61, and -0.57 for $h = 1$, 3, and 12, respectively. While the level

[11] Baker and Bloom (2013) use disaster-like events as instruments for stock market volatility with the objective of sorting out the causal relationship between uncertainty and economic growth.

of uncertainty increases with h (on average), the variability of uncertainty decreases because the forecast tends to the unconditional mean as the forecast horizon tends to infinity. Macro uncertainty exhibits spikes around the 1973-74 and 1981-82 recessions, as well as the Great Recession of 2007-09.

Looking across all uncertainty forecast horizons $h = 1$, 3, and 12, the 2007-09 recession clearly represents the most striking episode of heightened uncertainty since 1960. The 1981-82 recession is a close second, especially for forecast horizons $h = 3$ and 12. Indeed, for these horizons, these are the only two episodes for which macro uncertainty exceeds 1.65 standard deviations above its mean in our sample. Inclusive of $h = 1$, the three episodes are the only instances in which $\overline{\mathcal{U}}_t^y(h)$ exceeds, or comes close to exceeding, 1.65 standard deviation above its mean, implying far fewer uncertainty episodes than other popular proxies for uncertainty, as we show below. Heightened uncertainty is broad-based during these three episodes as the fraction of series with $\mathcal{U}_{jt}^y(h)$ exceeding their own standard deviation over the full sample are .42, .61, and .51 for $1, 3$, and 12 respectively. Further investigation reveals that the three series with the highest uncertainty between 1973:11 and 1975:03 are a producer price index for intermediate materials, a commodity spot price index, and employment in mining. For the 1980:01 and 1982:11 episode, uncertainty is highest for the Fed funds rate, employment in mining, and the 3 months commercial paper rate. Between 2007:12 and 2009:06, uncertainty is highest for the monetary base, non-borrowed reserves and total reserves. These findings are consistent with the historical account of an energy crisis around 1974, a recession of monetary policy origin around 1981, and a financial crisis around 2008 that created challenges for the operation of monetary policy.

Table 1 reports summary statistics of $\overline{\mathcal{U}}_t^y(1)$.[12] The table reports the first-order autocorrelation coefficient, estimates of the half-life of an aggregate uncertainty innovation from a univariate autoregression (AR) for $\overline{\mathcal{U}}_t^y(1)$, estimates of skewness, and kurtosis, and the maximum of IP-Corr(k) over k, where IP-Corr(k)= $|\text{corr}(\overline{\mathcal{U}}_t^y(1), \Delta IP_{t+k})|$ is the (absolute) cross-correlation of $\overline{\mathcal{U}}_t^y(1)$ with industrial production growth at different leads and lags, k. The same statistics are reported for other uncertainty proxies, discussed below. Several statistical facts about the estimate of aggregate uncertainty $\overline{\mathcal{U}}_t^y(1)$ stand out in Table 1.

First, the estimated half life of a shock to aggregate uncertainty is 53 months. By comparison, the estimated half life of a shock to stock market volatility (VXO) is 4 months. Thus, macro uncertainty is much more persistent than the most common proxy for uncertainty, a finding relevant for theories where uncertainty is a driving force of economic downturns, including those with more prolonged periods of below-trend economic growth. Second, the skewness of $\overline{\mathcal{U}}_t^y(1)$ is similar to that for VXO, but the kurtosis of $\overline{\mathcal{U}}_t^y(1)$ is lower than VXO. This implies that there are more extreme values in VXO, consistent with the visual inspection of the two series.

[12] The statistics for $\mathcal{U}_{jt}^y(3)$ and $\mathcal{U}_{jt}^y(12)$ (not reported) are very similar.

Third, aggregate uncertainty is strongly countercyclical and has a contemporaneous correlation with industrial production of -0.62. Moreover, a substantial part of the comovement between aggregate uncertainty and production is attributable to uncertainty leading real activity. The maximum of IP-Corr(k) conditional on $k > 0$ is -0.67 and occurs at $k = 3$. But there is also a substantial component of the comovement in which uncertainty lags real activity. At negative values of k, the maximum of IP-Corr(k) is -0.59 and occurs at $k = \square 1$. Of course, these unconditional correlations are uninformative about the causal relation between uncertainty and real activity. All that can be said is that there is a strong coherence between uncertainty and real activity.

Uncertainty in a series is defined above as the volatility of a purely unforecastable error of that series. It is potentially influenced by macro uncertainty shocks and idiosyncratic uncertainty shocks. To assess the relative importance of macro uncertainty $\overline{\mathcal{U}}_t^y(h)$ in total uncertainty (summed over all series), we compute, for each of the 132 series in the macro dataset

$$R^2_{j\tau}(h) = \frac{\text{var}_\tau(\hat{\varphi}_{j\tau}(h), \overline{\mathcal{U}}_t^y(h))}{\text{var}_\tau(\widehat{\mathcal{U}}_{jt}^y(h))}. \tag{13}$$

where $\hat{\varphi}_{j\tau}(h)$ is the coefficient from a regression of $\widehat{\mathcal{U}}_{jt}^y(h)$ on $\overline{\mathcal{U}}_t^y(h)$. Thus $R^2_{j\tau}(h)$ is the fraction of variation in $\mathcal{U}_{jt}^y(h)$ explained by macro uncertainty $\mathcal{U}_t^y(h)$ in the subsample. The statistic is computed for $h = 1, 3$, and 12, for the full sample, for recession months, and for non-recession months.[13] The larger is $R^2_t(h) \equiv \frac{1}{N_y}\sum_{j=1}^{N_y} R^2_{jt}(h)$, the more important is macro uncertainty in explaining total uncertainty.

Table 2 shows that the importance of macro uncertainty grows as the forecast horizon h increases. On average across all series, the fraction of series uncertainty that is driven by common macro uncertainty is much higher for $h = 3$ and $h = 12$ than it is for $h = 1$. Table 2 also shows that macro uncertainty $\overline{\mathcal{U}}_t^y(h)$ accounts for a quantitatively large fraction of the variation in total uncertainty in the individual series. For example, when the uncertainty horizon is $h = 3$ months, estimated macro uncertainty explains an average (across all series) of 16% of the variation in uncertainty over the non-recession sample. But it explains a much larger 26% in recessions. The results are similar for the $h = 12$ case. Results in the right panel of the table based on the common uncertainty factor $\overline{\mathbb{U}}_t(h)$ constructed by the method of principal components reinforce the point that macro uncertainty accounts for a larger fraction of the variation in total uncertainty during recessions.

[13] Recession months are defined by National Bureau of Economic Research dates. Macro uncertainty is estimated over the full sample even when the R^2 statistics are computed over subsamples.

5.1 The Role of the Predictors

We have emphasized the importance of removing the predictable variation in a series so as not to attribute its fluctuations to a movement in uncertainty. How important are these predictable variations in our estimates? Our forecasting regression is

$$y_{jt+1} = \phi_j^y(L)y_{jt} + \ {}_j^F(L)\hat{F}_t + \ {}_j^W(L)W_t + \sigma_{jt+1}^y \varepsilon_{jt+1}.$$

The future values of our predictors F and W are unknown and each predictor is forecasted by an AR(4) model. As explained above, time-varying volatility in their forecast errors also contributes to h-step-ahead uncertainty in the variable y_{jt} whenever $h > 1$. Figure 2 plots predictor uncertainty $\mathcal{U}_{kt}^F(h)$ for several estimated $\hat{F}_{kt}$ that display significant stochastic volatility and that are frequently chosen as predictor variables according to the hard thresholding rule. These are, $\hat{F}_{1t}$ (highly correlated with the stock market), $\hat{F}_{2t}$ (highly correlated with measures of real activity such as industrial production and employment), $\hat{F}_{4t}$ (highly correlated with measures of inflation), $\hat{F}_{5t}$ (highly correlated with the Fama-French risk factors and bond default spreads). This figure also displays estimates of uncertainty for two predictors in W: the squared value of the first factor $\hat{F}_{1t}^2$ and for the first factor formed from observations X_{it}^2, which we denote $\hat{G}_{1t}$. These results suggest that uncertainty in the predictor variables is an important contributor to uncertainty in the series y_{jt+h} to be forecast.

In addition to the stochastic volatility effect, the predictors directly affect the level of the forecast. An important aspect of our uncertainty measure is a forecasting model that exploits as much available information as possible to control for the economic state, so as not to erroneously attributing forecastable variations (as reflected in $\hat{F}_t$ and W_t) to uncertainty in series y_{jt+h}. Most popular measures of uncertainty do not take these systematic forecasting relationships into account. To examine the role that this information plays in our estimates, we re-estimate the uncertainty for each series based on the following (potentially misspecified) simple model with constant conditional mean:

$$y_{jt+1} = \mu + \tilde{\sigma}_{jt+1}\tilde{\varepsilon}_{jt+1}. \tag{14}$$

Figure 3 plots the resulting estimates of one-step ahead uncertainty $\mathcal{U}_{jt}^y(1)$ using this possibly misspecified model and compares it to the corresponding estimates using the full set of chosen predictors (chosen using the hard thresholding rule described above), for several key series in our dataset: total industrial production, employment in manufacturing, non-farm housing starts, consumer expectations, M2, CPI-inflation, the ten-year/federal funds term spread, and the commercial paper/federal funds rate spread. Figure 3 shows that there is substantial heterogeneity in the time-varying uncertainty estimates across series, suggesting that a good deal of uncertainty is series-specific. But Figure 3 also shows that the estimates of uncertainty in these series are significantly influenced by whether or not the forecastable variation is removed before computing uncertainty: when it is removed, the estimates of uncertainty tend to be lower, much so in some cases. Specifically, uncertainty in each of the eight variables shown in this figure is estimated to be lower during the 2007-09 recession when predictive content is removed than when not, especially for industrial production, employment, and the two interest rate spreads. The difference over time between the two estimates for these variables is quite pronounced in some periods, suggesting that much of the variation in these series is predictable and should not be attributed to uncertainty.[14]

Since stock market volatility is the most commonly used proxy for uncertainty, we further examine in Figure 4 how estimates of stock market uncertainty are affected by whether or not the purely forecastable variation in the stock market is removed before computing uncertainty. This figure compares (i) the estimate of uncertainty in the log difference of the $S\&P$ 500 index for a case where the conditional mean is assumed constant, implying as in (14) that no predictable variation is removed, with (ii) a case in which only autoregressive terms are included to forecast the stock market, as in

$$y_{jt+1} = \widetilde{\phi}_j(L)y_{jt} + \tilde{\sigma}_{jt+1}\tilde{\varepsilon}_{jt+1},$$

with (iii) a case in which all selected factors (using the hard thresholding rule) estimated from the combined macro and financial dataset with 279 indicators are used as predictors. Notice that the first case (constant conditional mean) is most akin to estimates of stock market volatility such as the VXO index studied by Bloom (2009)[15] and discussed further below. We emphasize that stock market volatility measures do not purge movements in the stock market of its predictable component and are therefore estimates of conditional volatility, not uncertainty. Of course, if there were no predictable component in the stock market, these two estimates would coincide. But Figure 4 shows that there is a substantial predictable component in the log change in the $S\&P$ price index, which, once removed, makes a quantitatively large difference in the estimated amount of uncertainty over time.[16] Uncertainty in the stock market is substantially lower in every episode when these forecastable fluctuations are removed compared to when they are not, and is dramatically lower in the recession of 2007-09 compared to what is indicated by ex-post conditional stock market volatility.

[14]We have also re-estimated common macro uncertainty, $\overline{\mathcal{U}}_t^y(h)$ without removing predictable fluctuations. The spikes appear larger than the base case that removes the forecastable component in each series before computing uncertainty. This is especially true for the $h = 1$ case, where presumably the predictive information is most valuable.

[15]This measure is unavailable before 1986 so Bloom (2009) uses *realized* volatility in the log difference of the S&P 500 Price Index during this period. We still refer to this composite measure as the "VXO Index."

[16]Evidence for predictability of stock returns is not hard to find. Cochrane (1994) found an important transitory component in stock prices. Ludvigson and Ng (2007) found substantial predictive information for excess stock market returns in the factors formed from the financial dataset X^f. For more general surveys of the predictable variation in stock market returns, see Cochrane (2005) and Lettau and Ludvigson (2010).

If we examine more closely our measure of stock market uncertainty, (given by the baseline estimate in Figure 4) and compare it to macro uncertainty $\mathcal{U}_t^y$ (Figure 1), we see there are important differences over time in the two series. In particular, there are many (more) large spikes in stock market uncertainty that are not present for macro uncertainty. Unlike macro uncertainty, several of the spikes in financial uncertainty occur outside of recessions. Because stock market volatility is arguably the most common proxy for uncertainty, we further examine the distinction between uncertainty and stock market volatility in the next section.

5.2 Uncertainty Versus Stock Market Volatility

In an influential paper, Bloom (2009) emphasizes a measure of stock market volatility as a proxy of uncertainty.[17] This measure is primarily based on the VXO Index, which is constructed by the Chicago Board of Options Exchange from the prices of options contracts written on the S&P 100 Index. In this subsection we compare our macro uncertainty estimates with stock market volatility as a proxy for uncertainty. We update this stock market volatility series to include more recent observations, and plot it along with our estimated macro uncertainty $\overline{\mathcal{U}}_t^y(h)$ for $h = 1$ in Figure 5. To construct his benchmark measure of uncertainty "shocks" (plausibly exogenous variation in his proxy of uncertainty), Bloom selects 17 dates (listed in his Table A.1) which are associated with stock market volatility in excess of 1.65 standard deviations above its HP-detrended mean. These 17 dates are marked by vertical lines in the figure. As emphasized above and seen again in Figure 5, $\overline{\mathcal{U}}_t^y(1)$ exceeds 1.65 standard deviations above its unconditional mean in only three episodes, suggesting far fewer episodes of uncertainty than that indicated by these 17 uncertainty dates.[18]

While $\overline{\mathcal{U}}_t^y(1)$ is positively correlated with the VXO Index, with a correlation coefficient around 0.5, the VXO Index is itself substantially more volatile than $\overline{\mathcal{U}}_t^y(1)$, with many sharp peaks that are not correspondingly reflected by the macro uncertainty measure. For example, the large spike in October 1987 reflects "Black Monday," which occurred on the 19th of the month when stock markets experienced their largest single-day percentage decline in recorded history. While this may accurately reflect the sudden increase in financial market volatility that occurred on that date, our measure of macroeconomic uncertainty barely increases at all. Indeed, it is difficult to imagine that the level of macro uncertainty in the economy in October 1987 (not even a recession year) was on par with the recent financial crisis. Nevertheless, when

[17] A number of other papers also use stock market volatility to proxy for uncertainty; these include Romer (1990), Leahy and Whited (1996), Hassler (2001), Bloom, Bond, and Van Reenen (2007), Greasley and Madsen (2006), Gilchrist, Sim, and Zakrajsek (2010), and Basu and Bundick (2011)

[18] Bloom (2009) counts uncertainty episodes by the number of times the stock market volatility index exceeds 1.65 standard deviations above its Hodrick-Prescott filtered trend, rather than its unconditional mean. If we do the same for $\overline{\mathcal{U}}_t^y(1)$, we find 5 episodes of heightened uncertainty: one in the early mid 1970s (1973:09 and 1974:11), one during the twin recessions in the early 1980s (1980:02 and 1982:02), 1990:01, 2001:10, and 2008:07.

the VXO index is interpreted as a proxy for uncertainty, this is precisely what is implied. Other important episodes where the two measures disagree include the recessionary period from 1980-1982, where our measure of uncertainty was high but the VXO index was comparatively low, and the stock market boom and bust of the late 1990s and early 2000s, where the VXO index was high but uncertainty was low.

5.3 Macro Uncertainty and Macroeconomic Dynamics

Existing empirical research on uncertainty has often found important dynamic relationships between real activity and various uncertainty proxies. In particular, these proxies are counter-cyclical and VAR estimates suggest that they have a large impact on output and employment in the months after an innovation in these measures. A key result is that a in rise some proxies (notably stock market volatility) at first depresses real activity and then increases it, leading to an over-shoot of its long-run level, consistent with the predictions of some theoretical models on uncertainty as a driving force of macroeconomic fluctuations.

We now use VARs to investigate the dynamic responses of key macro variables to innovations in our uncertainty measures and compare them to the responses to innovations in the VXO index as a proxy for uncertainty. For brevity in discussing the results, we will often refer to these innovations to uncertainty or stock market volatility (in the case of the VXO index) as "shocks." As is the case of all VAR analyses, the impulse responses and variance decompositions depend on the identification scheme, which in our case is based on the ordering of the variables.

A question arises as to which variables to include in the VAR. As a starting point, we choose a macro VAR similar to that studied in Christiano, Eichenbaum and Evans (2005, CEE hereafter). This VAR affords the advantage of containing a set of variables whose dynamic relationships have been the focus of extensive macroeconomic research. Since CEE use quarterly data and we use monthly data, we do not use exactly the same VAR, but instead include similar variables so as to roughly cover the same sources of variation in the economy.[19] We estimate impulse responses from a eleven-variable VAR, hereafter referred to as VAR-11. The ordering mimics

[19] Specifically, monthly industrial production and the PCE deflator are substituted for quarterly Gross Domestic Product GDP and its deflator, hours is used instead of labor productivity, average hourly earnings is for the manufacturing sector only because the aggregate measure does not go back to 1960, and the S&P 500 stock market index is substituted for quarterly corporate profits.

that of CEE:

$$\begin{bmatrix} \log\left(\text{real IP}\right) \\ \log\left(\text{employment}\right) \\ \log\left(\text{real consumption}\right) \\ \log\left(\text{PCE deflator}\right) \\ \log\left(\text{real new orders}\right) \\ \log\left(\text{real wage}\right) \\ \text{hours} \\ \text{federal funds rate} \\ \log\left(\text{S\&P 500 Index}\right) \\ \text{growth rate of M2} \\ \textit{uncertainty} \end{bmatrix} \tag{VAR-11}$$

Four versions of VARs-11 with twelve lags are considered with *uncertainty* taken to be either $\overline{\mathcal{U}}_t^y(1)$, $\overline{\mathcal{U}}_t^y(3)$, $\overline{\mathcal{U}}_t^y(12)$, or the VXO Index. The main difference from the CEE VAR is the inclusion of a stock price index and uncertainty. It is important to include the stock market index for understanding the dynamics of uncertainty since it is natural to expect the two variables to be dynamically related. In all cases, we place the measure of uncertainty last in the VAR. The shocks to which dynamic responses are traced are identified using a Cholesky decomposition, with the same timing assumptions made in CEE that allows identification of federal funds rate shocks.[20]

In addition to VAR-11, it is also of interest to compare the dynamic correlations of our uncertainty measures with common uncertainty proxies using a VAR that has been previously employed in the uncertainty literature. To do so, we estimate impulse responses from a eight-variable model as in Bloom (2009), hereafter referred to as VAR-8:

$$\begin{bmatrix} \log(\text{S\&P 500 Index}) \\ \textit{uncertainty} \\ \text{federal funds rate} \\ \log(\text{wages}) \\ \log(\text{CPI}) \\ \text{hours} \\ \log(\text{employment}) \\ \log(\text{industrial production}) \end{bmatrix}. \tag{VAR-8}$$

Following Bloom (2009), VAR-8 uses twelve lags of industrial production, wages, hours. Unlike VAR-11, VAR-8 uses employment for the manufacturing sector *only.* Bloom (2009) considers a 15-point shock to the error in the VXO equation. This amounts to approximately 4 standard deviations of the identified error. We record responses to 4 standard deviation shocks in $\overline{\mathcal{U}}_t^y(h)$, so the magnitudes are comparable with those of VXO shocks. However, we make one departure

[20]We have confirmed that the dynamic responses of the non-uncertainty variables to a federal funds rate shock (interpreted by CEE as a monetary policy shock) in a VAR that does not include any uncertainty measure are qualitatively and quantitatively very similar to those reported in CEE. These results are available upon request.

from the estimates in Bloom (2009). We do not detrend any variables using the filter of Hodrick and Prescott (1997), while Bloom did so for every series except the VXO index. Because the HP filter uses information over the entire sample, it is difficult to interpret the timing of an observation.[21]

Figure 6 shows the dynamic responses of output and employment in VAR-11. Shocks to $\overline{\mathcal{U}}_t^y(h)$ sharply reduce production and employment, with the effects persisting well past the 60 month horizon depicted. The last row of this figure compares the responses when the VXO index is used as a proxy for uncertainty. Both the magnitude and the persistence of the responses of production and employment are much smaller. The responses to $\overline{\mathcal{U}}_t^y(h)$ are far more protracted than those to the VXO Index, which underscores the greater persistence of these measures as compared to popular uncertainty proxies. Indeed, the response of employment to a VXO disturbance is barely statistically different from zero shortly after the shock and outright insignificant at other horizons. The response of production to a VXO shock is also only marginally different from zero for the first 3 months, becoming zero thereafter. An important difference in these results from those reported in Bloom (2009) is that shocks to any of these measures (including VXO) do not generate a "volatility overshoot," namely, the rebound in real activity following the initial decline after a positive uncertainty shock. This finding echoes those in Bachmann, Elstner, and Sims (2013). Unlike the findings in Bachmann, Elstner, and Sims (2013), however, the short-run (within 10 months) responses to our uncertainty shocks are sizable.

Figure 7 shows the dynamic responses of output and employment in VAR-8. The responses of these variables, both in terms of magnitude and persistence, to the macro uncertainty measures $\overline{\mathcal{U}}_t^y(h)$ are similar to those reported in Figure 6 using VAR-11. Disturbances to the VXO index appear to have larger and somewhat more persistent effects in VAR-8 than in VAR-11. But the responses to VXO shocks even in this VAR are not as large or persistent as those to innovations in macro uncertainty $\overline{\mathcal{U}}_t^y(h)$. Again, there is no volatility overshoot in response to any of the uncertainty measures, including VXO. The overshoot found by Bloom (2009) appears to be sensitive to whether the VXO data are HP filtered.[22]

To study the quantitative importance of uncertainty shocks for macroeconomic fluctuations, Table 3 reports forecast error variance decomposition for production, employment and hours and compares them with the decompositions when VXO is used instead as the proxy for uncertainty in the VAR-11. We use k here to distinguish the VAR forecast horizon from the uncertainty forecast horizon h. The table shows the fraction of the VAR forecast error variance that is attributable to common macro uncertainty shocks in $\overline{\mathcal{U}}_t^y(h)$ over several horizons, including the

[21] Results using HP filtered data and the original Bloom VAR are reported in the on-line supplementary material file for this paper.

[22] After a careful inspection of the code kindly provided by Bloom, we find that contrary to a statement in the paper, Bloom (2009) HP filters all data in the VAR for these impulse responses *except* the VXO index.

horizon k for which shocks to the uncertainty measure $\overline{\mathcal{U}}_t^y(1)$ or VXO are associated with the greatest fraction of VAR forecast error variance (denoted k =max in the table).

From Table 3 we can see that uncertainty shocks are associated with much larger fractions of real activity explained than are VXO shocks. Shocks to $\overline{\mathcal{U}}_t^y(12)$, for example, are associated with a maximum of 29% of the forecast error variance in production, 31% of the forecast error variance in employment, and 12% of the forecast error variance in hours. By contrast, the corresponding numbers for VXO shocks are 6.9%, 7.6%, and 2.3%, respectively. Thus, uncertainty shocks are associated with over four times the variation in production and employment and over five times the variation in hours compared to VXO shocks.

To put the results of Table 3 into perspective, Table 4 shows what fraction of the variation in these variables is attributable to monetary policy shocks, identified here, following CEE, by a shock to the federal funds rate in the VAR-11. Interestingly, in the VAR-11 where $\overline{\mathcal{U}}_t^y(12)$ is included as the measure of uncertainty, shocks to the federal funds rate account for roughly the same amount of variation in production, employment, and hours as do shocks to macro uncertainty measures $\overline{\mathcal{U}}_t^y(12)$. Shocks to the federal funds rate are associated with a maximum of 29% of the forecast error variance in production, 32% of the forecast error variance in employment, and 10% of the forecast error variance in hours. These are almost identical to the fraction explained by shocks to $\overline{\mathcal{U}}_t^y(12)$. These results suggest that the dynamic relationship of uncertainty with the real economy may be as quantitatively important as monetary policy shocks.

We can use the same variance decompositions to ask how much of uncertainty variation is associated with variation in innovations of the other variables in the system. These results are not reported in the table, but we discuss a few of them here. At the $k = \infty$ horizon, we find that stock return innovations are associated with the largest fraction of variation in $\overline{\mathcal{U}}_t^y(12)$, equal to 15.26%, followed by price level innovations (11.9%) and innovations to industrial production (9.56%). These numbers are roughly of the same order of magnitude as those for the fraction of forecast error variance in production growth explained by $\overline{\mathcal{U}}_t^y(12)$ for $k = \infty$ (equal to 15.75%). These variance decompositions are of course specific to the ordering of the variables used in the analysis. But as uncertainty is placed *last* in the VAR, the effects of uncertainty shocks on the other variables in the system are measured after we have removed all the variation in uncertainty that is attributable to shocks to the other endogenous variables in the system. That the effects of uncertainty shocks are still non-trivial is consistent with the view that uncertainty has important implications for economic activity.

These variance decomposition results are similar if we instead use VARs that include both VXO and our uncertainty measures $\overline{\mathcal{U}}_t^y(h)$. From such VARs, we find that the big driver of VXO are shocks to VXO, not uncertainty. This reinforces the conclusion that stock market volatility is driven largely by shocks other than those to broad-based economic uncertainty, suggesting researchers should be cautious when using this measure as a proxy for uncertainty.

We have reported results only for the base-case estimates described above. An on-line supplementary file provides additional results designed to check the sensitivity of our results to various assumptions made above. These exercises are based on (i) alternative weights used to aggregate individual uncertainty series; (ii) alternative location statistics of stochastic volatility to construct individual uncertainty series; (iii) alternative conditioning information based on recursive (out-of-sample) forecasts to construct diffusion index forecasts (iv) alterative measures of volatility of individual series such as GARCH and EGARCH.[23] The key findings are qualitatively and quantitatively similar to the ones reported here. We note one finding in particular, namely that the results above are not sensitive to whether we use out-of-sample (recursive) or in-sample forecasts; indeed the correlation between the resulting uncertainty measures is 0.98.[24]

5.4 Comparison with Measures of Dispersion

This subsection compares the time-series behavior of $\overline{\mathcal{U}}_t^y(h)$ with four cross-sectional uncertainty proxies studied by Bloom (2009). These are:

1. The cross-sectional dispersion of firm stock returns. This is defined as the within-month cross-sectional standard deviation of stock returns for firms with at least 500 months of data in the Center for Research in Securities Prices (CRSP) stock-returns file. The series is also linearly detrended over our sample period (1960:07-2011:12).

2. The cross-sectional dispersion of firm profit growth. Profit growth rates are normalized by average sales on a monthly basis, so that this measure captures the quarterly cross-sectional standard deviation profits. We formulate a year-over-year version to minimize seasonal variation equal to $\frac{\text{profits}_{it} - \text{profits}_{it-4}}{0.5(\text{sales}_{it}+\text{sales}_{it-4})}$, where $i = 1, 2, \ldots, N_t$ indexes the firms and N_t denotes the total number of firms observed in month t. The sample is restricted to firms with at least 150 quarters of data in the Compustat (North America) database.

3. The cross-sectional dispersion of GDP forecasts from the Philadelphia Federal Reserve Bank's biannual Livingston Survey. This is defined as the biannual cross-sectional stan-

[23]Results based on the GARCH/EGARCH estimates indicate the number and timing of big uncertainty episodes, as well as the persistence of uncertainty, is very similar to what is found using our base-case measure of macro uncertainty. What is different is the real effect of uncertainty innovations from a VAR, once orthogonalized shocks are analyzed. This is to be expected because GARCH type models (unlike stochastic volatility) have a shock to the second moment that is not independent of the first moment, a structure inconsistent with the assumptions of an independent uncertainty shock presumed in the uncertainty literature. Using a GARCH-based uncertainty index thus creates additional identification problems that are beyond the scope of this paper.

[24]Note also that, in the recursive forecast estimation the parameters of the forecasting relation change every period, so this speaks directly to the question of the role played by parameter stability in our estimates, suggesting that parameter instability is not important in our FAVAR.

dard deviation of forecasts of nominal GDP one year ahead. The series is also linearly detrended over our sample period (1960:07-2011:12).

4. The cross-sectional dispersion of industry-level total factor productivity (TFP). This is defined as the annual cross-sectional standard deviation of TFP growth rates within SIC 4-digit manufacturing industries, calculated using the five-factor TFP growth data computed by Bartelsman, Becker, and Gray as a part of the NBER-CES Manufacturing Industry Database (`http://www.nber.org/data/nbprod2005.html`).[25]

These updated series, along with $\overline{\mathcal{U}}_t^y(1)$ are displayed in Figure 8. As was true in the case of stock market volatility in the previous subsection, these measures exhibit quite different behavior from macroeconomic uncertainty. Stock return dispersion tells a story roughly similar to the VXO Index, with a particularly large increase in uncertainty leading up to the 2001 recession that is not present in our measure of macro uncertainty. Firm profit dispersion actually suggests a relatively low level of uncertainty during the 1980-82 recessions when macro uncertainty was high, with a sharp increase towards the end of the 1982 recession, by which time macro uncertainty had declined. GDP forecast dispersion points to a level of uncertainty during each of the 1969-70 and 1990 recessions which is on par with the level of uncertainty during the 2007-09 recession. Again, this contrasts with macro uncertainty which is at a record high in the 2007-09 recession but was not high in the previous episodes. Industry TFP dispersion shows almost no increase in uncertainty during the 1980-82 recessions. and displays the largest increase during the recent financial crisis.

It is instructive to consider the different statistical properties of these dispersion measures as they compare to those for the estimated aggregate uncertainty index. Table 1 provides the statistics. To match the frequency of the dispersion measure, we aggregate our monthly series $\overline{\mathcal{U}}_t^y(h)$ using averages over the desired period.

The statistics using these proxies for uncertainty paint a similar picture to that obtained using the VXO Index. In particular, the responses of $\overline{\mathcal{U}}_t^y(1)$ to its own shock from an autoregression are far more prolonged than those of the dispersion proxies. For example, the response of the dispersion in firm-level stock returns to its own shock has a half-life of 1.9 months, compared to 52.5 months for $\mathcal{U}_{jt}^y(1)$.

We also consider impulse responses of production and employment for the eleven-variable VAR, but using these measures of dispersion as the proxy for uncertainty. These results are reported in Figure 9 and can be summarized as follows. The dynamic responses using dispersions to proxy for uncertainty do not in general display the intuitive pattern that production and

[25] There is a jump in the 1997 industry TFP dispersion measure that occurs purely because of a move from NAICS to SIC industry classification codes. We therefore drop this year and interpolate to obtain the continuous panel.

employment should fall as a result of an uncertainty shock. Production falls the most on impact in response to shocks to the cross-sectional dispersion in industry-level TFP, but the response of employment is more muted. In the case of stock return dispersion, we see no statistically significant response in production or employment to an innovation. Shocks to the dispersion in firm profits lead to an *increase* in production and employment, as do shocks to the cross-sectional dispersion in subjective GDP forecasts.

Overall, these results show that, like the VXO proxy, increases in measures of cross-sectional dispersion do not necessarily coincide with increases in broad-based macro uncertainty, where the latter is associated with a large and persistent decline in real activity. Like stock market volatility over time, measures of dispersion may vary for many reasons that are unrelated to broad-based macroeconomic uncertainty.

6 Results: Firm-Level Common Uncertainty

In this section we turn from our analysis of common macroeconomic uncertainty to examine common variation in uncertainty at the firm level. Rather than studying uncertainty across many different variables, we now study uncertainty on the same variable across many different firms. Specifically, we measure uncertainty in the profit growth of individual firms. For the firm-level dataset, the unit of observation is the change in firm pre-tax profits $P_{i,t}$, normalized by a two-period moving average of sales, $S_{i,t}$, following Bloom (2009). Given the seasonality in this series, we instead form a year-over-year version of this measure, as detailed in the data appendix. After converting to a balanced panel, we are left with 155 firms from 1970:Q1-2011:Q2 without missing values.[26] For each firm, the series to be forecast is normalized pretax profits, so again $y_{it} = X_{it}$. For the firm-level results, as for the macro results, we form forecasting factors F_t from the panel $\{X_{it}\}_{i=1}^{N_{xp}}$, as well as $\{X_{it}^2\}_{i=1}^{N_{xp}}$ where $N_{xp} = 155$, the number of cross-sectional firm-level observations. We find evidence of two factors in $\{X_{it}\}_{i=1}^{N_{xp}}$ and one factor in $\{X_{it}^2\}_{i=1}^{N_{xp}}$. The W_t vector of additional predictors includes the macro factors estimated from the macro data set. As before, a conservative t test is used to include only the predictors that are statistically significant.

One important consideration that is relevant to this microeconomic context is the construction of our panel. Since we need a reasonable number of time series observations to estimate the stochastic volatility processes, we require that the panel be balanced. This leads us to drop about 400 firms per quarter on average. In particular, many of the firms operating towards the beginning of our sample are excluded, because they do not survive until 2011:Q2. This

[26]A limitation with Compustat data is that its coverage is restricted to large publicly traded firms. The Census Bureau's ASM data are more comprehensive, but limited to annual observations. Similarly, (industry level) total factor productivity may be preferred over profits as the source of uncertainty, but these industry level data eliminate much of the uncertainty at the firm level (Schaal (2012)).

eliminates a large fraction of the cross-sectional variation before 1995. Because of this survivorship bias, it is difficult to conclude that our estimated aggregate firm-level uncertainty measure represents a comprehensive measure of the uncertainty facing firms since 1970. But note that we will compute the cross-sectional standard deviation of firm profits *within* this same balanced panel and compare it to our estimate of common firm-level uncertainty from the panel. Since the two measures are computed over the same panel of firms, any differences between them cannot be attributable to survivorship bias.

Figure 10 displays the estimated common uncertainty in firm-level profits $\overline{\mathcal{U}}_t^y(h)$ over time for $h = 1$, 3, and 4 quarters. Like the measure of macroeconomic uncertainty analyzed above, these estimates point to a rise in uncertainty surrounding the 1973-75,1980-82 recessions, but not of the same magnitude. Instead, there are larger increases in common firm-level uncertainty surrounding the 2000-01 and 2007-09 recessions. However, this type of aggregate uncertainty is less countercyclical: the correlation of each of these measures with industrial production growth is negative, but smaller in absolute value than is the correlation of the macro uncertainty measures with production growth. This figure also compares our measures of common firm-level uncertainty $\overline{\mathcal{U}}_t^y(h)$ to the popular proxy for common firm-level uncertainty given by on the cross-sectional dispersion in firm profit growth normalized by sales, denoted $\mathcal{D}_t^B$ (see equation (3)). As the figure shows, the two measures behave quite differently, with many more spikes in $\mathcal{D}_t^B$ than in common firm-level uncertainty. Indeed, the dispersion measure exceeds 1.65 standard deviations above its mean dozens of times, while common firm-level uncertainty measures only do so a handful of times. Like the VXO index, there appear to be many movements in the cross-sectional standard deviation of firm profit growth that are not driven by common shocks to uncertainty across firms.

To assess the relative importance of macro uncertainty $\overline{\mathcal{U}}_t^y(h)$ in total uncertainty, we again compute, for each of the 155 firms in the firm-level dataset, and for $h = 1$ to 6, the $R_{jt}^2(h)$ as defined in (13), averaged over t. As above, this exercise is performed for the full sample, for recession months, and for non-recession months. Table 4 shows that common firm-level uncertainty comprises a larger fraction of the variation in total uncertainty during recessions that during non-recessions, as was the case for common macroeconomic uncertainty. Indeed, the common firm-level common uncertainty we estimate explains an average of 18% of the variation in total uncertainty for an uncertainty horizon of $h = 4$ quarters in non-recessions, but it explains double that in recessions. These results echo those using the macro uncertainty measures. Other results (using VARs for example) are qualitatively similar and omitted to conserve space.

7 Conclusion

In this paper we have introduced new time series measures of macroeconomic uncertainty. We have strived to ensure that these measures be comprehensive and as free as possible from both the restrictions of theoretical models and/or dependencies on a handful of economic indicators. We are interested in *macroeconomic* uncertainty, namely uncertainty that may be observed in many economic indicators at the same time, across firms, sectors, markets, and geographic regions. And we are interested in the extent to which this macroeconomic uncertainty is associated with fluctuations in aggregate real activity and financial markets.

Our measures of macroeconomic uncertainty fluctuate in a manner that is often quite distinct from popular proxies for uncertainty, including the volatility of stock market returns (both over time and in the cross-section), the cross-sectional dispersion of firm profits, productivity, or survey-based forecasts. Indeed, our estimates imply far fewer important uncertainty episodes than do popular proxies such as stock market volatility, a measure that forms the basis for the 17 uncertainty dates identified by Bloom (2009). By contrast, we uncover just three big macro uncertainty episodes in the post-war period: the months surrounding the 1973-74 and 1981-82 recessions and the Great Recession of 2007-09, with the 2007-09 recession the most striking episode of heightened uncertainty since 1960. These findings and others reported here suggest that there is much variability in the stock market and in other uncertainty proxies that is not generated by a movement in genuine uncertainty across the broader economy. This occurs both because these proxies over-weight certain series in the measurement of macro uncertainty, and because they erroneously attribute forecastable fluctuations to a movement in uncertainty.

Our estimates nevertheless point to a quantitatively important dynamic relationship between uncertainty and real activity. In an eleven variable monthly macro VAR, common macro uncertainty shocks have effects on par with monetary policy shocks and are associated with a much larger fraction of the VAR forecast error variance in production and hours worked than are stock market volatility shocks. Our estimates also suggest that macro uncertainty is strongly countercyclical, explaining a much larger component of total uncertainty during recessions than in non-recessions, and far more persistent than common uncertainty proxies.

In this paper we have deliberately taken an atheoretical approach, in order to provide a model-free index of macroeconomic uncertainty that can be tracked over time. Such an index can be used as a benchmark for evaluating any DSGE model with (potentially numerous) primitive stochastic volatility shocks. Our measure of uncertainty conveniently aggregates uncertainty in the economy derived from all sources into one summary statistic. In some cases, it may be useful to construct sub-indices. These can be easily constructed using our framework.

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	Uncertainty measured by		
Statistic (Monthly)	VXO	$\mathcal{D}$(Returns)	$\overline{\mathcal{U}}_t^y(1)$
AR(1) coefficient	0.85	0.70	0.99
Half Life	4.13	1.92	52.58
Skewness	2.18	1.30	1.81
Kurtosis	11.05	5.51	7.06
IP-Corr(0)	-0.32	-0.45	-0.62
$\max_{k>0}$IP-Corr(k)	-0.43	-0.47	-0.67
At lag $k =$	6	2	3
$\max_{k<0}$IP-Corr(k)	-0.30	-0.43	-0.59
At lag $k =$	-1	-1	-1

Statistic (Quarterly)	$\mathcal{D}$(Profits)	$\overline{\mathcal{U}}_t^y(1)$
AR(1) coefficient	0.76	0.93
Half Life	2.55	10.23
Skewness	0.36	1.77
Kurtosis	2.47	6.75
IP-Corr(0)	-0.37	-0.64
$\max_{k>0}$IP-Corr(k)	-0.34	-0.70
At lag $k =$	1	1
$\max_{k<0}$IP-Corr(k)	-0.37	-0.53
At lag $k =$	-1	-1

Statistic (Semi-Annual)	$\mathcal{D}$(Forecasts)	$\overline{\mathcal{U}}_t^y(1)$
AR(1) coefficient	0.45	0.85
Half Life	0.86	4.18
Skewness	0.24	1.74
Kurtosis	2.19	6.41
IP-Corr(0)	-0.41	-0.64
$\max_{k>0}$IP-Corr(k)	-0.34	-0.68
At lag $k =$	1	1
$\max_{k<0}$IP-Corr(k)	-0.35	-0.40
At lag $k =$	-1	-1

Statistic (Annual)	$\mathcal{D}$(TFP)	$\overline{\mathcal{U}}_t^y(1)$
AR(1) coefficient	0.33	0.61
Half Life	0.63	1.40
Skewness	1.71	1.76
Kurtosis	8.56	6.24
IP-Corr(0)	-0.55	-0.69
$\max_{k>0}$IP-Corr(k)	-0.33	-0.47
At lag $k =$	1	1
$\max_{k<0}$IP-Corr(k)	-0.24	-0.24
At lag $k =$	-26	-26

Table 1: Summary Statistics. This table displays a number of summary statistics characterizing various proxies. IP-Corr(k) is the absolute cross-correlation coefficient between a measure of uncertainty u_t and 12 month moving average of industrial production growth in period $t + k$, ie. IP-Corr(k)=$|\text{corr}(u_t, \Delta \ln IP_{t+k})|$. A positive k means uncertainty is correlated with future IP. Half-lifes are based on estimates from a univariate AR(1) model for each series. The maximum correlation, at different leads/lags, with the growth rate of IP (12 month moving average) is also reported. $\overline{\mathcal{U}}_t^y(1)$ denotes base case estimated aggregate uncertainty. $\mathcal{D}(\cdot)$ represents dispersion, i.e. the cross-sectional standard deviation. Monthly series are aggregated to quarterly, semi-annual, and annual series by averaging monthly observations over each larger period.

	Average R^2 From Regressions of Individual Uncertainty on Macro Uncertainty					
	$\overline{\mathcal{U}}^y(h) = \frac{1}{N_y}\sum_{j=1}^{N_y}\widehat{\mathcal{U}}_{jt}(h)$			$\overline{\mathbb{U}}^y(h) = \sum_{j=1}^{N_y} w_j\widehat{\mathcal{U}}_{jt}(h)$		
h	full sample	recession	non-recession	full sample	recession	non-recession
1	0.18	0.19	0.12	0.17	0.17	0.12
2	0.22	0.24	0.15	0.22	0.24	0.15
3	0.24	0.26	0.16	0.23	0.25	0.16
4	0.25	0.26	0.17	0.23	0.24	0.16
5	0.26	0.27	0.18	0.24	0.25	0.16
6	0.27	0.28	0.19	0.25	0.26	0.16
7	0.28	0.29	0.19	0.25	0.27	0.17
8	0.29	0.30	0.20	0.25	0.27	0.17
9	0.29	0.30	0.20	0.25	0.28	0.17
10	0.29	0.31	0.21	0.25	0.28	0.17
11	0.30	0.31	0.21	0.25	0.29	0.17
12	0.30	0.31	0.21	0.25	0.29	0.17

Table 2: Cross-sectional averages of R^2 values from regressions of $\mathcal{U}_{jt}^y(h)$ on $\overline{\mathcal{U}}_t^y(h)$ or $\overline{\mathbb{U}}_t^y(h)$ over different subsamples. Uncertainty estimated from the monthly, macro dataset. Recession months are defined according to the NBER Business Cycle Dating Committee.

Relative Importance of Uncertainty in VAR-11

Production:				
	$\mathcal{U}_t^y(1)$	$\mathcal{U}_t^y(3)$	$\mathcal{U}_t^y(12)$	VXO
$k=1$	0.00	0.00	0.00	0.00
$k=3$	1.78	2.08	2.13	0.48
$k=12$	11.29	15.79	15.22	0.91
$k=\infty$	7.87	8.79	15.76	6.93
$\max k$	174	171	174	184
$k=\max$	17.02	20.86	28.54	6.93
Employment:				
	$\mathcal{U}_t^y(1)$	$\mathcal{U}_t^y(3)$	$\mathcal{U}_t^y(12)$	VXO
$k=1$	0.00	0.00	0.00	0.00
$k=3$	0.90	0.98	0.86	1.06
$k=12$	9.15	13.23	13.08	1.11
$k=\infty$	6.66	7.51	14.25	7.64
$\max k$	105	106	107	184
$k=\max$	16.40	20.06	31.00	7.64
Hours:				
	$\mathcal{U}_t^y(1)$	$\mathcal{U}_t^y(3)$	$\mathcal{U}_t^y(12)$	VXO
$k=1$	0.00	0.00	0.00	0.00
$k=3$	1.76	1.88	1.26	0.12
$k=12$	8.11	11.36	10.53	1.16
$k=\infty$	7.38	8.98	11.93	2.15
$\max k$	21	16	37	43
$k=\max$	9.21	11.96	12.34	2.32

Table 3: Decomposition of variance in production, employment and hours due to uncertainty in VAR-11. The VAR uses variables in the following order: log(industrial production), log(employment), log(real consumption), log(implicit consumption deflator), log(real value new orders, consumption and non-defense capital goods), log(real wage), hours, federal funds rate, log(S&P 500 Index), growth rate of M2, and *uncertainty* that is either VXO Index or $\overline{\mathcal{U}}_t^y(h)$. Real variables are obtained by dividing nominal values by the PCE deflator. We estimate separate VARs in which *uncertainty* is either one of $\overline{\mathcal{U}}_t^y(h)$, $h=1,3,12$ or the VXO index. Each panel shows the fraction of forecast-error variance of the variable given in the panel title at VAR forecast horizon k that is explained by the uncertainty measure named in the column. The row denoted "max k"gives the horizon k for which the uncertainty variable named in the column explains the maximum fraction of forecast error variance. The row denoted "$k=$ "max gives the fraction of forecast error variance explained at max k. The data are monthly and span the period 1960:07-2011:12.

Relative Importance of FFR in VAR-11

Production:				
	FFR-$\mathcal{U}_t^y(1)$	FFR-$\mathcal{U}_t^y(3)$	FFR-$\mathcal{U}_t^y(12)$	FFR-VXO
$k = 1$	0.00	0.00	0.00	0.00
$k = 3$	0.06	0.04	0.02	0.01
$k = 12$	5.86	5.27	4.00	7.17
$k = \infty$	33.67	31.39	28.96	39.07
$\max k$	∞	∞	∞	∞
$k = \max$	33.67	31.39	28.96	39.07
Employment:				
	FFR-$\mathcal{U}_t^y(1)$	FFR-$\mathcal{U}_t^y(3)$	FFR-$\mathcal{U}_t^y(12)$	FFR-VXO
$k = 1$	0.00	0.00	0.00	0.00
$k = 3$	0.06	0.03	0.01	0.02
$k = 12$	6.99	6.33	4.87	8.26
$k = \infty$	36.02	33.14	31.89	39.47
$\max k$	185	190	357	148
$k = \max$	41.30	39.35	34.83	52.74
Hours:				
	FFR-$\mathcal{U}_t^y(1)$	FFR-$\mathcal{U}_t^y(3)$	FFR-$\mathcal{U}_t^y(12)$	FFR-VXO
$k = 1$	0.00	0.00	0.00	0.00
$k = 3$	0.44	0.48	0.56	0.72
$k = 12$	4.58	4.30	3.54	6.36
$k = \infty$	12.92	12.08	9.79	17.21
$\max k$	∞	∞	∞	∞
$k = \max$	12.92	12.08	9.79	17.21

footnoteTable 4: Decomposition of variance in production, employment and hours due to FFR in VAR-11.

Average R^2 From regressions of Firm-Level Uncertainty on Common Uncertainty

	$\overline{\mathcal{U}}^y(h)$			$\overline{\mathbb{U}}^y(h)$		
h	full sample	recession	non-recession	full sample	recession	non-recession
1	0.15	0.29	0.14	0.12	0.27	0.11
2	0.18	0.34	0.16	0.16	0.32	0.14
3	0.19	0.35	0.17	0.17	0.33	0.15
4	0.20	0.36	0.18	0.18	0.33	0.16
5	0.21	0.36	0.18	0.18	0.33	0.16
6	0.21	0.36	0.19	0.18	0.32	0.16

Table 4: Cross-sectional averages of R^2 values from regressions of $\mathcal{U}_{jt}^y(h)$ on $\overline{\mathcal{U}}_t^y(h)$ or $\widehat{\mathcal{U}}_t^y(h)$ over different subsamples. Uncertainty estimated from the quarterly firm-level dataset with observations on firm profit growth rates normalized by sales. Recession months are defined according to the NBER Business Cycle Dating Committee. The data are quarterly and span the period 1970:Q1-2011:Q2.

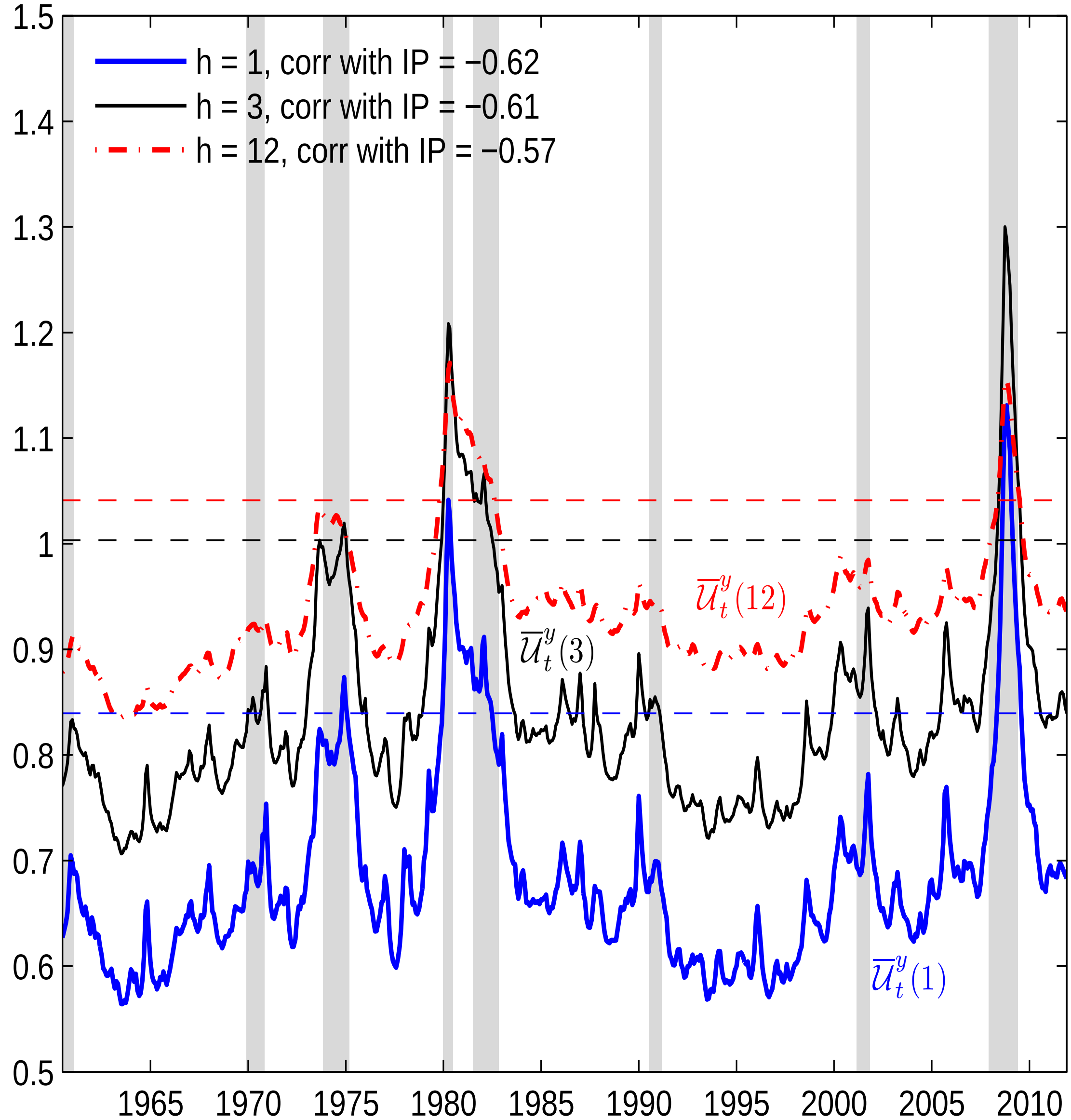

Figure 1: Aggregate Uncertainty: $\overline{\mathcal{U}}_t^y(h)$ for $h = 1, 3, 12$. Horizontal lines indicate 1.65 standard deviations above the mean of each series. Industrial Production (IP) growth is computed as the 12-month moving average of monthly growth rates (in percent). The data are monthly and span the period 1960:07-2011:12.

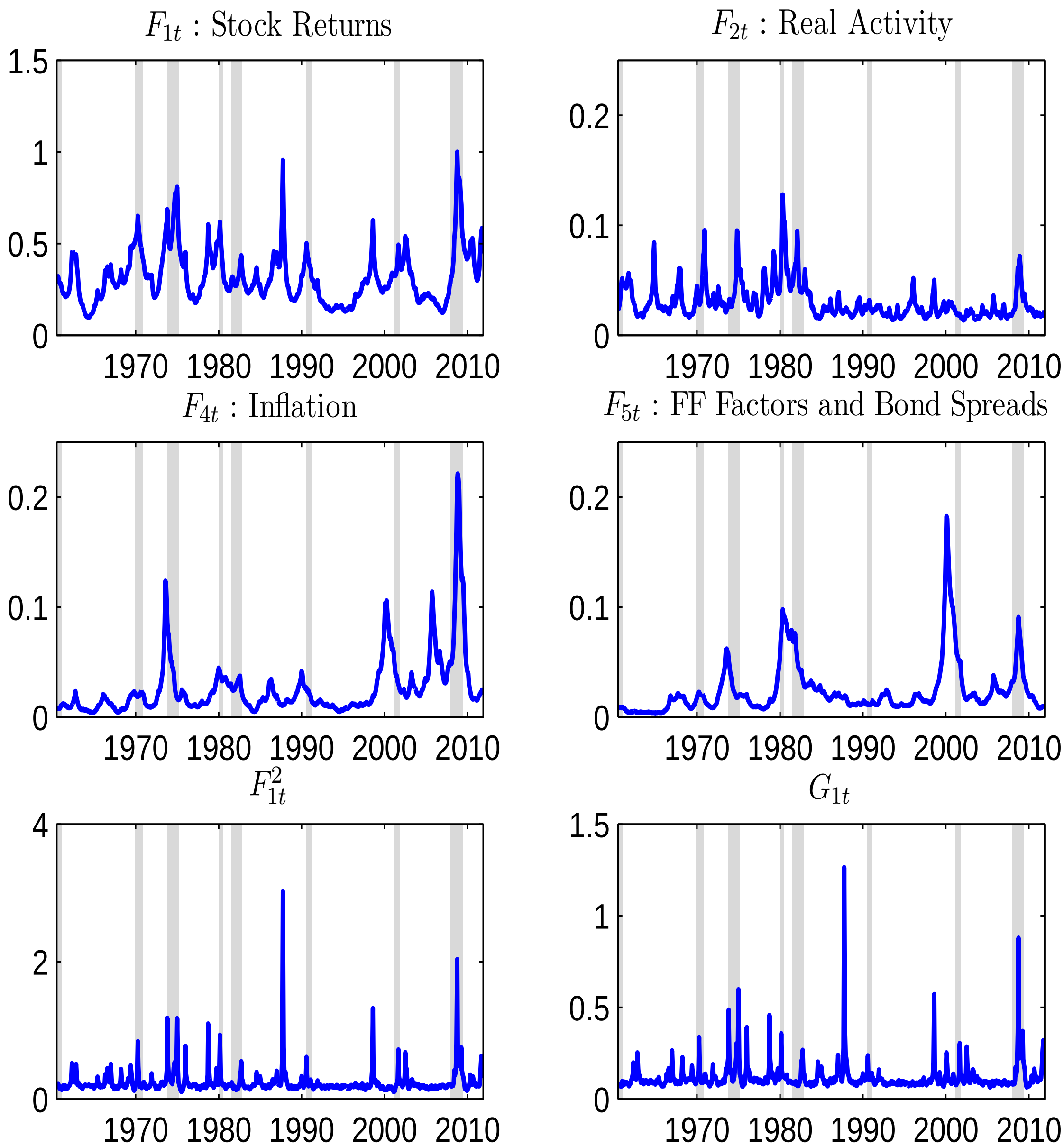

Figure 2: Predictor Uncertainty: This plot displays uncertainty estimates for 6 of the 14 predictors contained in the vector $Z_t \equiv (F_t', W_t')'$. F_t denotes the 12 factors estimated from X_{it}, and $W_t \equiv (F_{1t}^2, G_{1t})'$, where G_{1t} is the first factor estimated from X_{it}^2. Titles represent the types of series which load most heavily on the factor plotted; "FF Factors" means the Fama-French factors (HML, SMB, UMD). The sample period is 1960:01-2011:12.

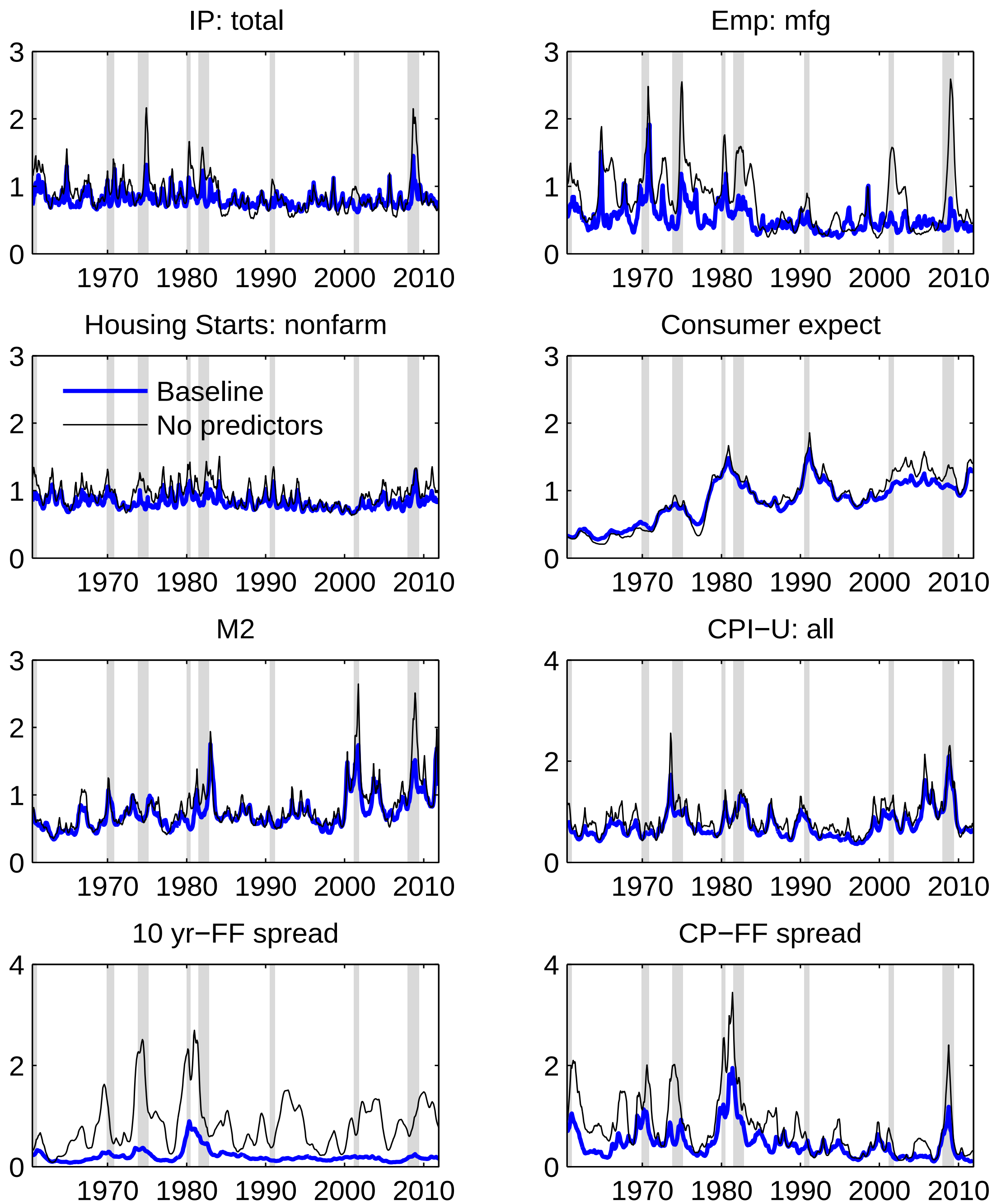

Figure 3: The Role of Predictors: These plots display two estimates of $\mathcal{U}^y_{jt}(1)$ for several key series in our data set. The first is constructed using the full set of predictor variables ("Baseline"); the second is constructed using no predictors ("No predictors"). The data are monthly and span the period 1960:07-2011:12.

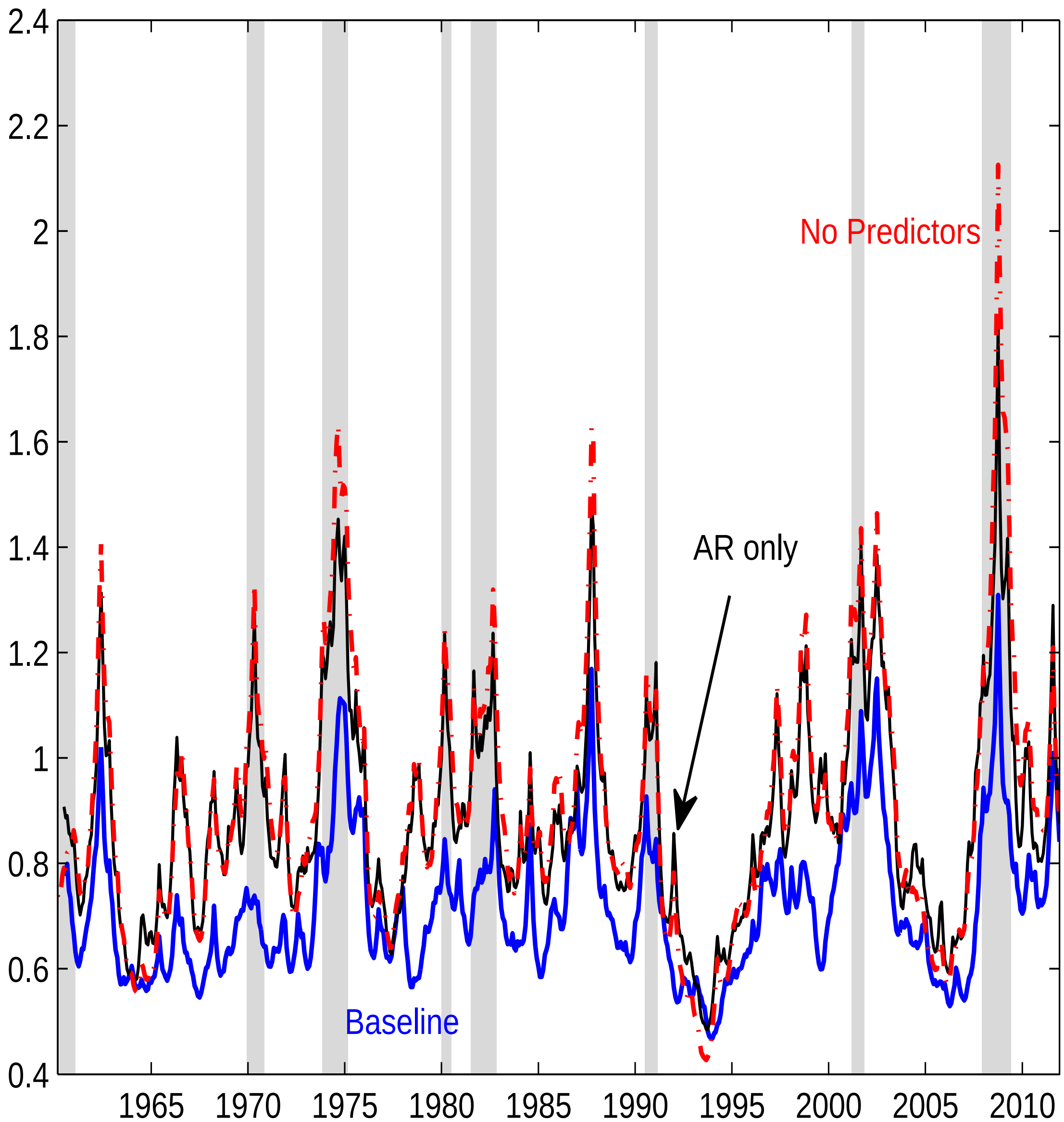

Figure 4: Uncertainty in the S&P 500 Index. These plots show estimates of $\mathcal{U}^{y}_{SP500,t}(1)$ for the S&P 500 Index based on three different forecasting models. "No Predictors" indicates that no predictors were used, "AR only" indicates that only a fourth-order autoregressive model was used to generate forecast errors, and "Baseline" indicates that the full set of predictor variables was used to generate forecast errors. The sample period is 1960:01-2011:12.

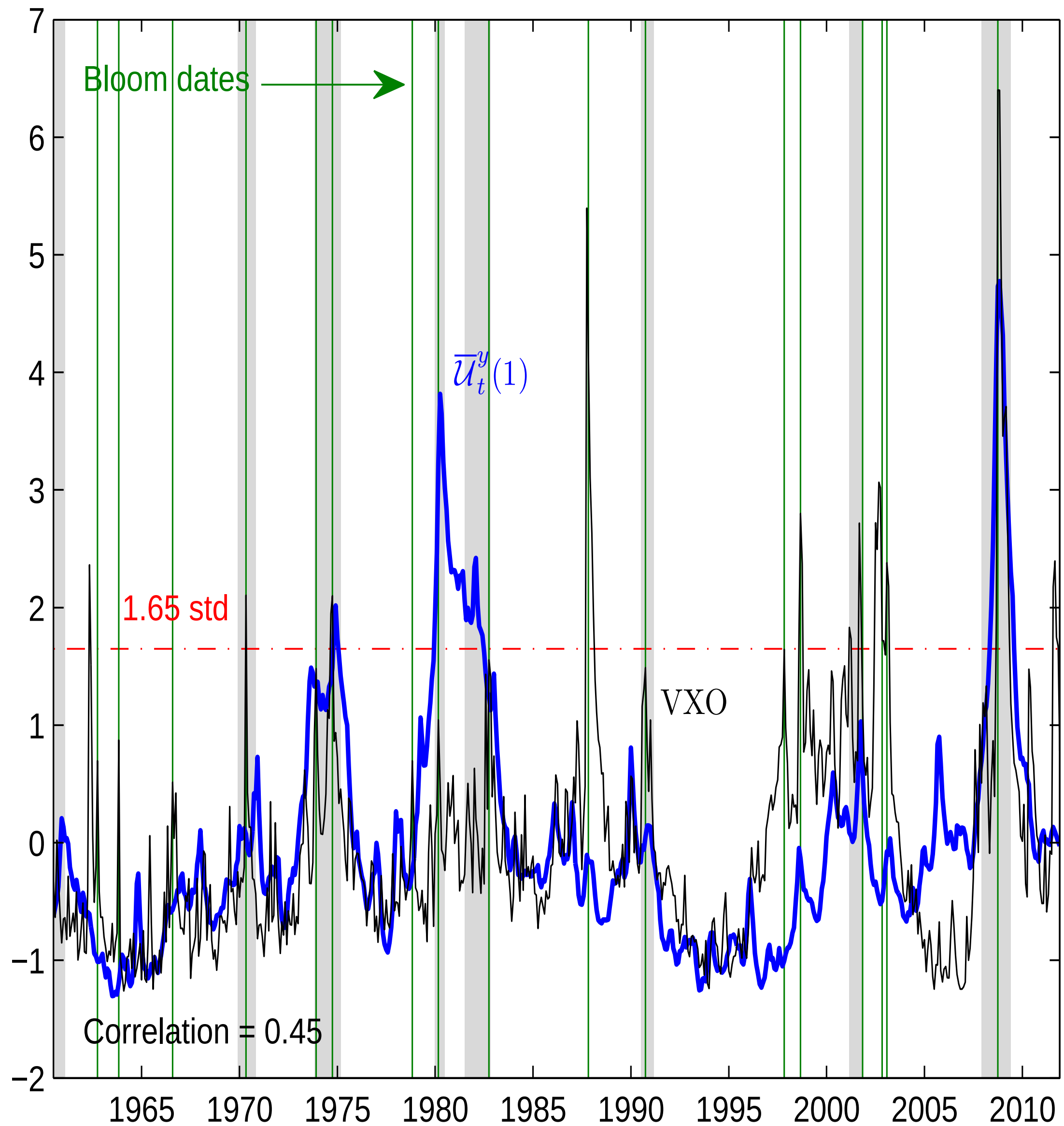

Figure 5: Stock Market Implied Volatility and Uncertainty: This plot shows $\overline{\mathcal{U}}_t^y(1)$ and the VXO index, expressed in standardized units. The vertical lines correspond to the 17 dates in Bloom (2009) Table A.1, which correspond to dates when the VXO index exceeds 1.65 standard deviations above its HP (Hodrick and Prescott, 1997) filtered mean. The horizontal line corresponds to 1.65 standard deviations above the unconditional mean of each series (which has been normalized to zero). The data are monthly and span 1960:07-2011:12.

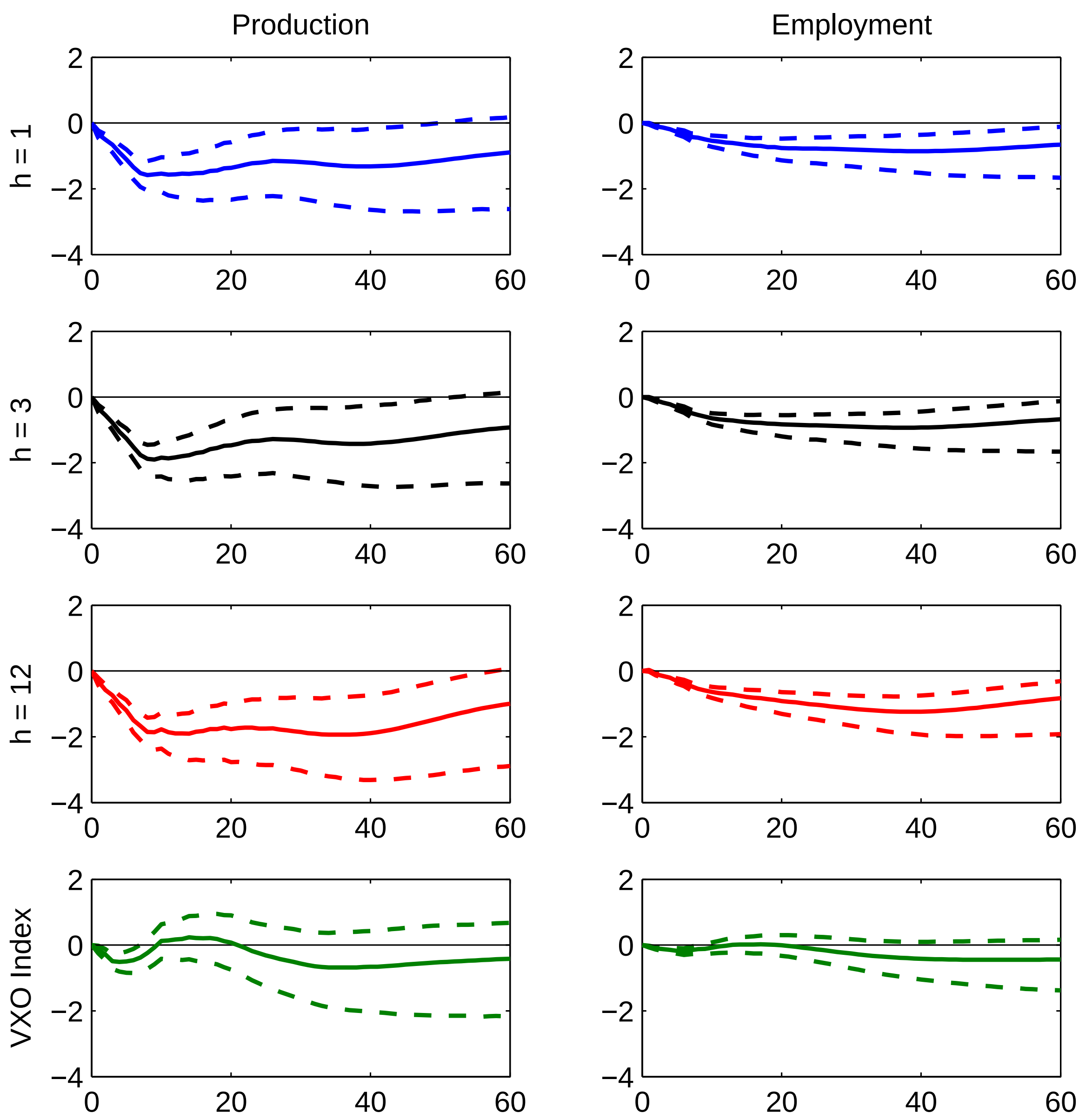

Figure 6: Impulse response of production and employment from estimation of VAR-11 using $\overline{\mathcal{U}}_t^y(h)$ or VXO as uncertainty

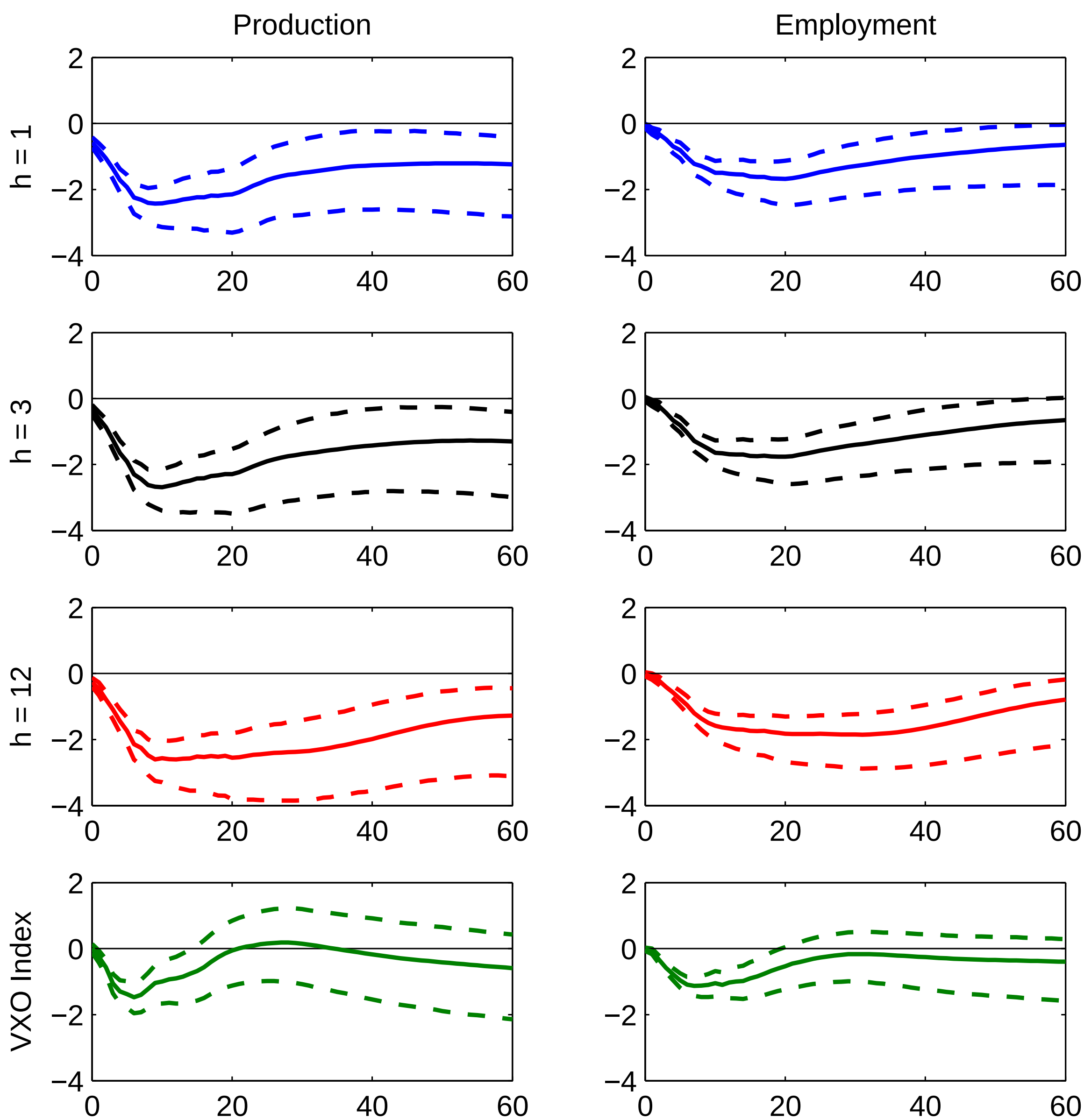

Figure 7: Impulse response of production and employment from estimation of VAR-8 using $\overline{\mathcal{U}}_t^y(h)$ or VXO as uncertainty

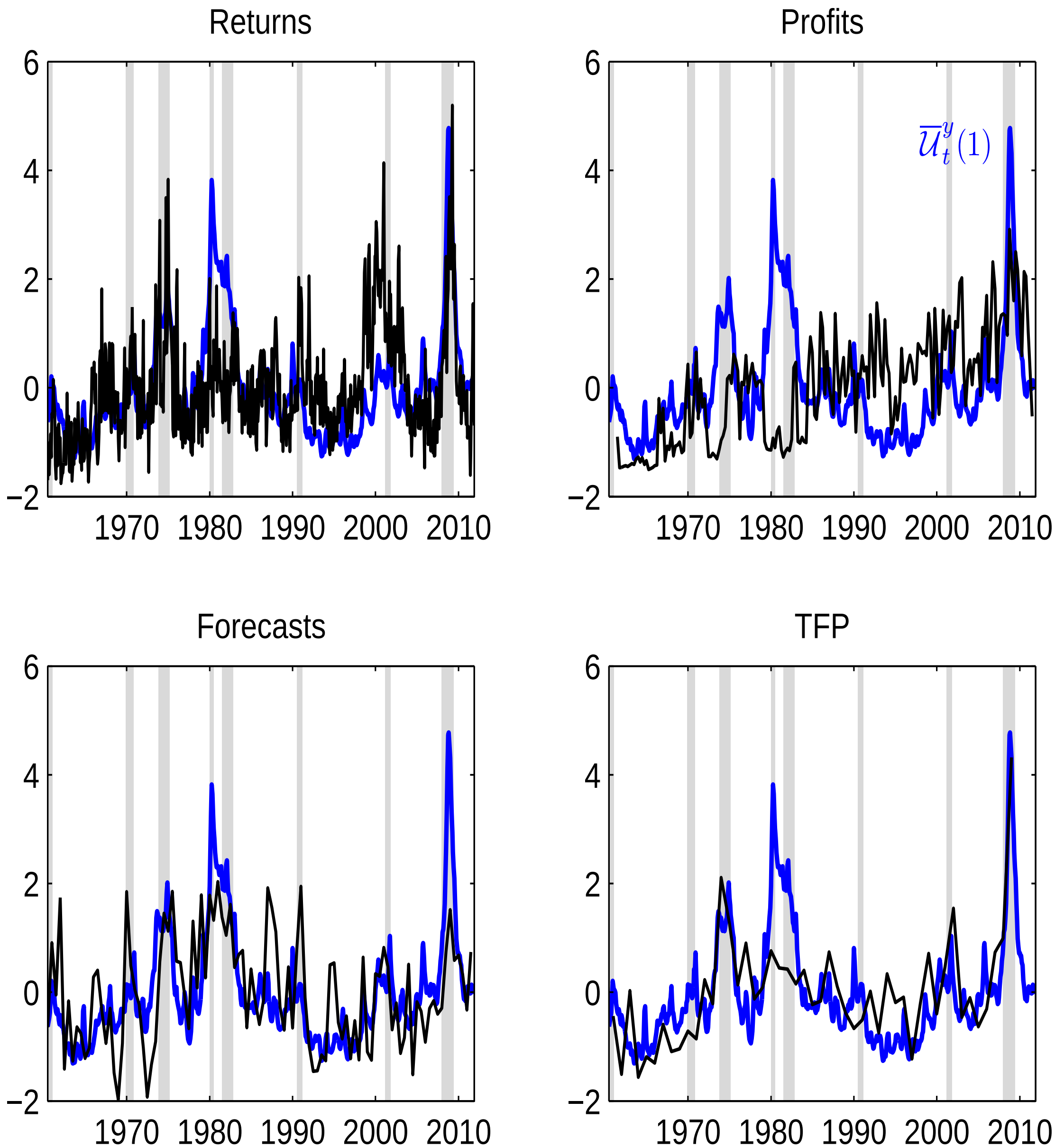

Figure 8: Cross-sectional Dispersion and Uncertainty: This plot shows $\overline{\mathcal{U}}_t^y(1)$ and four dispersion-based proxies, expressed in standardized units. The proxies are (in clockwise order from the northwest panel) the cross-sectional standard deviation of: monthly firm stock returns (CRSP), quarterly firm profit growth (Compustat), yearly SIC 4-digit industry total factor productivity growth (NBER-CES Manufacturing Industry Database), and half-yearly GDP forecasts (Livingston Survey).

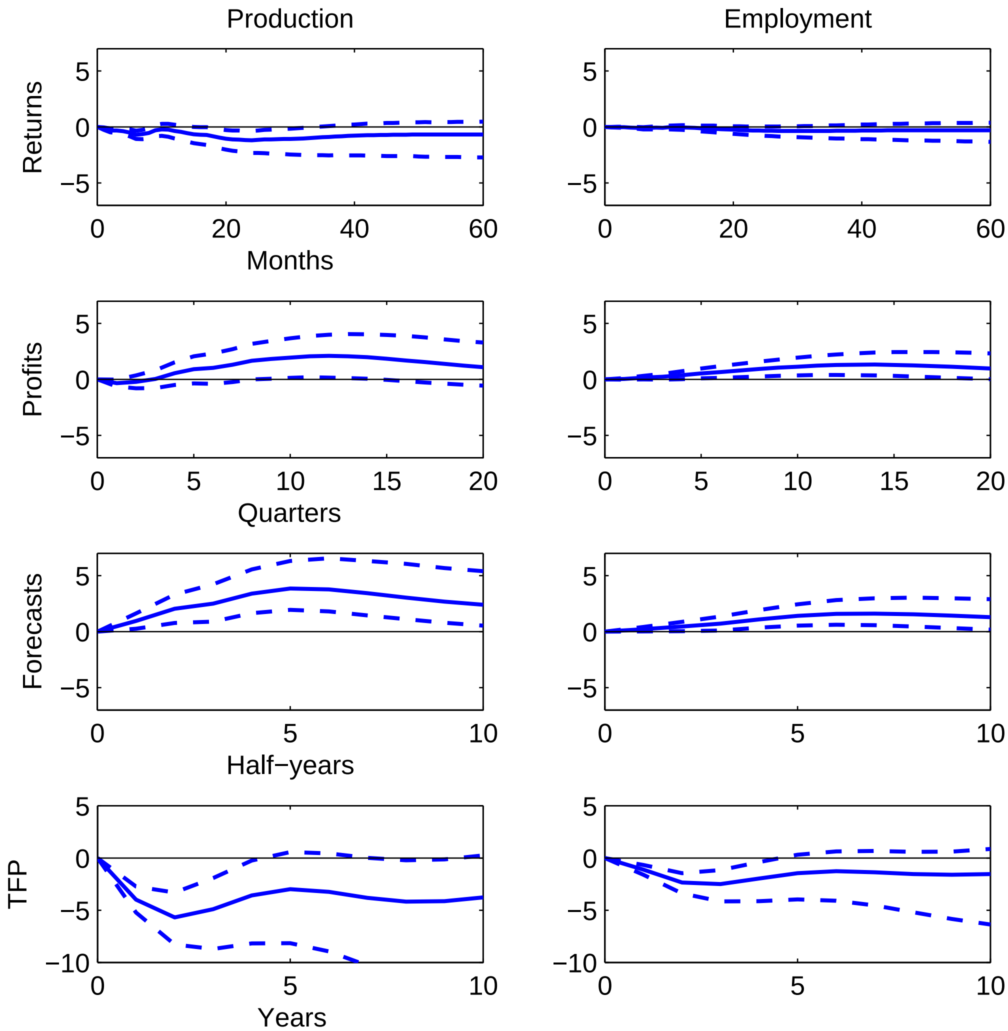

Figure 9: Impulse response of production and employment from estimation of VAR-11 using four dispersion measures $\mathcal{D}_t$ as uncertainty: (i) "Returns"is the cross-sectional standard deviation of firm stock returns; (ii) "Profits"is the cross-sectional standard deviation of firm profits; (iii) "Forecasts"is the cross-sectional standard deviation of GDP forecasts from the Livingston Survey; (iv) "TFP"is the cross-sectional standard deviation of industry-level total factor productivity.

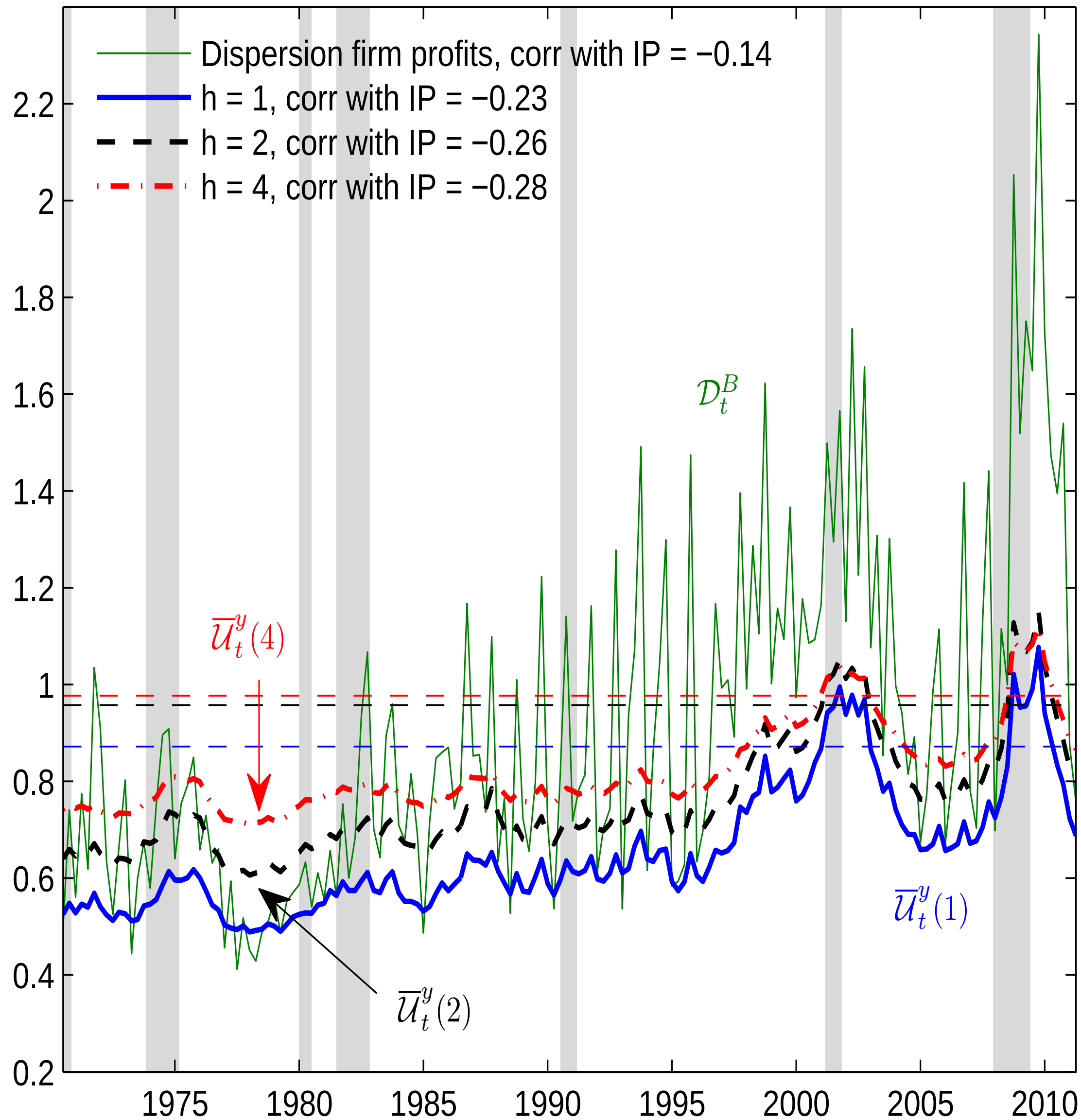

Figure 10: Firm-level Uncertainty: $\overline{\mathcal{U}}_t^y(h)$ for $h = 1, 2, 4$. Horizontal lines indicate 1.65 standard deviations above the mean of each series. The thin solid line marked "Dispersion in firm profits"is the cross-sectional standard deviation of firm profit growth, normalized by sales, and denoted $\mathcal{D}_t^B$. The dispersion is taken after standardizing the profit growth data. Industrial Production (IP) growth is computed as the 12-month moving average of monthly growth rates (in percent). The data are monthly and span the period 1970:Q1-2011:Q2.