Measuring macroeconomic uncertainty from surveys – a mixed frequency approach☆

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Abstract

We propose a new method of measuring economic uncertainty, using dispersions of forecasts from both household and professional surveys of various frequencies. With a mixed-frequency state-space model, we construct an uncertainty measure of the perceived current state of the US economy and an uncertainty measure of the one-year ahead expected state of the economy. Although distinctively constructed, we show our measures of uncertainty are highly correlated with most other existing measures. Impulse responses show uncertainty shocks lead to a contraction in economic activity, and monetary policy expansion reduces uncertainty, implying endogenous uncertainty is an additional channel for countercyclical monetary policy.

Keywords: Economic uncertainty, survey data, mixed frequency, state-space model
JEL Classification: D80, E66, E50,C81

1. Introduction

We provide new measures of aggregate macroeconomic uncertainty. We jointly consider dispersions of 35 variables from both survey of consumers (Michigan Survey of Consumers) and professionals (Survey of Professional Forecasts and the Livingston Survey) arriving at different frequencies. We construct a mixed-frequency measure of economic uncertainty based on the dispersion of nowcasts of current economic indicators, and a measure of uncertainty based on the dispersion of forecasts of one-year ahead economic indicators. Macroeconomic policies, including monetary policy, are shown to have delayed impacts through these uncertainty measures on the economy. The measures based on nowcasts of current economic indicators should reflect the uncertainty of the effect of past macroeconomic policies and current unexpected economic shocks. In contrast, uncertainty measures based on forecasts should also incorporate the uncertainty of the effects of current and future expected economic

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policies. Therefore endogenous uncertainty is shown to be an important channel through which countercyclical monetary policy can operate.

There is an increasing consensus on the contractionary effects of uncertainty in driving business cycle fluctuations. For example, using a stock market volatility indicator as the measure of uncertainty, Bloom (2009) shows positive uncertainty shocks reduce employment and production, and subsequently become expansionary. Similarly, Jurado et al. (2015) construct a measure of economic uncertainty based on forecast error variances, and find increases in economic uncertainty are contractionary. Caggiano et al. (2014) show that the impact of uncertainty shocks is particularly large for unemployment if one allows a non-linearity that distinguishes recessions from other episodes.

Ideally, measurable uncertainty will resemble the probability of occurrence of events. At an aggregate level, uncertainty measures should best be represented by the dispersion of individual density forecasts of economic indicators. However, given the difficulty of providing direct measures, economists are forced to approximate the true level of uncertainties.

While there is growing consensus of its effects, there is less consensus about the various approximate measures of economic uncertainty (see Bloom (2014) for a survey of uncertainty measures). A popular measure of uncertainty is the Chicago Board Options Exchange Market Volatility—the VIX index. This gives market expectations of the 30 day ahead volatility implied by S&P500 option prices (for example see: Bloom (2009), Caggiano et al. (2014) and Bekaert et al. (2013)). However, the VIX index essentially measures the volatility of the stock market and may not be a good proxy for aggregate macroeconomic uncertainty. Jurado et al. (2015) propose an alternative measure of macroeconomic uncertainty based on the idea that a rise in uncertainty means economic variables become less predictable. Thus they construct an uncertainty measure based on the weighted average of the variance of forecast errors (the unpredictable component) from a large factor model. Baker et al. (forthcoming) construct an economic policy uncertainty index based on the weighted average of text scans of the top 10 American newspapers for dispersions of survey responses related to economic policies. However, uncertainty based on the newspaper coverage of media reports may not fully represent the uncertainty that economic agents perceive, even though in a world without information rigidity (for example, see Mankiw and Reis (2002) and Mankiw et al. (2004)), the two might be correlated.

Another popular approach to measure uncertainty uses survey dispersions of forecasts of economic indicators. The dispersion of cross-sectional survey forecasts reflects the level of disagreements among economic agents. An increase in the dispersion indicates agents disagree more with each other when forecasting an economic indicator, which reflects an increase in the level of uncertainty. The advantage of using disagreement in surveys is that the measure is constructed from expectations of the future state of the economy. It is these expectations that should manifest in individuals' economic decisions, and thus the aggregate economy. For example, Bachmann et al. (2013) uses dispersions of firm surveys from both Germany and US as the measure of economic uncertainty and find increases in uncertainty reduce employment and production. One problem with forecasts dispersion is that it could simply reflect heterogeneous, but certain forecasts. Utilizing the micro structure of the data, they show that the forecast dispersion is highly correlated with the standard deviation of forecast errors (which are not prone to heterogenous forecasts), and thus provide suggestive evidence that using forecast disagreement is a good approximation of true uncertainty.

One potential problem with existing uncertainty measures using survey data is that they are based on one particular survey, and very often rely on a specific economic indicator in the survey, thus making it hard to generalise to the aggregate economy. However there are a wide range of surveys with dispersions of cross-sectional responses that are available, and these surveys apply singly a wide range of economic indicators that respondents are asked to forecast. For example, Zarnowitz and Lambros (1987) uses inflation as the underlying economic indicator, Bloom (2014) uses the forecast dispersion of GDP growth rates and Bachmann et al. (2013) utilises a dispersion measure of a qualitative question on general business cycle conditions.

Our paper addresses this problem of using just single indicators by estimating aggregate macroeconomic uncertainty from dispersions of forecasts across a wide range of economic surveys and economic indicators. Since different surveys release their forecasts at different times, we employ a mixed-frequency state-space model to handle this timing issue. Our mixed-frequency approach provides for a more efficient way of utilising economic information than previously published measures.

When we compare our measures of economic uncertainty against other popular measures, we do find significant differences, but in general there are strong co-movements. This is especially true during recessions.

Consistent with the literature, we find that increases in economic uncertainty reduce employment and industrial production. We also find that an unexpected expansionary monetary policy change can reduce the level of uncertainty. These two results have an important implication for countercyclical monetary policy—they imply an additional transmission mechanism.

The rest of the paper is organised as follows. Section 2 describes the survey data used in the estimation. Section 3 outlines the mixed-frequency state-space framework. Section 4 presents our estimated measures of aggregate macroeconomic uncertainty and compares them with other popular measures. Section 5 shows the impact of positive uncertainty shocks is contractionary and Section 6 shows that unexpected monetary policy can help to reduce the level of uncertainty. Section 7 concludes.

2. The survey data

We consider both surveys on consumers and professional forecasters in this study. The survey on consumers comes from the Michigan Survey of Consumers (MSC). Since January 1978, around 500 U.S. households have been surveyed each month on their one-year ahead and five-year ahead inflation expectations. The data exhibits a considerable degree of disagreement among these households in any given month, even in relatively low and stable inflation periods.

For professional forecasters, we use both the Survey of Professional Forecasters (SPF) and the Livingston Survey (LV), which are both maintained by the Federal Reserve Bank of Philadelphia. The SPF survey is the oldest quarterly survey of macroeconomic forecasts in the US, and contains expectations of a rich set of economic indicators since 1968. These variables include measures of economic activity, inflation, interest rates and spreads in financial markets. The Livingston survey is the oldest continuous biannual survey of economists' expectations, originated by columnist Joseph Livingston in 1946. The survey respondents are economists from industry, government and academia. It covers a wide range of economic indicators including measures of economic activity, inflation, interest rates and a stock price index.

Both SPF and LV survey ask the respondents to indicate their current evaluations, and their one-year ahead forecasts of economic indicators. The evaluations of current economic indicators—essentially nowcasts—reflect the perceptions of respondent on the current state of the economy. The disagreements about the current state of the economy are likely to reflect the diverse interpretations of the effects of past economic shocks, evaluations of past macroeconomic policies and current unexpected economic shocks. On the other hand, the disagreements of one-year ahead forecasts are more likely to reflect the diverse expectations of the future course of the economy and the evaluations of the current and the future expectations of macroeconomic policies.

Table 1 shows the economic indicators used in each of the surveys. The data can be grouped into three broad categories: measures on financial market indicators, inflation and economic activity. The only quantitative question from the MSC is about households' forecasts of expected future inflation.

Both SPF and the LV covers economic indicators in all three categories. They both ask questions about the level of returns and interest rates, with the LV focusing more on sovereign debt yields and the SPF focusing more on corporate bonds and the return on shares. In addition, SPF also asks respondents to forecast interest rates spreads. These forecasts contain useful information about perceived risk premia, and therefore about perceived uncertainty in the economy.

Although both SPF and LV ask respondents about CPI inflation, SPF also asks about the

	MSC: Monthly		SPF: Quarterly		LV: Biannually	
	Current	1 year ahead	Current	1 year ahead	Current	1 year ahead
Financial market indicators						
Level: AAA corporate bond yield	–	–	✓	✓	–	–
Level: bank prime loan rate	–	–	–	–	✓	✓
Level: 3 month T-bill rate	–	–	✓	✓	✓	✓
Level: 10 year bond rate	–	–	✓	✓	✓	✓
Spread: 10 year - 3 month T-bill	–	–	✓	✓	–	–
Spread: AAA - BAA bond	–	–	✓	✓	–	–
Spread: AAA - T-bill	–	–	✓	✓	–	–
Spread: BAA - T-bill	–	–	✓	✓	–	–
Growth: stock price index	–	–	–	–	✓	✓
Inflation measures						
Growth: average weekly earnings	–	–	–	–	✓	✓
Growth: PPI inflation	–	–	–	–	✓	✓
Growth: CPI inflation	–	✓	✓	✓	✓	✓
Growth: core CPI inflation	–	–	✓	✓	–	–
Growth: GDP deflator	–	–	✓	✓	–	–
Growth: PCE inflation	–	–	✓	✓	–	–
Growth: core PCE inflation	–	–	✓	✓	–	–
Activity measures						
Level: unemployment rate	–	–	✓	✓	✓	✓
Level: NAIRU	–	–	✓	–	–	–
Growth: nominal GDP	–	–	✓	✓	✓	✓
Growth: industrial production	–	–	✓	✓	✓	✓
Growth: new housing starts	–	–	✓	✓	✓	✓
Growth: real consumption	–	–	✓	✓	–	–
Growth: real non-residential investment	–	–	✓	✓	✓	✓
Growth: residential investment	–	–	✓	✓	–	–
Growth: federal government spending	–	–	✓	✓	–	–
Growth: nominal retail sales	–	–	–	–	✓	✓
Growth: auto sales	–	–	–	–	✓	✓
Month data available:	1-12		2,5,8,11		6,12	
Note: MSC: Michigan Survey of Consumers; SPF: Survey of Professional Forecasters; LV: Livingston Survey						

Table 1: Variables used

GDP deflator and PCE inflation. On the other hand, the LV survey focuses more on the supply side, asking respondents to provide their evaluations of PPI inflation and average weekly earning growth. Both surveys also cover a wide range of economic activity indicators, including the unemployment rate, nominal GDP, industrial production, new housing starts and real investment growth. SPF further asks about the current NAIRU rate (the medium-run equilibrium unemployment rate), and additional aggregate demand indicators such as current and one-year ahead consumption, residential investment and federal government spending growth. On economic activity, LV focuses more on retailing, including the growth of retail sales and auto sales.

The varied timing of the surveys is crucial for the construction of our uncertainty indices, and thus is addressed ideally in a mixed-frequency framework. We use the month of the deadline of surveys to approximate the true information set that a respondent would possess in making nowcast and forecast decisions. Telephone surveys are conducted every month for the MSC survey, which serves as the base frequency for our model. SPF surveys are sent out at the end of the first month of the indicated quarter, and the respondents are asked to respond by the middle of second month of the indicated quarter.[1] Since the true information set available at the time of making forecasting decisions is bounded by the second month of the quarter, we assume the timing of the survey is in February, May, August and November. Similarly, the biannual LV survey is mailed out in May and November, after the CPI data has been released for the previous month. The FED asks the survey to be returned before the next release of the CPI in June or December. We therefore use June and December as the months that these forecasting decisions are made.

For each of the economic indicators in these surveys, we use the inter-quantile range as the measure of disagreement between forecasters. The inter-quartile range is defined as the difference between the 75th and 25th percentile of forecasts, and it is a more outlier-robust measure of dispersion compared to the standard deviation. For each period (monthly for MSC, quarterly for SPF and biannually for LV), the inter-quartile ranges of current(one-year ahead) evaluations of economic indicators are calculated from the cross-sectional evaluations of current(one-year ahead) forecasts of economic indicators. These dispersion measures can be accessed from the University of Michigan's and the Philadelphia FED's website.[2] We standardize the dispersions series to have a mean of 0 and a standard deviation of 1, Figure 1 shows these evaluation dispersions.

In total, there are 35 dispersion series for each nowcast and one-year ahead forecasts. The sample period for nowcast dispersions is bounded by the availability of the SPF survey, which covers 1968:11 to 2016:02. Though some data are available from 1946 for the LV survey for the 12 month ahead forecast, the official dispersion data are not available until 1961, and so the sample period used is from 1961:01 to 2016:02.

The top panel of Figure 1 shows time-series of nowcast dispersions of current economic indicators and the lower panel shows the forecast dispersions of one-year ahead economic indicators, with the shaded areas indicating NBER recession dates. Although there are con-

[1] For example, the 2010 quarter 1 surveys were sent out by the end of January 2016, the deadline for the response was the third week of February 2016.

[2] For Michigan survey of consumers, the data can be downloaded at https://data.sca.isr.umich.edu/data-archive/mine.php; for Survey of Professional forecasters, the data can be accessed at https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/historical-data/dispersion-forecasts; for Livingston, the data can be accessed at https://www.philadelphiafed.org/research-and-data/real-time-center/livingston-survey/historical-data.

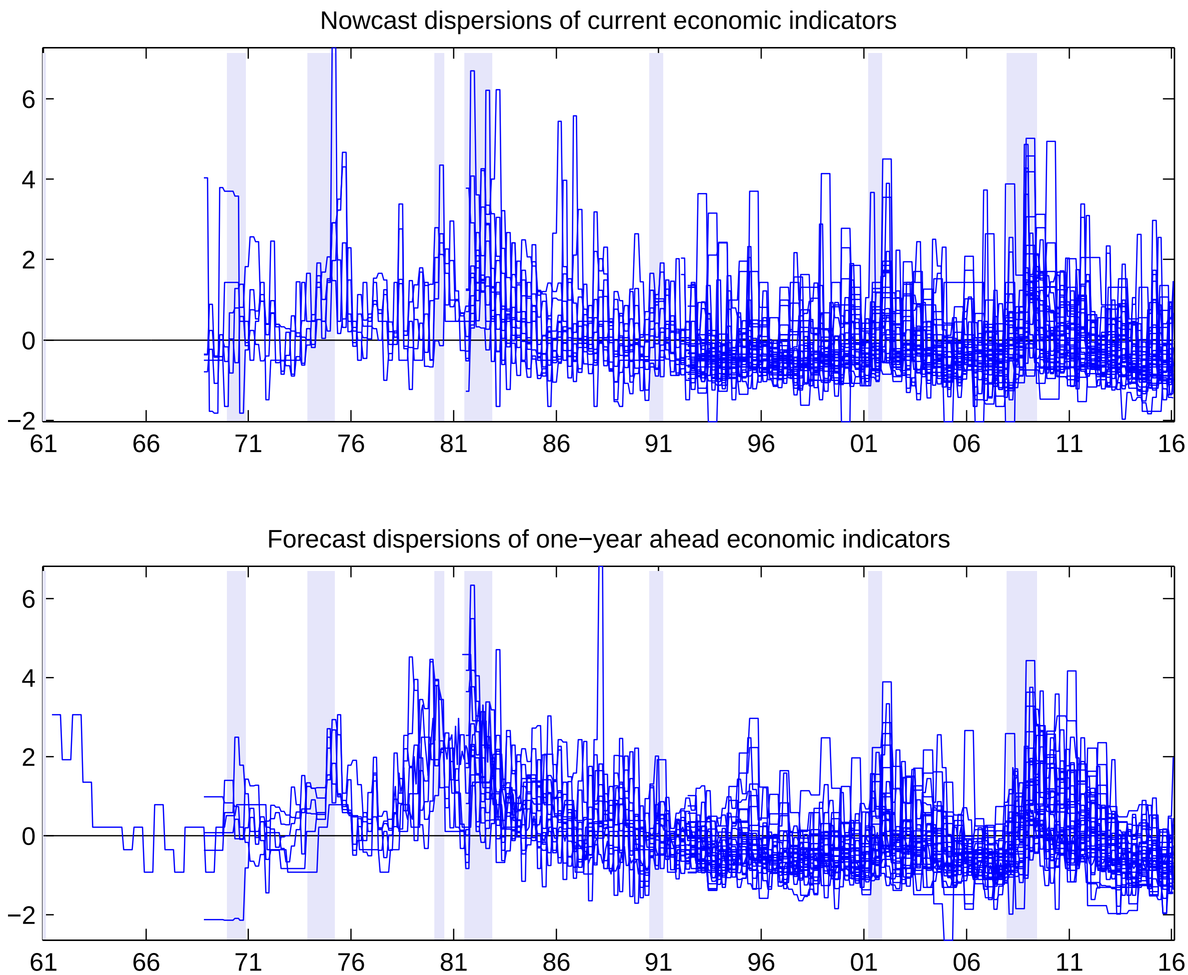

Figure 1: Survey data

siderable idiosyncratic movements among dispersions of the different underlying economic indicators, there is also strong co-movements among these dispersions. This is particularly true when there is a recession. However Figure 1 highlights the fact that using the dispersion of only one economic indicator may be misleading in measuring aggregate macroeconomic uncertainty.

3. The econometric framework: mixed frequency state-space model

Since the frequency of MSC, SPF and LV ranges from monthly to biannual, our dataset is mixed-frequency. We accommodate this data structure by using the mixed-frequency state-space model (eg: Aruoba et al. (2009) and Sheen et al. (2015)). Denote u_t^i ($i \in \{0, 12\}$) as the unobserved uncertainty index for nowcasts (where $i = 0$) and one-year ahead forecasts (for

$i = 12$). Y_t^i represents the observed data series on dispersion for i. Our monthly state-space model has the following form:

$$u_t^i = \rho^i u_{t-1}^i + \epsilon_t^i \qquad \epsilon_t^i \sim N(0, P^i) \tag{1}$$

$$Y_t^i = \gamma^i X_t^i + \beta^i u_t^i + \eta_t^i \qquad \eta_t^i \sim N(0, Q^i) \tag{2}$$

where ρ^i measures the persistence of the uncertainty index u_t^i, and ϵ_t^i denotes the innovation of u_t^i with mean zero and variance P^i. We allow the observed data to be conditioned by X_t^i and the unobserved state, where γ^i and β^i capture the loadings of the respective components. Q^i is the variance covariance matrix of measurement errors, η_t^i. We use for X_t^i the previous observed value of Y_t^i as a predetermined component.

Denote $u_{t|t-1}^i$ and $\Sigma_{t|t-1}^i$ as the model predicted uncertainty index for i and their associated variance at time t given time $t-1$ information, $u_{t|t}^i$ and $\Sigma_{t|t}^i$ as the updated values given time t information, the Kalman filter recursion is given by:

$$u_{t|t-1}^i = \rho^i u_{t-1|t-1}^i \tag{3}$$

$$\Sigma_{t|t-1}^i = \rho^i \Sigma_{t-1|t-1}^i \rho^{i'} + P^i \tag{4}$$

$$u_{t|t}^i = u_{t|t-1}^i + K_t^i v_t^i \tag{5}$$

$$\Sigma_{t|t}^i = \Sigma_{t|t-1}^i - K_t^i \beta^i \Sigma_{t|t-1}^{i'} \tag{6}$$

$$K_t^i = \Sigma_{t|t-1}^i \beta^{i'} (Q^i + \beta^i \Sigma_{t|t-1}^i \beta^{i'})^{-1} \tag{7}$$

$$v_t^i = (Y_t^i - \gamma^i X_t^i - \beta^i u_{t|t-1}^i) \tag{8}$$

where K_t^i is referred to as the Kalman gain matrix and v_t^i is the prediction error. The time t log-likelihood (L_t^i) of the uncertainty index u_t^i can be evaluated via the Kalman filter. Denoting the variance of the prediction error (v_t^i) as $\Psi^i = Q^i + \beta^i \Sigma_{t|t-1}^i \beta^{i'}$, we have:

$$\log L_t^i = -\frac{1}{2}\left(N^i \log 2\pi + \log|\Psi^i| + v_t^i (\Psi^i)^{-1} v_t^{i'}\right) \tag{9}$$

where N^i is the number of observations of Y^i at time t. If not all observations are available at time t, we replace the measurement equation (eq. 2) with:

$$Y_t^{i*} = \gamma^{i*} X_t^{i*} + \beta^{i*} u_t^i + \eta_t^{i*} \qquad \eta_t^{i*} \sim N(0, Q^{i*}) \tag{10}$$

where $Y_t^{i*} = S \times Y_t^i$ and S is a selection matrix that contains the value 1 if there is valid data for the corresponding Y_t^i and 0 if there is missing data. Since all data series are measures of dispersions, we do not need to account for time aggregation in the model. Maximizing the likelihood is equivalent to minimizing the prediction errors, v_t^i. We first use a simplex method to fine tune the starting values for 20 iterations, then switch to a quasi-Newton method with BFGS updates on the Hessian matrix for the rest of the estimation.[3] We restrict the variance of the state innovations, P^i, to be the mean of the measurement error variances.

Since our focus is to accurately estimate economic uncertainty indices using all available information, we apply the Kalman smoother to the states u_t^i after the parameters and state are jointly estimated. The mean of smoothed uncertainty index i is given by:

$$U_t^i = u_{t|T}^i = u_{t|t}^i + J_t^i(u_{t+1|T}^i - u_{t+1|t}^i) \tag{11}$$

where T is the length of data and $J_t^i = \Sigma_{t|t}^i \rho^{i'} (\Sigma_{t+1|t}^i)^{-1}$.

4. Estimates of economic uncertainty

Figure 2 shows the smoothed uncertainty indices based on nowcasts U^0 (blue solid line) and one-year ahead forecasts U^{12} (red dashed line). The shaded areas indicate NBER-dated recessions. The horizontal line is drawn at value 1.65—since the indices are standardised with zero mean and unit standard deviation, an uncertainty reading greater than 1.65 indicates that the uncertainty level in that period falls into the 5% level of significance.

In general, both indices show economic uncertainty 'jumps' at the beginning of a recession and 'dives' quickly after a recession. This reflects that economic agents disagree widely on the current and future expected course of the economy during economic downturns, but redevelop consensus on the state of the economy when the economy stabilizes. The uncertainty index based on nowcasts reflects the disagreement on the effects of past economic shocks and policies, and the likely immediate impact of current unexpected shocks. On the other hand the uncertainty index based on forecasts reflect more the uncertainty of the longer term impacts of current economic shocks and the delayed effect of current macroeconomic policies, as well as the likely course of future policies.

Both indices evidence four recessions in which uncertainty was significantly elevated (at 5%): the two oil shocks in the mid- and late 1970s, the early 1980s recession and the most recent 2008 global financial crisis. The early 1990s recession shows little effect, and both uncertainty indices gradually declined from the mid-1980s through to the early 2000s) including during the so-called 'great moderation' era in the 1990s and 2000s, when government policies were perceived as effective in managing business cycles and the economy had stable economic growth with a falling unemployment and inflation rate.

[3]Our estimation results are robust to the number of iterations used to fine tune the starting values.

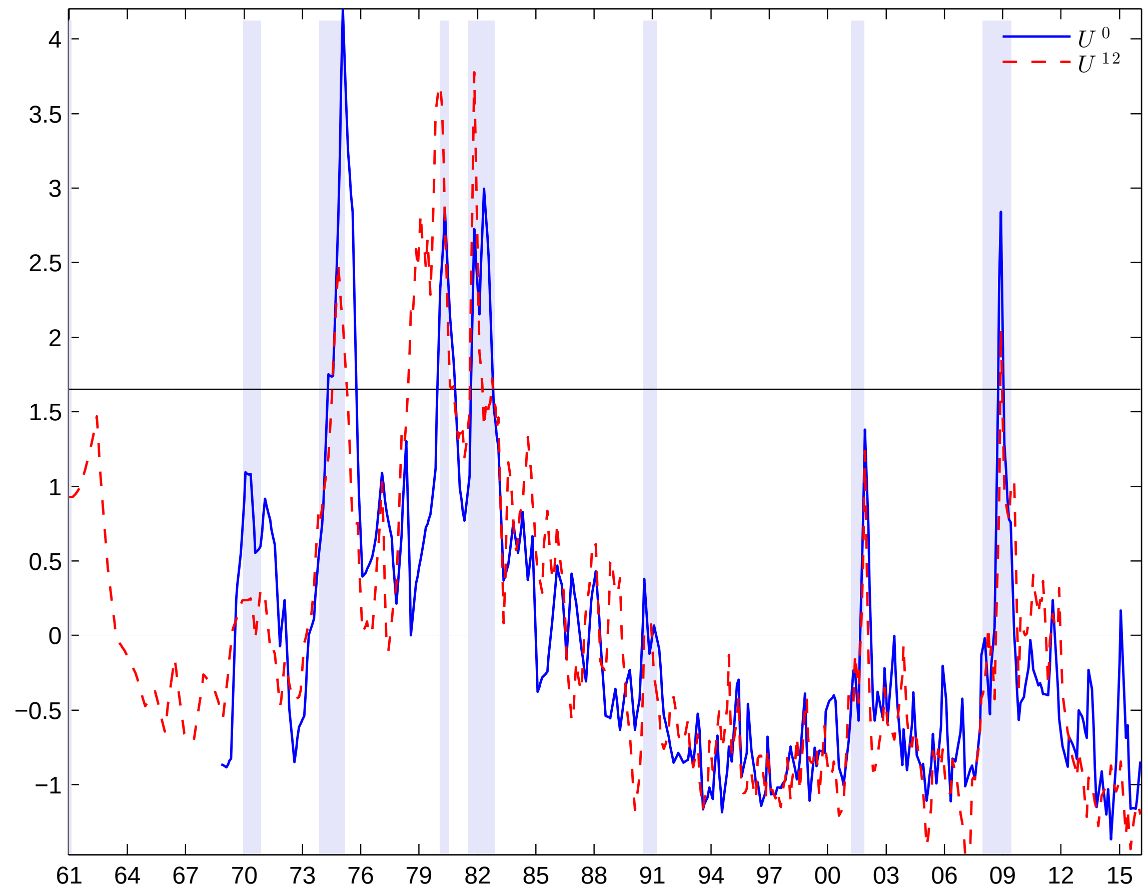

Figure 2: Estimated uncertainty indices

Though both measures indicate the 2008 global financial crisis was the most uncertain time since the mid-1980s, it is interesting to note that they disagree on the level of uncertainty when comparing to the two oil shocks in the 1970s. When evaluating the current state of the economy U^0 (nowcasts—blue solid line), economic agents appear equally uncertain about the impact of the unexpected economic shocks of the 2008 crisis as they were in the late 70s, but they seem to be more certain about the future course (one-year ahead—red dashed line) of the economy U^{12} for the 2008 financial crisis. Since U^{12} reflects the delayed impact of current policies and the expectation of the course of future policies, our measures of uncertainties seem to suggest that economic policies implemented in 2008 and expected after that helped to reduce uncertainty, compared to 1979. In particular, a lower reading of U^{12} compared to U^0 in 2008 may indicate that forward guidance on policies in this period may have helped to reduce the level of uncertainties regarding the future course of the economy.

4.1. Stylised facts of uncertainty

Table 2 shows the descriptive statistics of the two uncertainty indices. The uncertainty index of nowcasts (left panel) shows the lowest reading of uncertainty (-1.37) in the period between 2000:01 - 2016:02 and the maximum reading of 4.2 in the period before 1979:12. Both the median and mean of the index shows a decreasing trend overtime, reflecting a reduction of the central tendency of the level of uncertainty. The standard deviation is at par between the periods before 1979:12 and 1980:01-1999:12, but reduces significantly in 2000:01 - 2016:02. The skewness is positive for the full sample, and remains positive across all three sub-samples. Kurtosis is consistently above 3, indicating heavy tails. Both skewness and kurtosis indicate a right-skewed, heavy right tail uncertainty distribution. This is particular the case for the period between 2000:01-2016:02, where the index exhibits a sharp increase in skewness and kurtosis. The uncertainty index has a high AR(1) parameter throughout the whole sample indicating high persistence, and remains high for our three sample periods.

	Uncertainty from nowcasts U^0				Uncertainty from one-year ahead forecasts U^{12}			
	Full Sample	before 1979:12	1980:01 -1999:12	2000:01 -2016:02	Full Sample	before 1979:12	1980:01 -1999:12	2000:01 -2016:02
Min	-1.37	-0.89	-1.18	-1.37	-1.47	-0.72	-1.17	-1.47
Max	4.20	4.20	3.00	2.84	3.78	3.57	3.78	2.05
Median	-0.32	0.62	-0.36	-0.56	-0.27	0.09	-0.35	-0.75
Mean	-0.00	0.70	-0.03	-0.45	-0.00	0.42	0.05	-0.55
Standard deviation	1.00	1.01	1.02	0.62	1.00	0.94	1.08	0.64
Skewness	1.38	1.16	1.27	2.26	1.20	1.15	1.21	1.17
Kurtosis	4.85	4.95	3.86	10.06	4.30	3.60	4.16	4.31
AR(1) coefficient	0.98	0.97	0.98	0.94	0.98	1.02	0.96	0.95

Note: The AR(1) parameter is obtained by estimating $y_t = c + \beta y_{t-1} + e_t$.

Table 2: Descriptive statistics

All of the above characteristics remain true for the uncertainty index of the one-year ahead forecast measure, except that the maximum reading of this index is in period 1980:01-1999:12 and we do not observe a sharp increase in skewness and kurtosis for the period 2000:01-2016:02. The dramatic increases in skewness and kurtosis in the post 2000 sample for U^0 but not for U^{12} may indicate that although economic shocks in this period drive people to strongly disagree with each other on the likely implication on the current state of the economy (U^0), effective macroeconomic policies and perhaps forward guidance on the future course of these policies help to reduce that uncertainty when people forecast the future (U^{12}).

Overall, our estimates of the uncertainty indices exhibit the following characteristics. First, the level of economic uncertainty in the U.S. gradually decreases throughout our sample period, possibly due to an improving understanding of the economy and possibly better designed macroeconomic policies. Second, the reduction in the level of uncertainty is accompanied by a sharp reduction in the volatility of uncertainty in the period between 2000:01-

2016:02, which also corresponds to the period with the lowest uncertainty reading. Third, the distribution of uncertainty is characterised by many small values and fewer larger values (due to positive skewness and kurtosis exceeding 3). Fourth, the fact that the skewness and kurtosis are much lower for uncertainty of forecasts compared to uncertainty of nowcasts in the period between 2000-2016 may reflect the implementation of better macroeconomic policies, and possibly successful forward guidance. Fifth, the dynamics of these uncertainty measures exhibit high persistence.

4.2. Comparison with popular measures

We now compare our uncertainty indices with others that are commonly used and recently produced. A distinguishing feature of our approach is that we are able to make efficient use of any relevant and available information because it uses multivariate data no matter at what frequency the variables arrive.

There are several alternative measures of economic uncertainty. We will focus on four. First, volatilities derived from financial markets have long been used to approximate the amount of risk and uncertainty. Among these volatilities, the Chicago Board Options Exchange Market Volatility index, known as the VIX index, has been widely used to approximate uncertainties as perceived in financial markets. This univariate index is constructed based on expectations of 30 day ahead option prices, and measures the implied financial market volatility. Second, Jurado et al. (2015) (JLN) construct an economic uncertainty index based on the idea that economic uncertainty should decrease if more macroeconomic variables are predictable using econometric models. Therefore they construct the index based on the evaluations of prediction errors of an econometric model in a data rich environment, restricted to data arriving monthly. Since this uncertainty is based on the predictability of variables, it can be estimated based on particular forecast horizons, we compare below our measures with their measures based on one-month ahead and one-year ahead forecast. Third, using key words such as ‘uncertainty’ and ‘deficit’, Baker et al. (forthcoming) (BBD) construct an economic policy uncertainty index based on text scans of 10 leading American newspapers. The idea is that economic policy uncertainty originated in policy decisions should be reflected in newspaper discussions. Fourth, Bachmann et al. (2013) (BES) use a dispersion measure from business survey data to approximate economic uncertainty. This dispersion is based on a qualitative question on firms’ evaluations of the level of future general business activity. Respondent have three options—increase, decrease or no change. The dispersion measure is then calculated as the difference between the fractions of people who answered ‘increase’ and ‘decrease’.

Figure 3 shows the (normalised) comparison of the VIX index (brown thin line), the Jurado et al. (2015) uncertainty index (red dashed line), the Baker et al. (forthcoming) (BBD) economic policy uncertainty index (orange dash-dot line), the (Bachmann et al., 2013) (BES) uncertainty index from firm survey (black dotted line) and our uncertainty indices (blue thick line). The top panel shows the comparisons of the aforementioned popular measures with our uncertainty index of current state nowcasts and the lower panel shows the comparisons with our uncertainty index of one-year ahead forecasts.

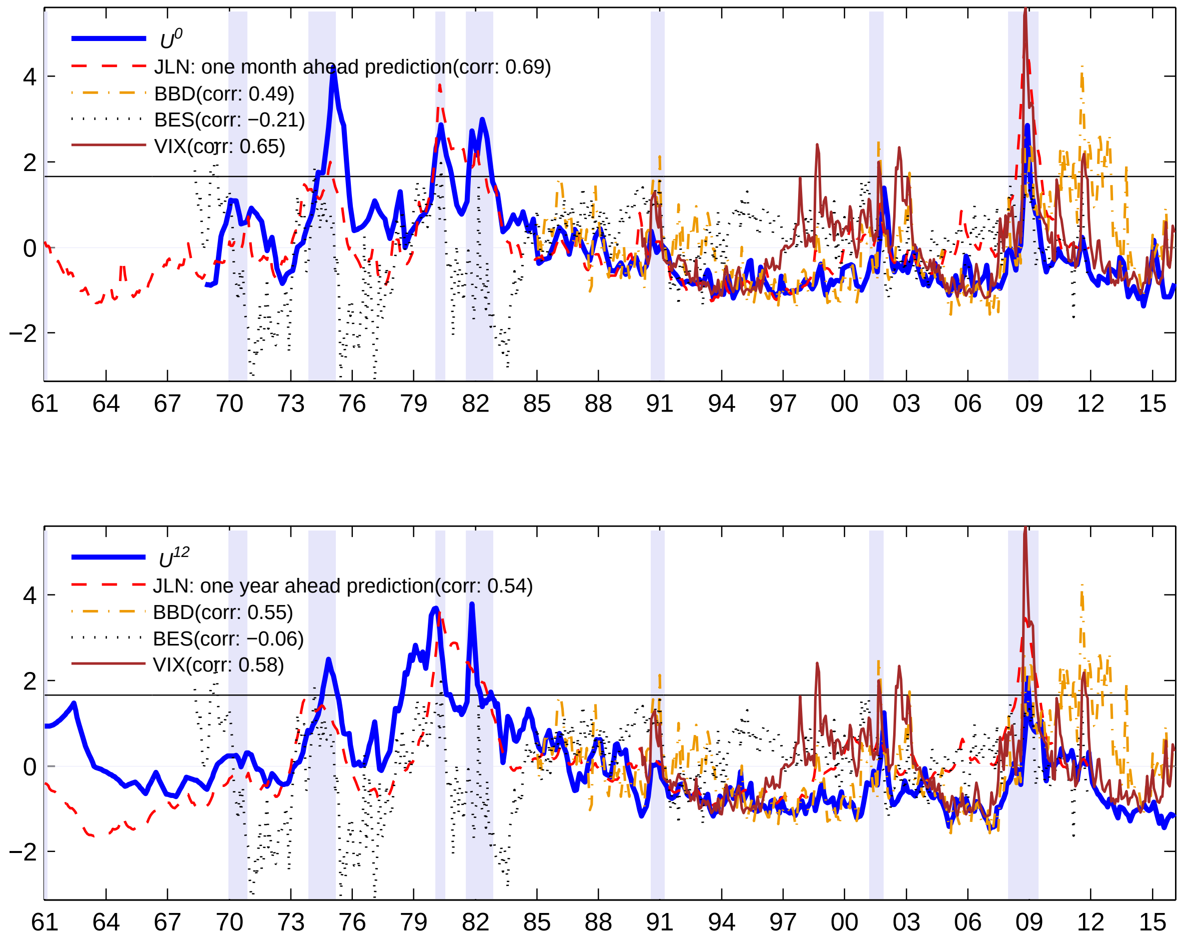

Figure 3: Comparison of uncertainty indices and the Jurado et al. (2015)(JLN) uncertainty index, Baker et al. (forthcoming) (BBD) economic policy uncertainty index, Bachmann et al. (2013) (BES) uncertainty index and the VIX index. Correlations with our index is shown in bracket.

Focusing on our nowcast uncertainty index (top panel), our estimate of uncertainty generally is highly correlated with the VIX and the Jurado et al. (2015)index, (0.65 and 0.69 respectively). The correlation with the Baker et al. (forthcoming) economic policy uncertainty index is slightly lower (0.49), possibly due to the fact that the Baker et al. (forthcoming) index measures uncertainty of economic policies in particular—while there is a tight link between policy uncertainty and macroeconomic uncertainty, they are essentially distinct concepts. The correlation with the BES uncertainty from firm survey ((Bachmann et al., 2013)) is small and negative. One reason was that their monthly measure of the index is based on one survey question on the general outlook of business conditions, so that the estimates are very noisy. This highlights the advantage of our method, which utilises the cross-sectional structure of dispersion data.

The movements of uncertainty between our measure and the Jurado et al. (2015) closely track each other. Both indices show an increase in uncertainty in the 1970s oil shocks, and exhibit reducing uncertainty throughout 1980s to 1990s with a jump in uncertainty during the 2008 financial crisis. However, our indicator indicates higher uncertainty during the two oil shocks and lower uncertainty during the global financial crisis comparing to the JLN uncertainty index. The JLN index also shows a slight increase in uncertainty between 2004 and 2007, whereas our indicator shows uncertainty remaining low during this period.

Comparing with the Baker et al. (forthcoming) economic policy uncertainty index, our uncertainty index shows a much lower and more stable uncertainty level following the early 1990s recession and the 2008 global financial crisis. This may reflect the fact that although the economic policies were widely discussed in the media and the effects were not yet certain in the media discussion, households and professional forecasters developed consensus on the current and the future course of policy and the economy.

The main difference between the VIX index and our measure lies in the period between 1996 to 2003, when the VIX shows high and volatile uncertainty movements. This may due to the fact that VIX measures the amount of uncertainty exclusively in the financial market, whereas our indicator measures general macroeconomic uncertainty.

Similar comparisons can be drawn for the uncertainty index from our one-year-ahead forecasts of the state of the economy.

5. The impact of uncertainty on economic activity

It has been documented in the empirical literature that uncertainty shocks have adverse impacts on economic activity (eg: Jurado et al. (2015), Bloom (2009), Bachmann et al. (2013) and Caggiano et al. (2014)). This adverse impact may arise because of frictions in markets. For example, Bernanke (1983) built a model with irreversible investments, so that the optimal timing decision on investment hinges on the trade-off between the potential loss of delaying the investment and the possible gain in waiting so that the outcomes become less uncertain. Increases in uncertainty will delay investments, therefore impeding rises in employment and output. Bloom (2009) built a model with labour and investment adjustment costs and shows the model is capable of driving sharp recessions when uncertainty rises and then subsequently expansions. Leduc and Liu (2016) shows increases in uncertainty effects resemble those of an adverse aggregate demand shock by lowering inflation and raising the unemployment rate. They show an option-value channel arises from search frictions in combination with nominal rigidities that magnify the effects of uncertainty shocks.

In this section we employ two popular VAR models in examining how our measures on economic uncertainty impact on economic activity. The first VAR model is based on Jurado et al. (2015), in the spirit of the Christiano et al. (2005) model. The following list contains the variables in the VAR(11) model. Industrial production is an index taken from the FRED database. Employment is measured by the total employees on non-farm payrolls. Real consumption is measured by real personal consumption expenditures. The PCE deflator is the associated chain-type price index for personal consumption expenditures. New orders are approximated by the Institute for Supply Management's new order index. The real wage is taken as the real average hourly earnings of production and non-supervisory employees and hours is the associated average weekly hours of those employees. We use the effective federal funds rate as the policy rate and S&P 500 index as the share market price. M2 is used to approximate money supply. Table A.1 shows the data sources and series IDs. Our monthly sample covers the period between 1965:06 and 2016:02.

$$\text{VAR(11)}: \quad \begin{pmatrix} \log(\text{Industrial production}) \\ \log(\text{Employment}) \\ \log(\text{Real consumption}) \\ \log(\text{PCE deflator}) \\ \text{New orders} \\ \log(\text{Real wages}) \\ \log(\text{Hours}) \\ \text{Fed rate} \\ \log(\text{SP500}) \\ \text{Growth of M2} \\ \text{Uncertainty} \end{pmatrix}$$

We run two versions of this VAR model by using either U^0 or U^{12} as the measure of uncertainty. The model is estimated by ordinary least squares and the structural shocks are identified using the Cholesky decomposition. Following Jurado et al. (2015), the ordering of the variables implies that shocks to all variables have an instantaneous impact on uncertainty, but uncertainty shocks do not have an instantaneous impact on all other variables. We call this model VAR(11), and it serves as our benchmark.

The assumption that uncertainty does not contemporaneously impact other variables is debatable. We therefore consider an alternative ordering that considers the most extreme case that uncertainty has an instantaneous impact on all other variables, which have no contemporaneous impacts on uncertainty. Therefore the ordering of the variables places uncertainty on the bottom, while the ordering of other variables remains the same. We label this model as VAR(11A).

The second VAR model (VAR(8)) is taken from Bloom (2009), and considers 8 variables including the SP500 index, uncertainty, the federal funds rate, wages, CPI, hours, employment and industrial production. The ordering of the variables implies uncertainty is only contemporaneously driven by the stock market, but fluctuations of uncertainty have contemporaneous impacts on all other six variables.

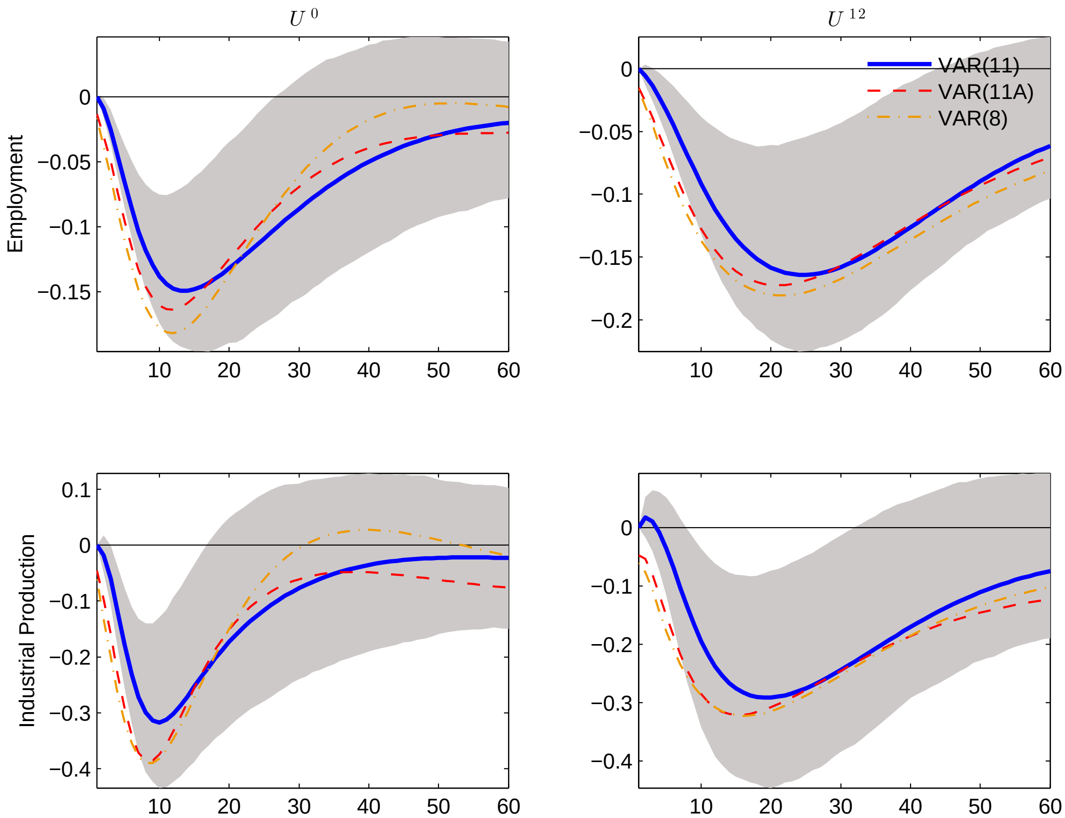

Figure 4: Impact of uncertainty on economic activity. VAR(11) and VAR(11A) are based on Jurado et al. (2015), with VAR(11) ordering uncertainty last and VAR(11A) ordering uncertainty first. VAR(8) is based on Bloom (2009). The shaded area represents the 90% confidence interval for our benchmark VAR(11) model.

Figure 4 shows the impulse responses of employment and industrial production to a one standard deviation shock to uncertainty for all three models, with the grey area indicating the 90 per cent confidence band for the benchmark VAR(11) model.

Using uncertainty based on nowcasts (U^0) as the measure (left panel), both employment and industrial production fall following a positive uncertainty shock for all three models. The effects reaches their troughs around a year following the shock. Comparing VAR(11) and VAR(11A), employment and industrial production respond contemporaneously by assumption in VAR(11A) but with a month lag in VAR(11). The impacts are greater in VAR(11A) compared to VAR(11), however the dynamic patterns are robust to the ordering of the uncertainty measure. Comparing VAR(11A) with VAR(8), both employment and industrial production fall quickly initially and then subsequently recovers slowly in the medium run (>24 months).

Similar conclusions can be drawn by using uncertainty based on one-year ahead forecasts (U^{12}), except for the timing of the responses. A one standard deviation shock to U^{12} has its largest impact around 18-20 months (compared to 10-12 months for nowcasts). One possible explanation is that changes in the evaluations of current uncertainty would change firms' hiring and production decisions quicker compared to their responses to their evaluations of the one-year ahead state of the economy. Due to market frictions (e.g. firing and hiring costs, staggered contracts), the real option value for firms to wait-and-see is higher for uncertainty of the future state of the economy.

	VAR(11)				VAR(11A)				VAR(8)			
	U^0		U^{12}		U^0		U^{12}		U^0		U^{12}	
	EMP	IP	EMP	IP	EMP	IP	EMP	IP	EMP	IP	EMP	IP
$k = 1$	0.0	0.0	0.0	0.0	1.0	0.6	1.2	0.7	1.4	1.0	1.3	0.9
$k = 6$	5.0	2.8	1.4	0.2	10.8	7.9	5.6	2.3	13.0	9.8	6.5	3.3
$k = 12$	11.1	7.0	5.1	2.4	16.4	11.7	10.7	6.1	20.2	14.8	12.7	8.0
$k = 24$	10.0	5.5	10.6	6.2	11.5	7.4	14.6	8.9	15.1	9.7	17.0	10.9
$k = 36$	7.5	4.1	11.9	6.8	7.8	5.3	14.2	8.7	9.8	6.5	16.3	10.1
$k = 60$	5.7	3.2	11.7	6.4	6.0	4.4	13.5	8.4	6.8	4.9	14.8	8.9
$k = 120$	5.1	2.9	10.8	5.8	5.4	4.5	12.7	8.3	6.1	4.4	14.1	8.1

Note: k indicates the forecast horizon that the forecast variance decomposition is based on. VAR(11) and VAR(11A) are based on Jurado et al. (2015) and VAR(8) is based on Bloom (2009).

Table 3: Variance decomposition

The left panel of Table 3 shows the forecast variance decomposition of the VAR(11) model, with k indicating the forecasting horizon. Focusing on U^0 as the measure of uncertainty, uncertainty shocks are relatively unimportant in the short-run (below 6 months), but explain around 11.1 per cent of fluctuations in employment and 7.0 percent of fluctuations in industrial production after 1 year. They become less prominent, but remain quantitatively significant in the long run (5.1 per cent for employment and 2.9 per cent for industrial production at 10 years). Shocks to uncertainty of the one-year ahead state of economy (U^{12}) are not quantitatively important for both employment and industrial production until 1 year (5.1 and 2.4 per cent respectively). However, uncertainty shocks are important in the medium run (11.9 and 6.8 per cent) and remain important in the long run (10.8 and 5.8 per cent respectively at 10 years). These results are consistent with what was shown in the impulse responses of Figure 4—the uncertainty of the current state U^0 has a more immediate impact than uncertainty of the one-year ahead state U^{12}, but U^{12} has a more persistent impact over the medium- to long-run.

The middle panel shows the variance decomposition for the VAR(11A) model, where the uncertainty measure is ordered first. Uncertainty shocks are quantitatively unimportant in the immediate short-run ($k = 1$), but explain a substantial amount of the fluctuations of real activity in the medium to long run, in particular employment. The uncertainty measure based on nowcasts (U^0) explains more variance of employment in the short to medium-run, while the uncertainty measure based on forecasts (U^{12}) is more important in the longer run.

The right panel of Table 3 shows the forecast variance decomposition for the VAR(8) model. Similar to the VAR(11) model, shocks to U^0 have an earlier, but a more transitory impact on employment and industrial production compared to shocks to U^{12}. However, the VAR(8) model shows uncertainty shocks play a more important role in driving economic activity, with peaks of 20.2 (14.8) per cent of fluctuation in employment (industrial production) that can be explained by shocks to uncertainty based on nowcasts (U^0) alone, and 17.0 (10.9) per cent explained by the shocks to the uncertainty of the one-year ahead forecasts (U^{12}).

In summary, positive uncertainty shocks reduce employment and industrial production. Shocks to uncertainty based on one-year ahead forecasts U^{12} have a more delayed, smaller but more persistent effect compared to shocks to uncertainty based on nowcasts U^0. Forecast variance decomposition shows in most cases that uncertainty matters more for employment compared to industrial production. Depending on the model, uncertainty alone can drive up to 20.2% (VAR(8)) of employment and 14.8% (VAR(8)) of industrial production at its peak.

6. Does monetary policy reduces uncertainty?

Since uncertainty is important in driving economic activity, it is important to know if monetary policy can mitigate these uncertainties. Using VIX as the indicator, Bekaert et al. (2013) find that an expansionary monetary policy can in fact reduce uncertainty.

One reason that surprises in monetary policy can impact on uncertainty may be that monetary policy surprises often convey strong signals reflecting the policy makers' evaluations of the current state of the economy against their medium run targets. This signalling effect may convince individuals about the current, and future course of the economy, thus providing a strong anchoring effect. This strong anchoring effect can both reduce uncertainty when individuals evaluate the economy, and also can help to reduce the disagreements among individuals by overcoming information rigidities.

Figure 5 shows the impulse responses of uncertainty U^0 and U^{12} given a negative one standard deviation monetary policy shock (expansion). The blue line shows the impulse response of uncertainty for the VAR(11) model, the red dashed line shows the response for the VAR(11A) model, and the brown dotted line for the VAR(8) model. Consistent across all models, both uncertainty measures quickly fall following this expansionary monetary policy shock. This may reflect the fact that expansionary monetary policy provides reassurance of medium run

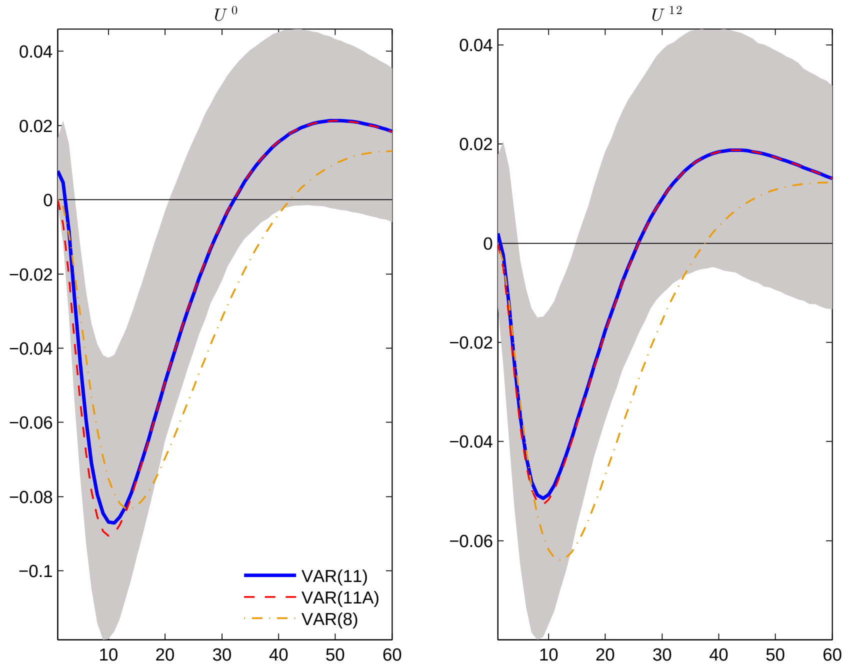

Figure 5: Impact of monetary policy expansion on uncertainty. VAR(11) and VAR(11A) are based on Jurado et al. (2015). VAR(11) orders uncertainty first and VAR(11A) orders uncertainty last. VAR(8) is based on Bloom (2009). The shaded area represents the 90% confidence interval for our benchmark VAR(11) model.

targeting by the central bank, especially during crisis and recessions, thus leading to a lower level of economic uncertainty. This may suggest that monetary policy can impact on the real economy by reducing the amount of uncertainty and thus the real option value of delaying investment and hiring. This reduction in uncertainty can thus moderate the fluctuations of employment and production.

Monetary policy shocks have a delayed impact on uncertainty, reaching a trough around 10 months after the shock under VAR(11) and VAR(11A) and a few months later under VAR(8). Though they disagree on the timing, all models exhibits overshooting of uncertainty over the average uncertainty level. However this overshooting is insignificant.

Table 4 shows the forecast variance decomposition of the economic uncertainty measures with respect to monetary policy shocks. Although the ordering of uncertainty shock involves two extreme assumption about the immediate impact of structural shocks, both VAR(11) and VAR(11A) are remarkably consistent on the impact of a FED rate shock on uncertainties. In the immediate short run, monetary policy is not an important driver of uncertainty fluctuations, but it gradually becomes important after a year. This is particularly true for uncertainty measures from nowcasts (U^0), where monetary policy shocks explain 18.1%(19.7%) at their peaks. Comparing VAR(11), VAR(11A) and VAR(8), while they all agree that monetary policy is important in driving uncertainty in the medium- to long-run(greater than 12

	VAR(11)		VAR(11A)		VAR(8)	
	U^0	U^{12}	U^0	U^{12}	U^0	U^{12}
$k = 1$	0.3	0.0	0.0	0.0	0.0	0.0
$k = 6$	2.3	1.7	3.5	2.0	1.1	1.5
$k = 12$	11.8	5.7	13.8	6.1	8.1	7.3
$k = 24$	18.1	6.6	19.7	6.9	18.3	12.9
$k = 36$	17.0	6.0	18.6	6.3	19.2	12.2
$k = 60$	16.9	6.2	18.3	6.5	18.4	10.9
$k = 120$	16.9	6.1	18.3	6.3	18.3	11.0

Note: k indicates the forecast horizon that the forecast variance decomposition is based on. VAR(11) and VAR(11A) are based on Jurado et al. (2015) and VAR(8) is based on Bloom (2009).

Table 4: Variance decomposition

months), they disagree on the source of uncertainty. VAR(11) and VAR(11A) indicate that monetary policy predominantly impacts on the uncertainty based on nowcasts U^0, while VAR(8) indicates monetary policy shocks are important in explaining both sources of uncertainty.

In summary, unexpected expansionary monetary policy shocks lower economic uncertainty in the short-run, reaching a trough around one year. The uncertainty level subsequently overshoots (insignificantly) the average level as it returns to its medium run value. Evidence from forecast variance decompositions show monetary policy is an important driving force of economic uncertainty, especially in the medium- to long-run. Given the established significant impact of uncertainty shocks on economic activity, and the established significant decrease (increase) of perceived uncertainty with monetary policy expansions (contractions), uncertainty is clearly an additional channel through which monetary policy can be transmitted to the real economy.

7. Conclusions

We have introduced a new way of measuring perceived economic uncertainty in the US using dispersions of forecasts of a wide range of economic variables from both household and professional surveys arriving at various frequencies. Our contribution is to provide new uncertainty measures that are based on disagreements from a wide range of economic indicators arising from both household and professional surveys. Our innovation is to implement a mixed-frequency state-state model, which allows us estimate an unobserved uncertainty measure of the perceived current state (nowcast) of the US economy and of the one-year ahead (forecast) expected state of the economy. While our measures of uncertainty are highly correlated with most other existing measures, there are important differences particularly in acute periods, when such measures really matter. Our mixed-frequency measure efficiently uses information arriving at different frequencies, which distinguishes it from other existing measures.

Uncertainty clearly matters and government can and should try to achieve significant improvements in the economy by finding ways to reduce disagreements among economic agents. Our uncertainty measures reflect disagreements and have have significant and important impacts on economic activity—in particular, employment and industrial production. If uncertainty in terms of survey disagreement rises by one standard deviation, employment and industrial production fall to a trough of -.15 to -.30% in 1 to 2 years. We also show that monetary policy expansions significantly reduce uncertainty, with a trough after a year of -.05 to -.09%—conversely, tighter monetary policy will worsen uncertainty within a year. Therefore endogenous uncertainty represents an extra channel (beyond the cost and availability of funds) through which counter-cyclical monetary policy operates. A detailed investigation into the details of the size and time variations of this uncertainty channel across business cycles is left for future research.

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Appendix A. Data

Variable	Source	Series ID
Industrial production	FRED	INDPRO
Employment	FRED	PAYEMS
Real consumption	FRED	DPCERA3M086SBEA
Hours	FRED	AWHNONAG
Wages	FRED	AHETPI
Fed rate	FRED	FEDFUNDS
M2	FRED	M2SL
CPI	FRED	CPIAUCSL
PCE deflator	Datastream	USCP...CE
New orders	Datastream	USNAPMNO
SP500	Datastream	S&PCOMP

Table A.1: Data source for VAR models