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Uncertainty and Economic Activity: Evidence from Business Survey Data†

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This paper uses survey expectations data to construct empirical proxies for time-varying business-level uncertainty. Access to the micro data from the German IFO Business Climate Survey permits construction of uncertainty measures based on both ex ante disagreement and ex post forecast errors. Ex ante disagreement is strongly correlated with dispersion in ex post forecast errors. Surprise movements in either measure lead to significant reductions in production that abate fairly quickly. We extend our analysis to US data, measuring uncertainty with forecast disagreement from the Business Outlook Survey. Surprise increases in forecast dispersion lead to more persistent reductions in production than in the German data. (*JEL* C53, C83, D81, E23, E27, E32, E37)

What is the impact of time-varying business uncertainty on economic activity? The seminal contribution in Bloom (2009) and recent macroeconomic events have renewed interest in the aggregate effects of time-varying uncertainty. In this paper, we construct measures of time-varying uncertainty from business surveys and examine their relationship with economic activity over the business cycle. Survey data are well-suited to measure the impact of business uncertainty on the economy because they are likely to capture the uncertainty of actual decision makers, as opposed to outside experts, the general public, or simple reflections of equilibrium asset price adjustments.

Our primary sources of survey data are the IFO Business Climate Survey (IFO-BCS) for Germany and the Philadelphia Fed's Business Outlook Survey (BOS) for the United States. Both of these are surveys of manufacturing firms and contain, on a monthly basis, qualitative information on the current state of, and expectations

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regarding, firms' business conditions. While we do not have probabilistic and quantitative forecasts about individual business situations, access to the confidential micro data in the IFO-BCS survey allows us to compare realized qualitative production changes to past production change expectations, and thus construct a qualitative measure of ex post forecast errors. The cross-sectional standard deviation of these forecast errors provides a natural aggregate index of business uncertainty. More disperse forecast errors are the likely result of a larger variance of firms' shocks, which is how much of the theoretical literature has thought about uncertainty fluctuations. An important contribution of this paper is to show that this ex post forecast error uncertainty index is strongly correlated with ex ante forecast disagreement in the survey, which has been used extensively in previous work as a proxy for uncertainty.[1] Their raw correlation exceeds 0.7 and their conditional correlations with measures of economic activity are quite similar. A potential problem with forecast disagreement is that it could simply reflect heterogeneous, but certain, expectations. By construction, this is excluded in the standard deviation of forecast errors. Hence, our findings can help lend credence to the use of forecast disagreement as a proxy for uncertainty more generally.

Section I describes the data in detail. In the IFO-BCS data, ex ante disagreement and ex post forecast error dispersion are unconditionally positively correlated with stock market volatility as well as with the average size of forecast errors. For the most part these measures are countercyclical. The survey-based uncertainty measures rise after the fall of the Berlin Wall well into the German reunification period and the ensuing recession around the First Gulf War. There is a similar spike during the Great Recession and the subsequent European debt crisis. For the US data, encouraged by the results from the IFO-BCS, we use forecast dispersion from the BOS survey as our uncertainty proxy and compare it to several other uncertainty measures used in the literature: stock market volatility, corporate bond spreads, and an economic uncertainty index based on Google News. Unconditionally, BOS forecast dispersion is positively correlated with stock market volatility and corporate bond spreads. All uncertainty measures are countercyclical, more strongly so than in Germany. Typically, the BOS uncertainty proxy spikes right before or at the beginning of a recession, similarly to the IFO-BCS uncertainty proxies.

In Section II, we analyze the dynamic, conditional responses of economic activity to surprise movements in our survey-based uncertainty measures for both Germany and the United States using structural vector autoregressions (SVARs).[2] There are

[1] Papers in the literature that use forecast disagreement as a proxy for uncertainty include Zarnovitz and Lambros (1987); Federer (1993); Bomberger (1996); Giordano and Söderlind (2003); Bond and Cummins (2004); Fuss and Vermeulen (2008); Clements (2008); Popescu and Smets (2010); and Baker, Bloom, and Davis (2012). Rich and Tracy (2010), as well as Boero, Smith, and Wallis (2008), have a more critical view about using disagreement as a proxy for uncertainty.

[2] Other papers that use SVARs to measure the effects of uncertainty include Bloom (2009), who estimates the effects of surprise increases in stock market volatility on industrial production; Gilchrist, Yankov, and Zakrajsek (2009) and Gilchrist and Zakrajsek (2012), who look at the dynamic effects of movements in corporate bond spreads; Alexopoulos and Cohen (2009), who look at the effects of movements in an index based on the incidence of the words like "uncertainty" and "economy" in the *New York Times*; and Baker, Bloom, and Davis (2012), who study the dynamic implications of increases in an index constructed to measure economic policy uncertainty. Other empirical papers making use of more microeconometric techniques include Leahy and Whited (1996), one of the first papers to document a negative relationship between uncertainty and firms' investment; Guiso and Parigi

several different channels by which higher uncertainty might impact economic activity. Our objective with the SVAR analysis is to provide some empirical evidence on which of those channels are most promising.

Early theoretical models in this literature are based on physical adjustment frictions, beginning with Bernanke (1983) and continuing with Dixit and Pindyck (1994), Bloom (2009), and Bloom et al. (2011). The basic idea is that the interaction between high uncertainty and nonsmooth adjustment frictions may lead firms to behave cautiously. Facing a more uncertain environment firms pause hiring and investment—they "wait and see" how the future unfolds. Through attrition this "wait and see" behavior leads to a drop in economic activity. After a number of periods, however, there is pent-up demand for production factors, so that the initial "bust" is followed by a quick pick-up and overshoot in economic activity. This class of models thus predicts that high uncertainty ought to be followed by a fairly quick "bust-boom" cycle.

There is also a growing literature that stresses the interaction of uncertainty and economic activity propagated through financial frictions. Gilchrist, Sim, and Zakrajsek (2010) argue that increases in firm risk lead to a rise in bond premia and the cost of capital which, in turn, triggers a prolonged decline in investment activity. Arellano, Bai, and Kehoe (2012) show that firms downsize investment projects to avoid default when faced with higher risk. Christiano, Motto, and Rostagno (2010) build a DSGE model with financial frictions in which risk shocks generate sizable and persistent reductions in output. Other examples in this literature include Dorofeenko, Lee, and Salyer (2008) and Chugh (2012).

Narita (2011) presents a model in which production units with agency problems are more likely to break up in uncertain times, leading surviving units to take on less risky projects, which leads to a slowly building, persistent decline in economic activity. Fernández-Villaverde et al. (2011) argue that shocks to interest rate volatility in small open economies, coupled with large investment adjustment costs, lead to persistent output declines. Panousi and Papanikolaou (2012) find evidence that high idiosyncratic risk interacts with managerial risk aversion to generate investment declines, more so the greater is the ownership share of managers.[3]

Another possibility is that high uncertainty is more a consequence of depressed economic activity than a cause, which we refer to as the "by product" hypothesis. Periods of recession are natural times of severed business practices and relationships, the reestablishment of which may generate uncertainty. Bachmann and Moscarini (2011) and Fostel and Geanakoplos (2012) provide theoretical explanations for this phenomenon in which bad times incentivize risky behavior, and hence lead to higher firm-level uncertainty. Van Nieuwerburgh and Veldkamp (2006), D'Erasmo

(1999); Fuss and Vermeulen (2008); Bloom, Bond, and Van Reenan (2007); and Bontempi, Golinelli, and Parigi (2010). Bond and Cummins (2004) use data on publicly traded US companies to show that various measures of uncertainty have low-frequency negative effects on firms' investment activities.

[3]The literature on uncertainty shocks has started investigating environments with nominal rigidities (without physical or financial frictions) and precautionary saving (Basu and Bundick 2011, and Mericle 2011). Another example is Vavra (2013), who argues that monetary policy becomes less effective in periods of high uncertainty. In his model, contrary to the "wait and see" intuition, firms adjust their prices more frequently when uncertainty is high, leading to more price flexibility in the aggregate. Other channels for the propagation of risk shocks include search frictions as in Schaal (2011), and investment through prior investment opportunities in Lee and Lee (2011).

and Moscoso Boedo (2012), and Tian (2012) propose other mechanisms capable of generating endogenously countercylical uncertainty.

In our empirical VAR analysis we find that a surprise movement in the survey-based measures of uncertainty is associated with a significant reduction in production and employment in both Germany and the United States. In the German data production declines and rebounds fairly quickly following an increase in uncertainty, in a manner at least broadly consistent with the predictions of the "wait and see" dynamics described above. Nevertheless, the fraction of output fluctuations explained by movements in the different uncertainty proxies is modest, consistent with the results in Bachmann and Bayer (2011b). The qualitative nature of the conditional response of production to a surprise increase in uncertainty in the United States is quite different from the one in Germany. In particular, the response of output to an innovation in uncertainty in the United States is slowly building, persistent, and prolonged—the peak negative response of output occurs almost two years after the shock, and there is limited evidence of a rebound effect. In both Germany and the United States, innovations to survey-based uncertainty proxies account for a larger fraction of the variance of production than do innovations to stock market volatility.

That the conditional responses of economic activity to surprise increases in measures of uncertainty are more consistent with "wait and see" in Germany than in the US is unsurprising. "Wait and see" dynamics rely on the presence of adjustment frictions, for example in the form of fixed costs of hiring and/or firing. Given stronger labor market regulations in Germany, it stands to reason that these adjustment frictions are more important in Germany than in the US. Our principal results for the US data—that surprise increases in uncertainty lead to protracted and persistent declines in economic activity—suggest that some of the other mechanisms proposed in the literature, in particular financial frictions, the "by product" hypothesis, or "wait and see" combined with an endogenous growth mechanism, may be more promising explanations for the observed empirical relationship between uncertainty and economic activity in the US.

I. Measuring Uncertainty

This section begins with a description of our data sources, both surveys of managers in manufacturing firms. The German data come from the monthly IFO Business Climate Survey (IFO-BCS), while the data for the United States are from the Federal Reserve Bank of Philadelphia's Business Outlook Survey (BOS) at the same frequency. From these we construct monthly uncertainty proxies and examine their behavior over the business cycle, their correlations with one another, and their correlations with other proxies for uncertainty used in the literature. The section concludes with a discussion of the validity of forecast disagreement as a proxy for uncertainty.

In addition to capturing the mood of actual decision makers, there are several reasons to think that high-frequency business survey data from narrowly defined segments of the economy are well-suited to measure business-level uncertainty. First, a recent literature (Bloom 2009, Bloom et al. 2011) has highlighted the so-called "wait and see" effect of uncertainty. These "wait and see" dynamics rely on adjustment frictions for capital or labor that are more likely to be operative in the short run, making high frequency data the best candidate to detect these dynamics. Readily available at a monthly frequency, survey-based data have an advantage over, for example, balance sheet data. Second, using cross-sectional dispersion measures to proxy for uncertainty rests on the assumption that respondents draw their idiosyncratic shocks from similar distributions, so that fluctuations in dispersion are the result of fluctuations in uncertainty and not merely compositional changes in the cross-section. Using data from narrowly defined segments of the economy (BOS) makes this assumption more likely to hold. Alternatively, large and broad surveys (IFO-BCS) allow us to test for these compositional effects directly. Finally, the business leaders that answer the IFO-BCS state that the results from the survey are an important tool in their planning process. Thus business leaders are likely to become more uncertain themselves after observing a strong increase in disagreement among peers at similar firms.

A. *Data Description*

The German IFO Business Climate Survey is one of the oldest and broadest business confidence surveys available (see Becker and Wohlrabe 2008, for more detailed information). Because the micro data are available in a processable form only since 1980, and because of longitudinal consistency problems for the construction and trade surveys, we limit our analysis to the manufacturing sector from 1980 through the end of 2010. In our analysis, we exclude all firms located in Eastern Germany, but none of our results depend on this choice.

An attractive feature of the IFO-BCS survey is the high number of participants, which also permits analyses at the 2-digit industry level. The average number of respondents at the beginning of our sample is approximately 5,000; toward the end the number is about half that at 2,000.[4] Participation in the survey is voluntary and there is some fraction of firms that are only one-time participants. However, conditional on staying two months in the survey, most firms continue to participate each month. For our purposes, the chief advantage of the IFO-BCS is that we have access to the underlying micro data of the survey. In particular, we can exploit the panel dimension of the survey to construct qualitative measures of ex post forecast errors. We therefore restrict attention to firms surveyed more than once. Our final sample comprises roughly 4,000 respondents at the beginning and 1,500 toward the end of the sample. In terms of firm size, the IFO-BCS contains all categories. About 9.4 percent of firms in our sample had less than 20 employees, roughly 32.0 percent had more than 20 but less than 100 employees, 47.3 percent employed between 100 and 1,000 people, and 11.3 percent had a workforce of more than 1,000.

Our analysis focuses on the following two questions from the survey:[5]

Q1 "*Expectations for the next three months*: *Our domestic production activities with respect to product X will* (*without taking into account differences in the*

[4] The IFO-BCS survey is technically at the product level, so the number of participants does not exactly conform to the number of firms, though we will use that terminology throughout the paper.

[5] Here we provide a translation, for the German original see Goldrian (2004, 18).

length of months or seasonal fluctuations) *increase, roughly stay the same, decrease*."

Q2 "*Trends in the last month*: *Our domestic production activities with respect to product X have* (*without taking into account differences in the length of months or seasonal fluctuations*) *increased, roughly stayed the same, decreased*."

The answers to either of these questions fall into three main qualitative categories: *Increase*, *Decrease*, and a neutral category. Define $Frac_t^+$ as the weighted fraction of firms in the cross section with "increase" responses at time t and $Frac_t^-$, similarly for decrease responses.[6] We can use these classifications to define an uncertainty proxy as the dispersion of the responses to the forward-looking survey question Q1:[7]

$$FDISP_t = \sqrt{Frac_t^+ + Frac_t^- - (Frac_t^+ - Frac_t^-)^2}\,. \tag{1}$$

Our construction of ex post forecast errors combines past responses to Q1 with current responses to Q2. To fix ideas, we proceed at first as if the production change expectation question and the production change realization question covered the same time horizon, say a month. Firms are recorded as expecting one of three outcomes in Q1: production is expected to go up, down, or stay the same. There are three similar realizations for the change in production in Q2, but they are retrospective. Suppose that a firm in the past expected production to rise (response to Q1 $= +1$). In the present (response to Q2), production could have risen, $+1$, stayed the same, 0, or declined, -1. We construct a qualitative metric of the forecast error by subtracting past change expectations (responses to Q1) from current change realizations (responses to Q2). So, for a firm that expected an increase in production, the realization of an increase would be coded as a 0 forecast error, no change in production would be coded as a -1 forecast error, and a decline in production would be coded as a -2 forecast error. Table 1 summarizes the possible forecast errors. Rows correspond to past forecasts and columns to current realizations. There are 9 combinations with 5 distinct outcomes: "large" positive or negative forecast errors (-2 or $+2$), positive or negative forecast errors (-1 or $+1$), and no qualitative forecast error (0).[8]

[6] To ensure representativeness of the sample, for our baseline results we weight each firm observation with the gross value added of the two-digit sector to which the firm belongs relative to the gross value added in manufacturing. Denote this weight by $\omega_{i,t}$. Then $Frac_t^+ \equiv \sum_i \omega_{i,t} \times 1_{\text{increase } response}$ and $Frac_t^- \equiv \sum_i \omega_{i,t} \times 1_{\text{decrease } response}$. All our results are similar using an unweighted dispersion measure. Table 4 (column 1 in row 5 and 6) shows that the (gross value added weighted) relative score, $Frac_t^+ - Frac_t^-$ (*PRODCHANGE*), for Q2, the question about realized production changes, is positively correlated with the growth rate of the manufacturing production index in Germany, which gives us further confidence in the usefulness of the IFO-BCS sample.

[7] This measure of dispersion is the cross-sectional weighted standard deviation of the survey responses when the *Increase* category is coded as $+1$, the *Decrease* category as -1, and the neutral category as 0. This is a standard quantification method for qualitative survey data.

[8] Nerlove (1983) is a seminal contribution that examines the statistical properties of qualitative survey-based expectation errors. More recently, Mueller and Koeberl (2007, 2009) use micro survey data from the Swiss Economic Institute's (KOF) Business Tendency Survey to infer firm-level shocks and their relation with the business cycle.

Table 1—Possible Expectation Errors: One Month Case

	$Increase_{i,t}$	$Unchanged_{i,t}$	$Decrease_{i,t}$
Expected $Increase_{i,t-1}$	0	−1	−2
Expected $Unchanged_{i,t-1}$	+1	0	−1
Expected $Decrease_{i,t-1}$	+2	+1	0

Notes: Rows refer to qualitative past production change expectations. Columns refer to qualitative current production change realizations.

There is an obvious complication that arises because Q1 asks about production change expectations over the next three months, whereas Q2 asks about production change realizations over the last month. Suppose, as an example, that a firm states in month $t-3$ that it expects production to increase in the next three months. Suppose further that one observes the following sequence of outcomes over those three months: production increased between $t-3$ and $t-2$, production did not change between $t-2$ and $t-1$, and production is reported to have declined between $t-1$ and t. Because of the qualitative nature of the survey responses in the IFO-BCS, we have to make assumptions about the cumulative production change over three months.

We define for every month t a firm-specific activity variable as the sum of the *Increase* instances minus the sum of the *Decrease* instances between $t-3$ and t from Q2:

$$REALIZ_{i,t} = \#(Increase_{i,t-k})_{k=0,\ldots,2} - \#(Decrease_{i,t-k})_{k=0,\ldots,2}. \tag{2}$$

$REALIZ_{i,t}$ can range from $[-3,3]$; in the hypothetical example given above, it would be equal to 0. The calculation of the forecast errors, $error_{i,t}$, is described in Table 2, and is based on a comparison of the signs of expected production changes and $REALIZ_{i,t}$. If the sign of the firms' expectation in $t-3$ and the sign of $REALIZ_{i,t}$ coincide, we assume no forecast error. Otherwise the assigned forecast error increases in $REALIZ_{i,t}$. Dividing by three is a normalization. $error_{i,t}$ then ranges from $\left[-\frac{4}{3},\frac{4}{3}\right]$. For example, $-\frac{4}{3}$ indicates a highly negative forecast error; in period $t-3$ the firm expected production to increase over the next three months, yet in each subsequent month production actually declined.

We construct an uncertainty proxy by taking the cross-sectional standard deviation, weighted by the two-digit gross-value added weights, of the observed forecast errors:

$$FEDISP_t = stdw\,(error_{i,t+3}). \tag{3}$$

Notice the timing in the definition of $FEDISP_t$, which is the same as in Bloom (2009) for stock market volatility; the standard deviation of *realized* expectation errors at date $t+3$ does not constitute *uncertainty* in $t+3$. Rather, it is the knowledge (in month t) of this standard deviation going up or down that makes decision-makers more or less uncertain at time t. It should be emphasized that this timing does not require decision makers to know anything about the future, other than that it is more or less uncertain.

Table 2—Possible Expectation Errors: Three Month Case

		$error_{i,t}$
Expected $Increase_{i,t-3}$	$REALIZ_{i,t} > 0$	0
Expected $Increase_{i,t-3}$	$REALIZ_{i,t} \leq 0$	$(REALIZ_{i,t} - 1)/3$
Expected $Unchanged_{i,t-3}$	$REALIZ_{i,t} > 0$	$REALIZ_{i,t}/3$
Expected $Unchanged_{i,t-3}$	$REALIZ_{i,t} = 0$	0
Expected $Unchanged_{i,t-3}$	$REALIZ_{i,t} < 0$	$REALIZ_{i,t}/3$
Expected $Decrease_{i,t-3}$	$REALIZ_{i,t} < 0$	0
Expected $Decrease_{i,t-3}$	$REALIZ_{i,t} \geq 0$	$(REALIZ_{i,t} + 1)/3$

Notes: $REALIZ_{i,t}$ is the sum of the *Increase* instances minus the sum of the *Decrease* instances between $t - 3$ and t, based on Q2. $error_{i,t}$ specifies the qualitative ex post production change forecast error of firm i in month t vis-à-vis a three-month production change expectation in month $t - 3$.

One can also create another statistic meant to proxy for uncertainty from the qualitative forecast errors. $MEANABSFE_t$ is a measure of the average size of idiosyncratic forecast errors, which one would expect to be larger in a more uncertain environment. In the expression below *meanw* denotes the two-digit gross value added weighted average:

$$MEANABSFE_t = meanw\left(|\,error_{i,t+3}|\right). \tag{4}$$

While we treat $FDISP_t$ and $FEDISP_t$ as our baseline survey-based proxies of uncertainty, we will also report results for $MEANABSFE_t$.

Next we turn to the data from the United States. The Business Outlook Survey (BOS) is a monthly survey conducted by the Federal Reserve Bank of Philadelphia. It has been in continuous operation since May 1968 and the structure of the survey has been essentially unaltered since its inception. The survey is sent to large manufacturing firms in the Third Fed district: Delaware, the southern half of New Jersey, and the eastern two-thirds of Pennsylvania. The survey is sent to the chief executive, a financial officer, or another executive. Participation is voluntary. Each month about 100–125 firms respond. The group of participating firms is periodically replenished as firms drop out or a need arises to make the panel more representative of the industrial mix of the region. We use data from May 1968 to December 2011.

The chief advantages of the BOS are its long time horizon and its focus on one, consistent, relatively homogeneous class of entities—large manufacturing firms.[9] The small number of respondents is a drawback. Because of its broad scope ("general business activity"), the main question of interest is:

Q3 "*General Business Conditions*: *What is your evaluation of the level of general business activity six months from now versus* [*CURRENT MONTH*]: *decrease*, *no change*, *increase?*"

[9] In Appendix C, available online, we also consider data from the Small Business Economic Trends Survey (SBETS). This survey is very similar to the BOS survey, except that it is focused on small companies and is not restricted to any region or sector. The results using this series are similar to the BOS.

Table 3—Correlation between BOS Activity Variables and Official Statistics

	General conditions	Shipments	$\Delta \ln MP$
$\Delta \ln MP$-monthly	0.55	0.45	1
$\Delta \ln MP$-quarterly	0.79	0.71	1
BLS monthly sect. and regio. empl.	0.55	0.59	0.55
Philadelphia FED coincident index	0.72	0.72	0.56
NIPA yearly sect. and regio. prod.	0.56	0.63	0.81

Notes: This table displays the unconditional pairwise contemporaneous correlations of BOS activity variables with different measures of economic activity. In the columns are the relative scores, $Frac_t^+ - Frac_t^-$, of one-month retrospective versions of Q3 and Q4 (available from 5/1968 through present), as well as the growth rate of overall production in manufacturing. In the rows are four different measures of economic activity (all in growth rates): manufacturing production at a monthly frequency and aggregated to a quarterly frequency; the sum of the seasonally adjusted monthly manufacturing employment series for Delaware, New Jersey, and Pennsylvania, available from the BLS from 1990 on (row 3); the monthly GDP-weighted sum of the Philadelphia FED Coincident Indices for Pennsylvania, Delaware, and New Jersey, available from 1979 on (row 4); and the GDP-weighted sum of the yearly NIPA quantity indices for the manufacturing sector for Delaware, New Jersey, and Pennsylvania, available from 1977 to 2010 (row 5). Each pairwise correlation is computed using the longest available time series.

As in the IFO-BCS, answers are coded into three discrete, qualitative categories: up/improved (+1), no change (0), and down/worse (−1). However, the broad scope might imply some potential ambiguity in the wording of Q3. Whereas the IFO-BCS specifically asks about firm-specific conditions, the BOS question is about "general business conditions." There is a similar question about shipments that is more specifically geared toward firm-specific conditions, Q4:

Q4 "*Company Business Indicators*: *Shipments six months from now versus* [*CURRENT MONTH*]: *decrease*, *no change*, *increase?*"

Trebing (1998) notes that answers to these two questions are highly correlated. In particular, the correlation between their relative scores, $Frac_t^+ - Frac_t^-$, is above 0.95. Trebing (1998) concludes that answers to Q3 are essentially indicators of firm-specific business conditions.

For the BOS we do not have access to the full panel of micro data as we do in the case of the IFO-BCS. Hence, we cannot construct uncertainty proxies based on ex post forecast errors. As such, our baseline uncertainty proxy for the BOS is cross-sectional forecast dispersion for Q3, supplemented by the same statistic for Q4, for which we only need publicly available data on the (unweighted) fraction of each category of response. It is defined as $FDISP_t$ for Germany above, except that $Frac_t^+$ and $Frac_t^-$ denote unweighted fractions.

Economic activity as measured both in the BOS survey and in the Philadelphia Fed district co-moves closely with aggregate manufacturing production, as Table 3 shows. We measure economic activity in the BOS by the relative score, $Frac_t^+ - Frac_t^-$, for one-month retrospective change versions of Q3 and Q4. These series can be interpreted as qualitative measures of business growth. Both measures of BOS activity are highly correlated with the monthly growth rate of the manufacturing industrial production index, even more so aggregated to a quarterly frequency. The same is true for growth rates of manufacturing employment in the Philadelphia Fed

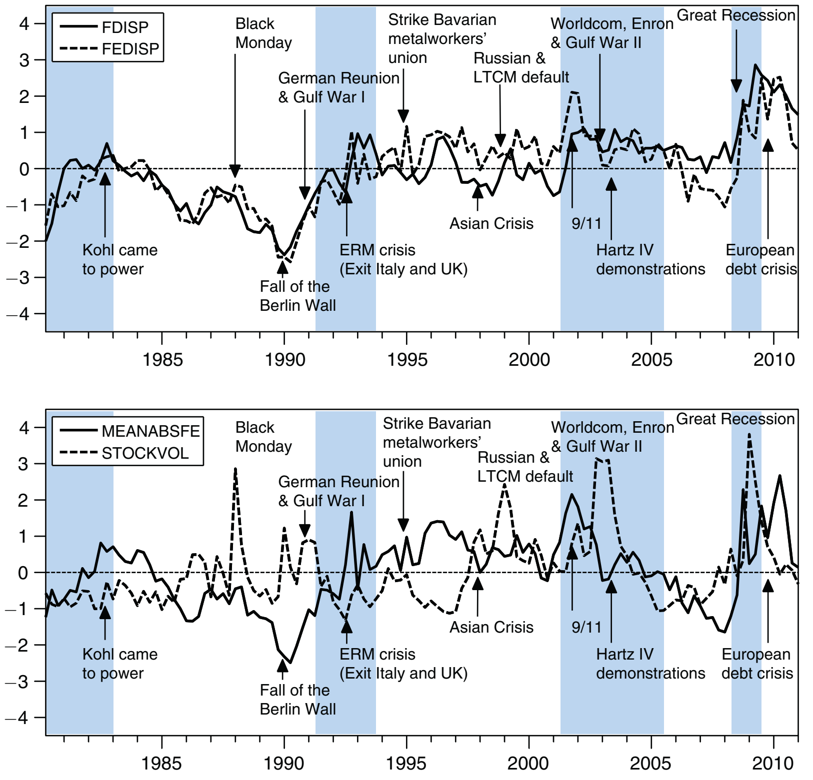

Figure 1. Uncertainty Measures: Germany

Notes: The upper panel shows the quarterly averages of the monthly time series of the IFO-BCS ex ante forecast dispersion *FDISP* and of the standard deviation of ex post forecast errors *FEDISP*. The lower panel plots the quarterly averages of the average absolute ex post forecast errors, *MEANABSFE*, from the IFO-BCS, and stock market volatility *STOCKVOL*. The sample period is I/1980–IV/2010. Each series has been demeaned and standardized by its standard deviation. Shaded regions show recessions as dated by the Sachverständigenrat (see Sachverständigenrat 2009, 261): I/1980–IV/1982, I/1991–III/1993, I/2001–II/2005, and I/2008–II/2009.

district, the Philadelphia Fed's State Coincident Index of economic activity aggregated up to the Philadelphia Fed district, and the yearly NIPA manufacturing GDP data for the same region. Moreover, all these regional measures are highly correlated with the growth rate of the overall manufacturing industrial production index, which shows that economic activity in the Philadelphia Fed district has similar fluctuations to overall manufacturing activity in the United States.

B. *Time Series Properties*

Figure 1 plots the time series of four different uncertainty proxies for Germany. For better readability of the graphs, we average the monthly series to a quarterly frequency. Because of different measurement scales, we demean the series and normalize each by its standard deviation. The upper panel plots *FDISP*, the cross-sectional survey forecast disagreement from the IFO-BCS, in the solid line, and *FEDISP*, the cross-sectional standard deviation of the qualitative forecast errors, as the dashed

Table 4—Basic Data Analysis: Germany

	PRODCHANGE	*FDISP*	*FEDISP*	*MEANABSFE*	*STOCKVOL*
Volatility	0.037	0.073	0.058	0.089	0.399
Skewness	−0.49	0.17	0.08	0.11	1.67
Kurtosis	3.61	3.42	3.32	3.09	5.97
First order autocorr.	0.91	0.95	0.85	0.85	0.79
Corr w/$\Delta \ln MP$-monthly	0.29	−0.08	0.01	−0.02	−0.07
Corr w/$\Delta \ln MP$-quarterly	0.64	−0.21	−0.10	−0.14	−0.20
Corr w/*PRODCHANGE*	1	−0.41	−0.33	−0.40	−0.21
Corr w/*FDISP*		1	0.71	0.59	0.19
Corr w/*FEDISP*			1	0.93	0.18
Corr w/*MEANABSFE*				1	0.09
Corr w/*STOCKVOL*					1

Notes: This table shows basic time series statistics for the various German uncertainty proxies as described in the text. *PRODCHANGE* is the (gross value added weighted) relative score, $Frac_t^+ - Frac_t^-$, for Q2. *FDISP* is the forecast disagreement index, based on Q1. *FEDISP* is dispersion in forecast errors, constructed as described in the text. *MEANABSFE* is the mean of the absolute value of forecast errors. *STOCKVOL* is a stock market volatility index from Deutsche Börse, which combines realized volatility until 12/1991 and an implied volatility index from 1/1992 onward. *MP* is a monthly seasonally adjusted manufacturing production index for West Germany from the Federal Statistical Office. "Volatility" is defined as the percentage time series standard deviation normalized by the mean (the coefficient of variation). For *PRODCHANGE* (column 1) we use the percentage time series standard deviation, as its mean is close to zero. The sample period is common across series: 1/1980–12/2010.

line. The bottom panel plots *MEANABSFE*, the cross-sectional average of the absolute value of the forecast errors, in the solid line, along with a stock market volatility index in the dashed line. As in Bloom (2009), this index has been concatenated from realized stock return volatility until December 1991 and an implied volatility index from January 1992 onward (see details in Table A1). Shaded regions depict recessions as dated by the Sachverständigenrat, the so-called "Economic Wise Men" (see Sachverständigenrat 2009, 261).

The upper plot shows how closely survey disagreement and dispersion in forecast errors track one another. Table 4, row 8, column 3 shows that both monthly series have an unconditional correlation of 0.71; aggregated to a quarterly frequency this correlation is 0.77. This gives us confidence that survey disagreement is a good proxy for uncertainty or risk shocks, especially in contexts where detailed micro data are not available. Both proxies of uncertainty rise significantly after the fall of the Berlin Wall, a time of major political and economic uncertainty in Germany. Reunification was followed by the First Gulf War and the crisis of the European Exchange Rate Mechanism, periods during which both of these series remained high. Both series spiked around 2001, coinciding with the bursting of the tech bubble, the September 11 attacks, and the ensuing mild recession in the United States. They increased at the start of the financial crisis in 2007 and remained elevated during the early stages of the European debt crisis. There are several other putatively high uncertainty events specific to Germany. One in particular took place in the early 1980s, at the beginning of the available sample. The recession of the early 1980s led to political upheaval and a complicated and long lasting transition of power from the Social Democrats to the Christian Democrats. Both survey measures of uncertainty increased substantially in this period, abating with the election of Chancellor Kohl, which was followed by a strong pro-business policy stance and a downward drift in the survey measures for a number of years.

The bottom panel shows that *MEANABSFE*, the cross-sectional average of the absolute value of the qualitative forecast errors (solid line), displays similar properties to both the *FEDISP* and the *FDISP* series—it rises in the wake of the fall of the Berlin Wall, around 2001, and again at the start of the global financial crisis and remains high at the onset of the European debt crisis. The stock market volatility series (dashed line) spikes in the early 2000s as well as during the financial crisis, though it is worth noting that these movements both occur after the various survey-based measures increase. Interestingly, German stock market volatility seems to have been largely unaffected by the European debt crisis. Stock market volatility spikes briefly after the fall of the Berlin Wall and at the beginning of the First Gulf War, but, again, seems unaffected by the first European currency crisis. There are also large spikes in the German stock market volatility series at the end of 1987, coinciding with the "Black Monday" crash in October of that year, and around the Asian Crisis as well as the Russian Default. Neither event had large macroeconomic consequences in Germany and neither shows up strongly in the survey-based series. Other events leading to putatively elevated uncertainty, such as the political aftermath of the early 1980s recession, hardly show up in stock market volatility.

Table 4 shows various unconditional business cycle statistics for the German uncertainty proxies. The volatilities of the survey-based uncertainty proxies, *FDISP*, *FEDISP*, and *MEANABSFE*, are similar, and smaller than the volatility of the stock market volatility index. The survey-based uncertainty proxies show close-to-Gaussian skewness and kurtosis, whereas the stock market volatility index has substantial positive skewness and fat tails. All this suggests that survey-based uncertainty proxies are likely to pick up more of the regular uncertainty fluctuations, whereas stock market volatility tends to reflect large and rare uncertainty events. This is largely a function of the coarseness of the survey-based indexes, which only permit one to observe three discrete categories.

All four uncertainty series, in particular the survey-based ones, are fairly persistent and positively correlated with one another. They are for the most part countercyclical, more so when the cycle is measured by survey-based activity measures (row 7 of Table 4) than the manufacturing production index (rows 5 and 6 of Table 4). This finding is consistent with the growing body of empirical evidence that most proxies for uncertainty co-move negatively with output over the business cycle. Bloom et al. (2011) document this for the sales growth of publicly traded firms (Compustat) and manufacturing plants (ASM). Berger and Vavra (2011), using the underlying micro data of the CPI, show that the dispersion of price changes is countercyclical. Bachmann and Bayer (2011a, b) show for a large multi-sector firm-level dataset that firm-level changes in value added, employment, and productivity display countercyclical dispersion.[10]

Switching gears, Figure 2 plots four different uncertainty proxies for the United States. As with the German data, we aggregate the monthly series up to a quarterly frequency to improve readability. For the same reason, we demean the series and normalize each by its standard deviation. The upper panel plots the dispersion series constructed from the BOS survey based on Q3 (*FDISP*, solid line) and the Google

[10]The correlations of *FDISP* and *FEDISP* with the overall balance sheet-based measure of uncertainty in Bachmann and Bayer (2011b) are, respectively, 0.57 and 0.27; for the corresponding uncertainty measure for the manufacturing sector these numbers increase to 0.61 and 0.33.

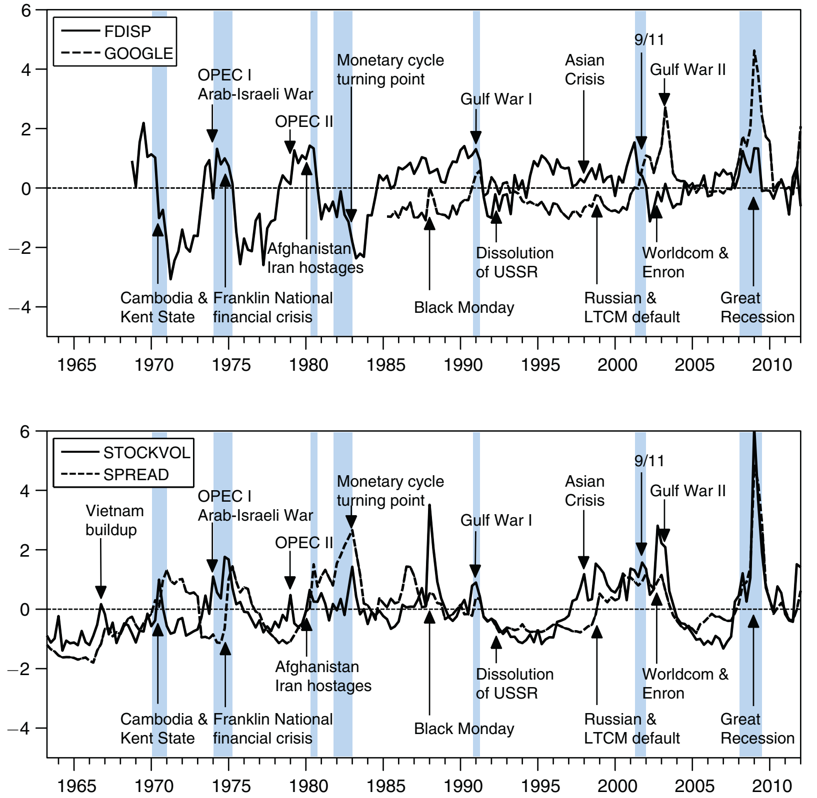

FIGURE 2. UNCERTAINTY MEASURES: UNITED STATES

Notes: The upper panel shows the quarterly average of the BOS ex ante forecast dispersion *FDISP* and the quarterly average of the Google News uncertainty index *GOOGLE*. The lower panel plots the quarterly averages of stock market volatility *STOCKVOL* and the corporate bond spread *SPREAD*. The sample for *FDISP* is II/1968–IV/2011, for *GOOGLE* it is I/1985–IV/2011, and for *STOCKVOL* as well as *SPREAD* it is II/1962–IV/2011. Each series has been demeaned and standardized by its standard deviation. Shaded regions show recessions as dated by the NBER.

News-based economic uncertainty index recently constructed by Baker, Bloom, and Davis (2012) (dashed line).[11] The lower panel plots the stock market volatility index from Bloom (2009) (solid line) along with a measure of the corporate bond spread (dashed line), defined as the monthly spread of the 30-year Baa-rated corporate bond yield index over the 30-year treasury bond yield (in months where the 30-year treasury bond was missing we used the 20-year treasury bond instead). Shaded regions depict recessions as dated by the National Bureau of Economic Research (NBER).

[11] We thank Scott Baker, Nick Bloom, and Steven Davis for providing us with their Google News subindex that is based on economic uncertainty only (as opposed to economic policy uncertainty). They count the number of articles in a given month mentioning "uncertainty" and phrases related to the economy and divide it by a backward-looking moving average of the number of articles containing the word "today" to account for the overall increasing volume of news. This series behaves similarly to the Alexopoulos and Cohen (2009) series based on the *New York Times* during the common sample period, with the exception of the immediate wake of September 11, when the series based on *New York Times* jumps more. For the period pre-1985, the Alexopoulos and Cohen (2009) series behaves similarly to stock market volatility.

The BOS forecast dispersion series is generally high in the early stages of recessions and low immediately after them. It jumps up around the time of the 1970s "oil shocks" (1974 and 1978), it rises at the end of the tech boom and immediately prior to the 2001 recession, and it rises at the early stages of the financial crisis in 2007. For events where the samples overlap, the Google uncertainty index exhibits many of the same features, although it tends to spike more strongly and somewhat after the BOS series, especially in the latter part of the sample. The latter feature is to be expected in a world where business uncertainty needs some time to be picked up by the media. The fact that during the financial crisis both indices spike more or less concomitantly is consistent with this story, as obviously the financial crisis was immediately in the minds of both the business community and the news media.

The bottom panel of Figure 2 plots stock market volatility (solid line) and the corporate bond spread (dashed line). The series display similar properties to one another. Like the Google News uncertainty index, they tend to spike in the middle and toward the end of recessions. Stock volatility shows its largest spikes in the wake of the 1987 crash and during the 2007–2009 financial crisis. It was also strongly affected by the Asian crisis. Interestingly, the Asian crisis has little noticeable effect on the BOS measure, the Google News measure, or the corporate bond spread. The collapse of LTCM manifests itself in the bond spread but less so in the other series. The September 11 attacks show up only as very short-lived increases in the stock market volatility index and the corporate bond spread and not at all in the BOS measure, whereas the news-based measure shows a persistent increase in uncertainty. Conversely, the putative build-up of uncertainty at the end of the tech boom is most clearly shown in the BOS dispersion measure and then the Google index, but hardly in stock market volatility.

Table 5 presents various unconditional business cycle statistics for the United States uncertainty proxies. In addition to the four series in the plots of Figure 2, we also show statistics for a variant of the BOS uncertainty index based on expectations about shipments, Q4, $FDISP_{SHIP}$. Consistent with the findings from the German data, the BOS dispersion series are significantly less volatile and more Gaussian than the other series. All five series are countercyclical as measured by the contemporaneous correlation with the growth rate of manufacturing production, and are, for the most part, positively correlated with one another. The only exception are the BOS dispersion series and the Google News uncertainty index, which are essentially uncorrelated.[12]

It should come as no surprise that these uncertainty measures are not perfectly correlated. For one, they likely reflect different kinds of uncertainty; the survey-based measures for both countries are relatively more likely to be driven by changes in idiosyncratic, business-level uncertainty, whereas series like stock market volatility more likely reflect fluctuations in aggregate uncertainty. Furthermore, movements in stock market volatility and corporate bond spreads apply to a specific segment of firms that are publicly traded and issue corporate debt. At least in Germany, this represents a small fraction of firms. All these measures originate from different, though complementary, sources: the survey-based data originate from business

[12] We will show in Section IIB, however, that their conditional effects on economic activity are similar, and, in fact, more similar to one another than to either the effects of stock market volatility and the corporate bond spread.

Table 5—Basic Data Analysis: United States

	FDISP	$FDISP_{SHIP}$	*GOOGLE*	*STOCKVOL*	*SPREAD*
Volatility	0.089	0.080	0.638	0.396	0.349
Skewness	−0.25	−0.05	2.07	1.73	2.52
Kurtosis	2.80	3.09	8.38	7.94	12.53
First order autocorr.	0.70	0.63	0.91	0.89	0.96
Corr w/$\Delta \ln MP$-monthly	−0.25	−0.25	−0.41	−0.29	−0.49
Corr w/$\Delta \ln MP$-quarterly	−0.32	−0.34	−0.64	−0.45	−0.72
Corr w/BOS general cond.	−0.44	−0.47	−0.47	−0.43	−0.52
Corr w/BOS shipments	−0.26	−0.28	−0.55	−0.43	−0.53
Corr w/*FDISP*	1	0.83	−0.09	0.19	0.22
Corr w/$FDISP_{SHIP}$		1	−0.05	0.25	0.23
Corr w/*GOOGLE*			1	0.58	0.62
Corr w/*STOCKVOL*				1	0.75
Corr w/*SPREAD*					1

Notes: This table shows basic time series statistics for the various US uncertainty proxies as described in the text. *FDISP* is the forecast disagreement index, based on Q3. $FDISP_{SHIP}$ is the forecast disagreement index, based on Q4. *GOOGLE* is the Google News subindex that is based on economic uncertainty from Baker, Bloom, and Davis (2012). *STOCKVOL* is the monthly measure of stock market volatility from Bloom (2009), which until 1986 is realized monthly stock market return volatility, and thereafter an implied volatility index. *SPREAD* refers to the monthly spread of the 30-year Baa-rated corporate bond yield index over the 30-year treasury bond yield (in months where the 30-year treasury bond was missing we used the 20-year treasury bond instead). "Volatility" is defined as the percentage time series standard deviation normalized by the mean (the coefficient of variation). *MP* is a monthly seasonally adjusted manufacturing production index. "Corr w/BOS general conditions" is the correlation of the various uncertainty measures with the relative score, $Frac_t^+ - Frac_t^-$, of the one-month retrospective version of Q3. "Corr w/BOS shipments" is the correlation of the various uncertainty measures with the relative score, $Frac_t^+ - Frac_t^-$, of the one-month retrospective version of Q4. The sample period is common across series: 1/1985–12/2011.

managers, the Google index is based on reflections of the news media, and stock market volatility and corporate bond spreads are the outcome of equilibrium price movements in asset markets, which may also be driven by forces unrelated to uncertainty. For example, corporate bond spread fluctuations may reflect time-varying credit conditions unrelated to changes in uncertainty. Finally, due to their qualitative nature the survey-based measures are poorly equipped to fully capture the magnitude of uncertainty increases during extreme events. Nevertheless, the fact that every kind of uncertainty measure spikes during the Great Recession, the time of the putatively highest economic uncertainty in the post-war era, is reassuring. None of the uncertainty proxies are a perfect measure of a multidimensional and complex phenomenon, but it is apparent that all of them can potentially contribute to our understanding of the effects of uncertainty on economic activity.

C. *Is Disagreement a Good Proxy for Uncertainty?*

Measuring the subjective uncertainty of individuals is inherently difficult. Ideally, one would like to elicit a subjective probability distribution over future events from managers, as has been done in Guiso and Parigi (1999) for Italian firms. However, to the best of our knowledge such probability distributions are not available repeatedly, at high frequencies, and over long time horizons. As we have seen, in most instances researchers instead have to rely on proxies.

One of the most common survey-based uncertainty proxies in the literature is disagreement of firm expectations, *FDISP* in our notation. Two potential problems with this uncertainty proxy can arise. First, time-varying, cross-sectional dispersion in survey responses might simply be due to different firms reacting differently to aggregate shocks even with constant uncertainty. For relatively homogeneous firms, like those sampled in the BOS, i.e., large manufacturing firms from a narrowly defined region, this is unlikely to be a serious problem. Second, time variation in the dispersion of expectations might simply reflect time variation in the heterogeneity of said expectations, without the dispersion in these expectations having anything to do with actual subjective uncertainty in the minds of business leaders.

Access to the rich underlying micro data from the IFO-BCS data allows us to address both of these concerns. To address the first—that different firms have different factor loadings to aggregate shocks—we decompose $FDISP_t^2$ for every month into the weighted average "within" variance of the 13 manufacturing 2-digit industries and the "between" variance of the same industries.[13] The cross-sectional "within" variance amounts to over 98 percent of the observed total cross-sectional variance on average. Over time, fluctuations in the "within" variance explain roughly 92 percent of the fluctuations in the total variance; the "between" variance explains less than 1 percent, with the rest being accounted for by the covariance term between "within" and "between" variances. A related calculation shows that almost all manufacturing subsectors (with the exception of the Chemical Industry) have countercyclical *FDISP* measures. Altogether, this means that time series movements in *FDISP* are not explained by manufacturing subsectors getting more or less different over the business cycle.

The second concern—that dispersion at time t simply reflects heterogeneous, but certain, expectations—can be addressed by comparing the time series properties of dispersion in ex post forecast errors, *FEDISP*, with ex ante forecast dispersion, *FDISP*. By construction, dispersion in ex post forecast errors excludes heterogeneous, but certain, disagreement in expectations. If the dispersion series were mainly driven by heterogeneous but certain disagreement then one would expect ex ante dispersion to be only weakly correlated with the the ex post forecast error standard deviation. As we have shown (in Table 4), however, these series are quite strongly correlated, 0.71 at a monthly frequency, and even higher when aggregated up to a quarterly frequency. Visually the series look very similar (see Figure 1), and all of the large movements in the two series are in common. As shown below, the dynamic relationship between either of these series and measures of economic activity in Germany is also quite similar.

In online Appendix A, we present, in addition, a simple and highly stylized two-period model where firms receive signals about their uncertain future business situations. We show, for this model, that if signals are neither perfectly informative nor perfectly uninformative, under Bayesian updating both the dispersion of firms' expectations and the average subjective uncertainty in the cross section increase in response to an increase in the cross-sectional variance of firms' future business situations.

[13] Since we have only very few observations from the Refined Petroleum Products industry, we ignore it in this decomposition.

II. Uncertainty and Activity: Dynamic Relationship

This section uses standard, recursively identified vector autoregressions (VARs) with our measures of uncertainty and traces out the dynamic responses of measures of economic activity to surprise increases in uncertainty. We do this using data for both Germany and then for the United States.

A. *Germany*

Our benchmark VARs are bivariate systems featuring a measure of uncertainty and a measure of economic activity. A bivariate system is a parsimonious way to model the joint dynamics of uncertainty and activity. The frequency of the series in the VARs is monthly, the VARs are estimated with 12 lags, and the activity variables enter the systems in levels. We order the uncertainty series first in a recursive identification, though our results are similar in the alternative ordering. The sample period for all VARs is common from January 1980–December 2010. The VARs include an exogenous dummy after 10/1990 to account for structural shifts after Germany's reunification.

Figure 3 shows impulse responses of three different measures of economic activity (manufacturing production, manufacturing employment, and average hours worked in manufacturing, all in logs) to our two baseline survey-based uncertainty measures from the IFO-BCS—*FDISP* and *FEDISP*. The shaded regions are $+/-$ one standard error Kilian (1998) bias-corrected bootstrap confidence intervals. Each panel in the figure is an estimated response to a one standard deviation innovation in uncertainty from a bivariate system estimated separately with different uncertainty-activity variable combinations.

The left column plots responses of manufacturing production to innovations in *FDISP* and *FEDISP*. Following a surprise increase in ex ante forecast dispersion, production declines by a little less than 0.5 percent on impact, continues to decline for about a year, and then rebounds back to its pre-shock path after about 2–3 years. The response of production to an innovation in *FEDISP* is quite similar, though the impact decline in production is not quite as large and the rebound occurs somewhat more quickly. Overall, these responses are qualitatively consistent with the "wait and see" dynamics emphasized in Bloom (2009); there is evidence of a fairly sharp decline and a quick rebound in production.

The middle panel of Figure 3 plots the impulse response of manufacturing employment to innovations in *FDISP* and *FEDISP*, while the right column plots the responses of average hours worked in manufacturing. Employment and average hours both decline following a surprise increase in either *FDISP* or *FEDISP*. The responses of the two labor input measures are somewhat different, however. The negative employment response is prolonged and quite persistent relative to the response of production, whereas average hours decline and recover much more quickly. While different from the "wait and see" pattern for employment found in Bloom (2009), this result is nevertheless consistent with the basic intuition for "wait and see" adapted to the institutional setting of the German labor market, where due to stricter labor market regulations and discretionary policy measures, such as short-time work programs, average hours per worker are more frequently used as a margin of adjustment.

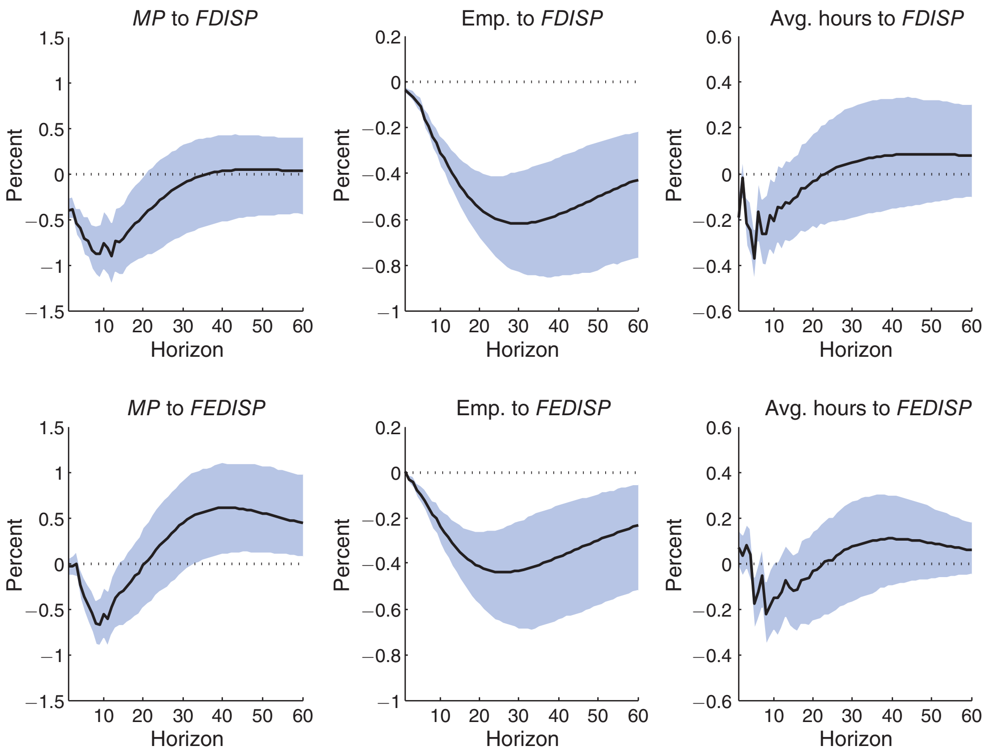

Figure 3. IRFs to Uncertainty: Germany

Notes: The upper row plots impulse responses of manufacturing production, manufacturing employment, and manufacturing average hours worked for West Germany (all in logs) to innovations in, obtained from separately estimating bivariate VARs with the IFO-BCS forecast dispersion index (ordered first) and the different activity variables. The bottom row is similarly constructed but using *FEDISP*, the dispersion in forecast errors. The frequency of the series in the VARs is monthly, the VARs are estimated with 12 lags, and activity variables enter the systems in levels. The sample period for all VARs is common from 1/1980–12/2010. The VARs include an exogenous dummy after Germany's reunification in October 1990. Shaded regions are +/− one standard error confidence bands from Kilian's (1998) bootstrap-after-bootstrap.

Figure 4 plots impulse responses of manufacturing production to surprise increases in four different uncertainty measures: ex ante forecast dispersion (*FDISP*) and dispersion in ex post forecast errors (*FEDISP*) as in the previous exercises, as well the mean absolute value of ex post forecast errors (*MEANABSFE*) and stock market volatility (*STOCKVOL*). The impulse responses of production to the four different uncertainty measures are quite similar to one another—in response to all four uncertainty series there is a decline in production followed by a relatively quick rebound. Table 6 displays a forecast error variance decomposition for production. The rows show the fraction of the VAR forecast error variance of production that is attributable to innovations in each of the uncertainty series over different forecast horizons. All three survey-based uncertainty series account for a larger fraction of the variance of production than do innovations in stock market volatility. At a 1 year horizon, for example, innovations in *FDISP* account for slightly more than 17 percent of the variance of production, while innovations in stock market volatility account for only about 6 percent of the variance of production. Although the estimated impulses

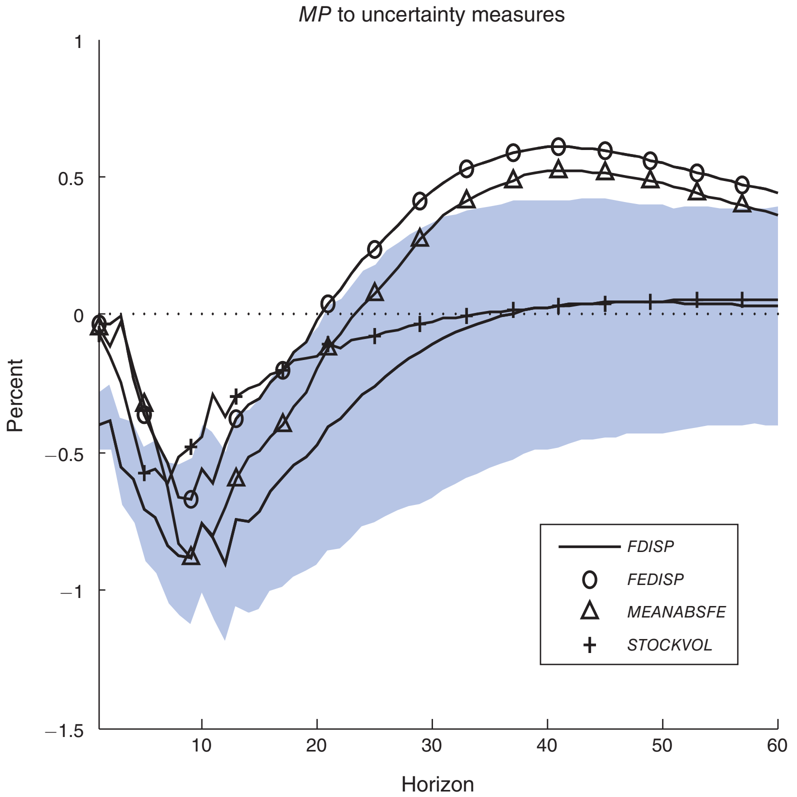

Figure 4. IRFs with Different Uncertainty Measures: Germany

Notes: This figure plots impulse responses of West German manufacturing production to innovations in various uncertainty measures. The responses are obtained from separately estimating a bivariate system with each different uncertainty measure and log manufacturing production. The frequency of the series in the VARs is monthly, the VARs are estimated with 12 lags, and manufacturing production enters the systems in levels. *FDISP* is the forecast disagreement index, based on Q1. *FEDISP* is dispersion in forecast errors, constructed as described in the text. *MEANABSFE* is the mean of the absolute value of forecast errors. *STOCKVOL* is a stock market volatility index from Deutsche Börse, which combines realized volatility until 12/1991 and an implied volatility index from 1/1992 onward. The sample period for all VARs is common from 1/1980–12/2010. The VARs include an exogenous dummy after Germany's reunification in October 1990. The shaded gray region is the +/− one standard error confidence band from the system using *FDISP*.

Table 6—MP Forecast Variance due to Uncertainty: Germany

Horizon	*FDISP*	*FEDISP*	*MEANABSFE*	*STOCKVOL*
$h = 1$	5.01	0.04	0.08	0.15
$h = 12$	17.26	7.45	11.60	5.59
$h = 36$	12.44	6.42	6.85	2.51
$h = 60$	9.49	11.24	8.93	1.86

Notes: The columns correspond to different measures of uncertainty used in the bivariate VAR systems for Germany. The rows show the fraction (multiplied times 100) of the total forecast error variance of log manufacturing production of West Germany due to innovations in uncertainty, where the uncertainty series is ordered first in a recursive identification. The frequency of the series in the VARs is monthly, the VARs are estimated with 12 lags, and manufacturing production enters the systems in levels. *FDISP* is the forecast disagreement index, based on Q1. *FEDISP* is dispersion in forecast errors, constructed as described in the text. *MEANABSFE* is the mean of the absolute value of forecast errors. *STOCKVOL* is a stock market volatility index from Deutsche Börse, which combines realized volatility until 12/1991 and an implied volatility index from 1/1992 onward. The sample period for all VARs is common from 1/1980–12/2010. The VARs include an exogenous dummy after Germany's reunification in October 1990.

responses of output to the different uncertainty proxies in Germany are consistent with the "wait and see" mechanism, it is important to note that the contribution of the different uncertainty series to the forecast error variance decomposition of production is nevertheless rather small, at around 10 percent at most forecast horizons.

We conducted a battery of different robustness checks, some of which are described in detail in online Appendix B. Our results are qualitatively robust to different trend assumptions on manufacturing production and our lag choice. We also considered, following Bloom (2009), an exercise in which we created a 0–1 indicator variable for periods of abnormally high uncertainty. Specifically, instead of using the actual uncertainty measure in the VAR, we replaced them with a derived uncertainty series that takes on one in the months where the underlying uncertainty measure was one time series standard deviation above its mean. The estimated impulse responses are quite similar to the original ones. Our results are also similar when we restrict the VARs only to the post-reunification sample. Finally, the qualitative results do not depend on the dimension of the estimated VARs. In particular, using the four German uncertainty proxies separately in a larger VAR with a stock market index, production, employment, average hours, the CPI, and the three-months Euribor as a measure of the nominal interest rate yields similar results to our baseline findings in bivariate VARs.

B. *United States*

Our benchmark VAR for the United States is also a bivariate system with a survey-based measure of uncertainty and a measure of economic activity. Our primary uncertainty measure for the United States is forecast dispersion in the general business situation question, Q3, from the BOS survey, *FDISP*, supplemented by an uncertainty measure based on forecast dispersion in the shipments question, Q4, $FDISP_{SHIP}$. The VARs are estimated with 12 lags, the activity variables enter in log-levels, and the uncertainty series is ordered first. The sample period is May 1968–December 2011.

Figure 5 is analogous to Figure 3 for Germany, plotting impulse responses of manufacturing production, employment, and average hours to innovations in *FDISP* and $FDISP_{SHIP}$ from the BOS. The responses to the two different survey uncertainty measures are quite similar to one another. As in the German data, a surprise increase in either uncertainty measure is followed by a significant decrease in economic activity. Unlike in the German data, however, the decline in production is very persistent, and there is no evidence of an important rebound or overshooting effect. The maximum decline in production is more than 1 percent, occurring at a horizon roughly 2 years subsequent to the initial shock. After this large decline there is little evidence of any rebound back to the pre-shock path—even at a 5-year horizon, production is still about 1 percent below its pre-shock level. There are also large, protracted declines in both the extensive and intensive measures of manufacturing labor input in response to increases in either uncertainty measure. It is instructive to compare the responses of average hours in Figure 5 to Figure 3. In the German data average hours decline following an increase in uncertainty, but then rebound quickly and even overshoot. In the US data, in contrast, the decline in average hours is much more persistent, with no overshoot at any horizon. Even 20 months after the shock, average hours are still 1 percent below their pre-shock level.

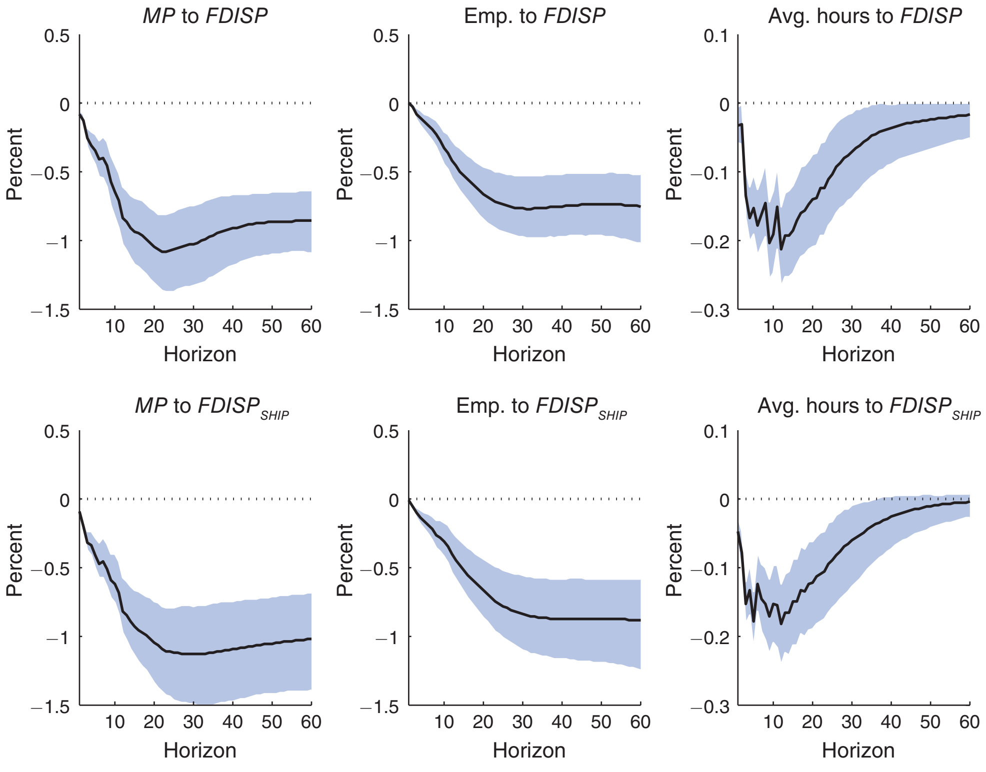

Figure 5. IRFs to Uncertainty: United States

Notes: The upper row plots impulse responses of manufacturing production, manufacturing employment, and manufacturing average hours worked (all in logs) to innovations in *FDISP*, obtained from separately estimating bivariate VARs with the BOS forecast dispersion index (ordered first) and the different activity variables. The bottom row is similarly constructed but using $FDISP_{SHIP}$, which is the forecast dispersion index based on BOS Q4. The frequency of the series in the VARs is monthly, the VARs are estimated with 12 lags, and activity variables enter the systems in levels. The sample period for all VARs is common from 5/1968–12/2011. Shaded regions are +/− one standard error confidence bands from Kilian's (1998) bootstrap-after-bootstrap.

Figure 6 in the left panel plots responses of manufacturing production to four different uncertainty proxies: BOS forecast dispersion, *FDISP*; the Google News uncertainty index, *GOOGLE*; S&P 500 stock market volatility as in Bloom (2009), *STOCKVOL*; and the corporate bond spread, *SPREAD*. The responses are obtained from separately estimating bivariate systems with 12 lags with the uncertainty proxies and log manufacturing production in levels. Qualitatively, the responses of production to all four series are similar—there is a gradual and highly persistent decline in production, with little evidence of a rebound at any forecast horizon. Table 7 shows the forecast error variance decomposition of manufacturing production at various forecast horizons. Innovations in any of the four uncertainty series account for important movements in production, more so than in Germany.[14] At a three-year forecast horizon, for example, innovations in BOS dispersion explain

[14]The magnitudes of the variation in production and employment accounted for by the BOS dispersion series are similar to those reported by Alexopoulos and Cohen (2009), using their *New York Times* uncertainty index over the period 1962–2008.

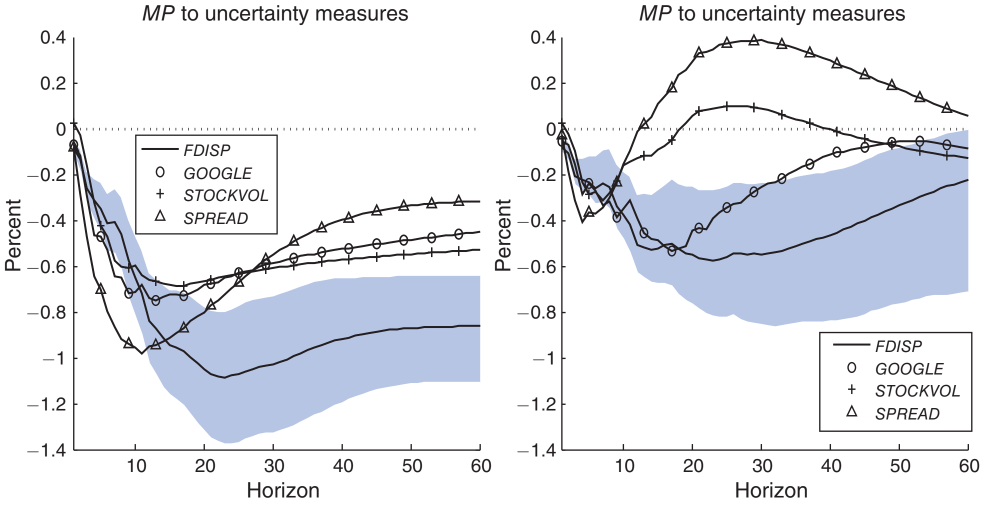

Figure 6. IRFs with Different Uncertainty Measures: United States

Notes: This figure plots in the left panel the response of log manufacturing production to various uncertainty measures. The responses are obtained from separately estimating a bivariate system with each uncertainty measure. The frequency of the series in the VARs is monthly, the VARs are estimated with 12 lags, and manufacturing production enters the systems in levels. *FDISP* is the forecast disagreement index, based on Q3. *GOOGLE* is the Google News subindex that is based on economic uncertainty from Baker, Bloom, and Davis (2012). *STOCKVOL* is the monthly measure of stock market volatility from Bloom (2009), which until 1986 is realized monthly stock market return volatility, and thereafter an implied volatility index. *SPREAD* refers to the monthly spread of the 30-year Baa-rated corporate bond yield index over the 30-year treasury bond yield (in months where the 30-year treasury bond was missing we used the 20-year treasury bond instead). The sample period for the VAR with *FDISP* is 5/1968–12/2011, for the one with *GOOGLE* 1/1985–12/2011, and for the ones with *STOCKVOL* and *SPREAD* 7/1962–12/2011. The shaded gray region is the +/− one standard error confidence band obtained from the system using *FDISP* as the uncertainty measure. The right panel displays similar results, but from a larger VAR, as in Bloom (2009), with the log level of the S&P 500 stock index, log manufacturing production, log manufacturing employment, log average hours worked in manufacturing, the log wage in manufacturing, the log aggregate CPI, the Federal Funds rate, and a measure of uncertainty, ordered second after the stock market level.

Table 7—MP Forecast Variance due to Uncertainty: United States

Horizon	*FDISP*	*GOOGLE*	*STOCKVOL*	*SPREAD*
$h = 1$	1.31	1.46	0.08	1.22
$h = 12$	11.85	19.56	11.08	29.42
$h = 36$	33.83	18.67	12.44	21.52
$h = 60$	39.08	17.95	12.04	16.95

Notes: The columns correspond to different measures of uncertainty used in the bivariate VAR system for the US. The rows show the fraction (multiplied by 100) of the total forecast error variance of log manufacturing production due to innovations in uncertainty, where the uncertainty proxy is ordered first in a recursive identification. The frequency of the series in the VARs is monthly, the VARs are estimated with 12 lags, and manufacturing production enters the systems in levels. *FDISP* is the forecast disagreement index, based on Q3. *GOOGLE* is the Google News subindex that is based on economic uncertainty from Baker, Bloom, and Davis (2012). *STOCKVOL* is the monthly measure of stock market volatility from Bloom (2009), which until 1986 is realized monthly stock market return volatility, and thereafter an implied volatility index. *SPREAD* refers to the monthly spread of the 30-year Baa-rated corporate bond yield index over the 30-year treasury bond yield (in months where the 30-year treasury bond was missing we used the 20-year treasury bond instead). The sample period for the VAR with *FDISP* is 5/1968–12/2011, for the one with *GOOGLE* 1/1985–12/2011, and for the ones with *STOCKVOL* and *SPREAD* 7/1962–12/2011.

about one-third of the forecast error variance of production. The Google uncertainty index and the corporate bond spread account for around 20 percent of the variance of production at the 3-year horizon, while stock volatility explains about 10 percent.

The qualitative nature of these estimated responses to an increase in uncertainty—in particular the persistent and protracted decline in production—differs substantially from the impulse responses estimated in Bloom (2009), who finds empirical evidence in support of the "wait and see" mechanism, with the estimated response of production to an increase in stock market volatility following a "bust-boom" cycle. Bloom's (2009) empirical analysis differs from ours in an important way, he estimates a substantially larger VAR system.[15]

The results using our survey-based uncertainty proxy from the BOS are robust to estimating a significantly larger VAR system. Figure 6 in the right panel presents responses of production to surprise increases in different measures of uncertainty in a way analogous to the bivariate VARs (in the left panel of Figure 6). These responses are obtained from estimating the eight variable system in Bloom (2009), which features the log level of the S&P 500 stock index, log manufacturing production, log manufacturing employment, log average hours worked in manufacturing, the log wage in manufacturing, the log aggregate CPI, the Federal Funds rate, and a measure of uncertainty. The exact variable definitions and sources are available in Tables A1 and A2. The systems are estimated with 12 lags, all variables enter in levels, and, following Bloom (2009), the uncertainty series are ordered second after the stock market level, though the results are largely invariant to this ordering assumption.

The response of production to an increase in BOS forecast dispersion, *FDISP*, is again negative, protracted, and highly persistent. As naturally occurs in a system with more autoregressive parameters to estimate, the response is somewhat less persistent than in the bivariate case, but the peak negative response still occurs at a horizon of around two years, and there is no evidence of a strong rebound effect. The response estimated when using the Google News uncertainty index is qualitatively similar to the one using *FDISP*, particularly over the first two years. A "wait and see" bust-boom cycle is not present. Smaller and larger VAR systems have different strengths and weaknesses; smaller VARs are parsimonious and can be more credibly estimated and identified, but large VARs may be less prone to misspecification problems. We take this robustness to different VAR specifications for both the survey and the news-based uncertainty indices as an encouraging sign of their usefulness in measuring uncertainty.

[15] There are two other differences. In Bloom (2009) an HP filter is applied to all of the series before estimating the VAR, and there is a focus on "large" uncertainty events. HP filtering prior to estimation is neither a common nor a recommended practice in the SVAR literature. Including all variables in levels, as we and many other SVAR papers do, is a specification that is robust to cointegration among trending variables; see, for example, Christiano, Eichenbaum, and Evans (1999, 2005), Uhlig (2005), and the references therein. HP filtering the data precludes by construction very persistent or permanent effects of uncertainty shocks. It turns out that the HP filtering does not matter in Bloom's (2009) larger VAR system, but it does make a difference in the smaller systems. Bloom (2009) also focuses on a 0–1 indicator variable meant to capture periods when stock market volatility is abnormally high. In online Appendix B we alter our baseline VARs by creating a similar index for periods in which BOS forecast dispersion is more than one standard deviation above its mean. Including this in the VAR system yields very similar results to using the actual forecast dispersion series. The same holds true for the Google News uncertainty index and stock market volatility. Only *SPREAD* starts to show somewhat stronger rebound dynamics.

Table 8—MP Forecast Variance due to Uncertainty: United States, Large System

Horizon	*FDISP*	*GOOGLE*	*STOCKVOL*	*SPREAD*
$h = 1$	1.48	1.04	0.13	0.18
$h = 12$	7.90	11.45	4.24	6.95
$h = 36$	19.03	17.23	1.63	7.69
$h = 60$	21.22	12.08	1.54	8.09

Notes: See notes to Table 7. The VARs feature the log level of the S&P 500 stock index, log manufacturing production, log manufacturing employment, log average hours worked in manufacturing, the log wage in manufacturing, the log aggregate CPI, the Federal Funds rate, and a measure of uncertainty. The systems are estimated with 12 lags, all variables enter in levels, and the uncertainty series are ordered second after the stock market level.

The response with stock market volatility is quite different, both from the responses with *FDISP* and *GOOGLE*, but also from the response to stock market volatility in the bivariate system. In particular, production declines and rebounds fairly quickly, in a manner broadly consistent with the implications of "wait and see." Incidentally, the response to an innovation in corporate bond spreads is similar to the response to stock volatility, with a strong decline-rebound effect. Table 8 shows the forecast error variance decomposition of production in this larger VAR system. Innovations in BOS forecast dispersion account for 10–20 percent of the forecast error variance of production at horizons from 1 to 5 years. Innovations in the Google News uncertainty index also account for significant movements in production. Surprise movements in stock volatility, in contrast, account for less than 5 percent of the forecast error variance of production at all horizons. Movements in corporate bond spreads are somewhere in the middle. One possible interpretation of these results is that asset market variables (stock volatility and the corporate bond spread) pick up a kind of uncertainty that is not captured by survey-based and news-based uncertainty indices and that triggers "wait and see" dynamics. Judging from the forecast error variance decomposition in Table 8, if this is the case these "wait and see" dynamics are nevertheless small in comparison to whatever mechanism drives the larger and more persistent responses to the survey and news-based uncertainty indices.

Another possible interpretation for these differences is that policy reacts differently to movements in asset market conditions than to movements in uncertainty picked up by other measures. Experimentation with different-sized VAR systems provides some credence to this interpretation. In particular, the large rebound effect in production subsequent to a surprise increase in stock volatility depends critically on whether or not nominal variables (the log CPI and the Fed Funds rate) are included in the VAR. The upper row of Figure 7 shows responses of production to innovations in stock market volatility and BOS forecast dispersion in the large VAR system discussed above as well as in the same system, but without the CPI and the Fed Funds rate. The responses of production to BOS forecast dispersion are similar in the two systems and statistically indistinguishable. The response of production to a surprise increase in stock market volatility is quite different when the nominal variables are not in the VAR. In particular, the response of production to stock volatility is quite persistent, in a manner qualitatively similar to the response to forecast dispersion. The bottom row of the figure plots the impulse response of the Fed Funds rate to innovations in stock market volatility and BOS forecast dispersion in the eight variable system. Here there is a noticeable difference—the funds rate

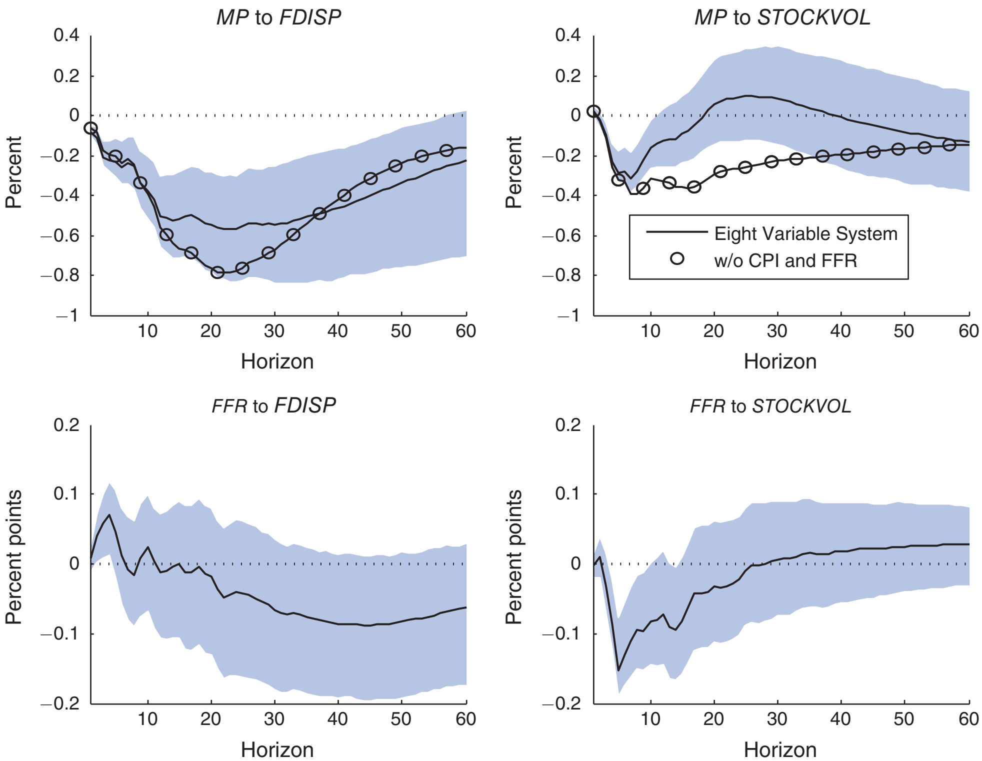

Figure 7. IRFs With and Without Nominal Variables: United States

Notes: This figure plots impulse responses obtained from estimating six and eight variable VAR systems with either *FDISP* or *STOCKVOL* as uncertainty measures. The eight variable system is the same as described in the notes to Figure 6; the six variable system drops the log CPI and the Federal Funds rate from this system. The upper panel plots responses of production to innovations in the two uncertainty proxies in both the six and eight variable systems, where the uncertainty proxies are ordered second after the stock market level. The bottom panel plots responses of the Fed Funds rate to innovations in the uncertainty series from the eight variable system. Shaded regions are +/− one standard error confidence bands from the eight variable system.

drops sharply soon after an increase in stock market volatility, whereas it essentially does not react at all to a movement in forecast dispersion. This is at least suggestive that the rebound effect in the response to stock market volatility may be driven by endogenously expansionary monetary policy, rather than arising as a consequence of pent-up factor demand from the "wait and see" channel.

The online Appendix B conducts the same robustness checks for the United States as for Germany regarding "large" uncertainty shocks, trend assumptions for activity variables, and lag choice. We also checked for robustness to a structural break occurring at the time of the "Great Moderation," using 1984 as a cutoff. In all cases we obtain similar results when looking at the dynamic relationship between *FDISP* from the BOS and economic activity. One potential concern with the BOS survey is its focus on large manufacturing firms. Online Appendix C presents results using an alternative but similar survey for the United States—the Small Business Trends Survey (SBETS), conducted by the National Federation of Independent Businesses (NFIB). It is explicitly focused on small firms, and asks questions very similar to the BOS survey. Constructing a measure of forecast dispersion in an analogous way, we obtain very similar impulse responses of manufacturing production to surprise movements in the forecast dispersion series based on this survey. This gives us confidence that our results are not driven by firm composition.

C. *Discussion*

What can explain the qualitatively different impulse response functions of economic activity to innovations in business uncertainty in Germany compared to the United States? Germany (see Figures 3 and 4) features bust-boom cycles at least broadly consistent with "wait and see" dynamics, whereas the evidence for "wait and see" effects in the United States is much more mixed (see Figures 5 and 6). In fact, the bulk of the evidence leads us to conclude that surprise increases in uncertainty have more persistent negative effects on economic activity in the United States than in Germany.

The "wait and see" channel relies on frictions to adjusting labor and capital in the short run. Among OECD countries during the time period we analyze, the United States had the lowest index of "employment protection," which seeks to quantify the "procedures and costs involved in dismissing individuals or groups of workers and the procedures involved in hiring workers on fixed-term or temporary work agency contracts."[16] Germany's employment protection index, in contrast, is well above the average of the OECD countries. We view this index as an imperfect but useful measure of the costs of adjusting labor in the two countries. Given the putative difference in the cost of adjusting labor in the two countries, it stands to reason that "wait and see" might be a more important mechanism through which uncertainty affects economic activity in Germany than in the United States. Indeed, this pattern is borne out in the data, where, for the most part, we find that surprise increases in uncertainty in Germany lead to much shorter lived effects on production than in the United States.

The persistent, prolonged negative response of production to a surprise increase in the survey and news-based uncertainty measures in the United States is, of course, consistent with "wait and see" dynamics, if combined with an endogenous growth mechanism—R&D investment, embodied technological change, or human capital investment, for example. If the R&D sector has features making the "wait-and-see" mechanism particularly strong, then persistent, but transitory uncertainty shocks could lead to prolonged, if not permanent, effects on economic activity.

Alternatively, the prolonged negative response of production to a surprise increase in uncertainty might also indicate that channels other than "wait and see" may be relatively more important in the United States. A number of recent papers have brought attention to such alternative channels. Arellano, Bai, and Kehoe (2012) build a quantitative general equilibrium model in which an increase in uncertainty, in the presence of imperfect financial markets, leads firms to downsize projects to avoid default; this impact is exacerbated through an endogenous tightening of credit conditions and leads to a persistent reduction in output. Similarly, Christiano, Motto, and Rostagno (2010) develop a larger scale New Keynesian model with financial

[16] For details, see www.oecd.org/employment/protection.

frictions in which risk shocks have persistent effects on output. A common element in these papers is that uncertainty interacts with financial frictions to generate sizeable and persistent reductions in production.

Another friction that might propagate uncertainty shocks are agency problems: Panousi and Papanikolaou (2012) present a model of agency costs in which increases in idiosyncratic risk lead risk-averse managers to cut back on investment and present some empirical evidence for their theory. This effect is larger in firms where managers own a higher fraction of the firm. If in uncertainty-induced recessions mostly owner-managers are left over because outside equity dries up, a persistent decline in economic activity could ensue. Narita (2011) develops a model in which high uncertainty interacts with agency problems to lead to the destruction of projects and induces lower levels of risk-taking in the aggregate, which serves as a propagation mechanism for the initial uncertainty shock because lower risk projects have lower average returns.

An alternative interpretation of the persistent and prolonged implications of high uncertainty for production in the United States is that high uncertainty is driven by some kind of first moment shock that has long lived effects on production. One might refer to this explanation as the "by product" hypothesis, with high uncertainty perhaps more a consequence of a poor economy than a driving force. Van Nieuwerburgh and Veldkamp (2006) present a model in which agents have poor information when production is low, giving rise to endogenously high uncertainty in recessions. D'Erasmo and Moscoso Boedo (2012) build a model in which positive TFP shocks lead to higher intangible expenditures, such as investments in a customer base, which in turn lead to lower firm-level volatility. Bachmann and Moscarini (2011), Fostel and Geanakopolos (2012), and Tian (2012) offer additional theoretical explanations for this phenomenon, the gist of which is that bad economic times incentivize risky behavior.

There is some suggestive evidence in our VAR systems consistent with the "by product" interpretation. In particular, there is a high degree of contemporaneous negative correlation between innovations in uncertainty measures and forward-looking variables like confidence indexes and stock market levels. Figure 8 plots impulse responses of four different uncertainty series in the United States (BOS forecast dispersion, stock market volatility, the corporate bond spread, and the Google uncertainty index) to innovations in either a confidence index, $Frac_t^+ - Frac_t^-$ from the general conditions Q3 from the BOS survey (*CONF*), or the S&P 500 stock market level (*STOCK*).[17] These responses are obtained from separately estimating three variable systems with the confidence/stock market level, an uncertainty measure, and log manufacturing production, this time with the confidence/stock market-level variable ordered first. The plots are responses of uncertainty to a negative confidence/stock market innovation. In all cases there is a significant and persistent increase in the uncertainty measures to a surprise decline in confidence or the stock market. We view the responses in Figure 8 as at least consistent with, if not dispositive of, the "by product" hypothesis.[18]

[17] The results are fairly similar regardless of whether we use the confidence series or the stock market level, but are naturally somewhat stronger for the BOS dispersion series when matched with the BOS confidence series.

[18] The results in Figure 8 also suggest that whatever effects of uncertainty shocks we find, be they propagated through "wait and see" dynamics or otherwise, likely constitute an upper bound of the pure uncertainty effect, as at least partially uncertainty innovations may be driven by first-moment shocks.

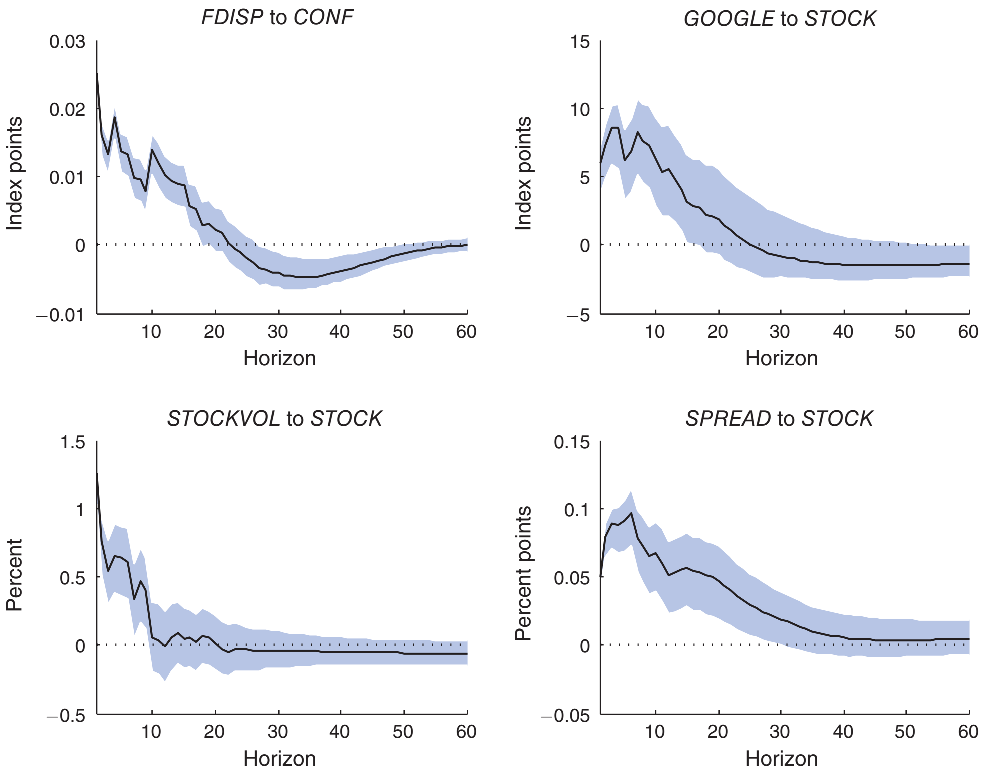

Figure 8. IRFs of Uncertainty Measures to First Moment Shocks: United States

Notes: The impulse responses in this figure are based on estimating three variable VAR systems with a measure of uncertainty, log manufacturing production, and either a measure of "confidence"—based on the relative score, $Frac_t^+ - Frac_t^-$ from Q3 (*CONF*)—or the stock market level (*STOCK*). The plots are responses of the different uncertainty measures to a *negative* innovation in confidence/stock market level, where the latter is ordered first. The frequency of the series in the VARs is monthly, the VARs are estimated with 12 lags, and the confidence/stock market level variable as well as manufacturing production enter the systems in levels. *FDISP* is the forecast disagreement index, based on Q3. *GOOGLE* is the Google News subindex that is based on economic uncertainty from Baker, Bloom, and Davis (2012). *STOCKVOL* is the monthly measure of stock market volatility from Bloom (2009). *SPREAD* refers to the monthly spread of the 30-year Baa-rated corporate bond yield index over the 30-year treasury bond yield. The sample period for the VAR with *FDISP* is 5/1968–12/2011, for the one with *GOOGLE* 1/1985–12/2011, and for the ones with *STOCKVOL* and *SPREAD* 7/1962–12/2011. Shaded gray regions are +/− one standard error confidence bands.

III. Conclusion

This paper adds to the growing theoretical and empirical literature on the economic consequences of uncertainty shocks. In particular, it proposes measuring business-level uncertainty from business survey data in both Germany and the United States.

The paper makes two main contributions. First, access to the confidential micro data from the IFO-BCS survey in Germany allows us to compare the properties of ex ante survey disagreement with measures based on qualitative ex post forecast errors. The cross-sectional dispersion of forecast errors is a natural metric for the uncertainty in firms' environments. Dispersion in ex post forecast errors turns out to be strongly correlated with dispersion in ex ante forecasts, which lends credence to the widespread practice of proxying for uncertainty with survey disagreement. Second, we analyze the dynamic relationship between uncertainty and economic activity in both Germany and the United States. The results for Germany are broadly consistent with the implications of the “wait and see” channel, highlighted in the recent literature. Nevertheless, the overall significance of this channel for aggregate fluctuations appears to be small. Surprise increases in uncertainty in the US, in contrast, have much more persistent and larger effects on economic activity, pointing to the importance of other channels for the uncertainty-output nexus, such as financial frictions, agency problems, or a “by product” interpretation.

Our results for the US suggest that research in the following four areas may prove fruitful: “wait and see” mechanisms in endogenous growth environments; fully specified mechanisms that endogenously generate uncertainty in bad economic times; more empirical research as to the direction of causality between first and second-moment shocks (such as, for instance, in Baker and Bloom 2012); and more theoretical and empirical research on stabilization policy in the context of large uncertainty effects.

Appendix: Data Description

Table A1—Data Sources: Germany

Variable	Description	Source
PRODCHANGE	Two-digit gross value added weighted relative score, $Frac_t^+ - Frac_t^-$, for Q2; monthly, manufacturing, West Germany, seasonally adjusted; same sample, for which we can compute qualitative forecast errors; available 1/1980–12/2010	IFO-BCS
FDISP	Two-digit gross value added weighted cross-sectional standard deviation for Q1; monthly, manufacturing, West Germany, seasonally adjusted; same sample, for which we can compute qualitative forecast errors; available 1/1980–12/2010	IFO-BCS
FEDISP	Two-digit gross value added weighted cross-sectional standard deviation of the qualitative forecast errors, as described in the main text; monthly, manufacturing, West Germany, seasonally adjusted; available 1/1980–12/2010	IFO-BCS
MEANABSFE	Two-digit gross value added weighted cross-sectional average of the absolute value of the qualitative forecast errors, as described in the main text; monthly, manufacturing, West Germany, seasonally adjusted; available 1/1980–12/2010	IFO-BCS
STOCKVOL	Concatenated series of the monthly volatility of daily DAX 30 returns (from 1/1980–1/1991) and the implied volatility index from DAX options (VDAX) (from 1/1992–12/2010)	Deutsche Börse
Manufacturing production (*MP*)	Index (2005=100), constant prices, manufacturing, West Germany, seasonally adjusted; from 2003 on interpolated from a quarterly index using the Chow-Lin procedure with the monthly manufacturing industrial production index from all of Germany as the reference time series; used from 1/1980 to 12/2010	Federal Statistical Office
Manufacturing employment	Manufacturing, all workers, West Germany, seasonally adjusted; used from 1/1980–12/2010	IAB
Manufacturing average hours	Manufacturing, seasonally adjusted; used from 1/1980–12/2010	Eurostat

Note: All series were downloaded off the Internet from the cited sources in March 2012 at the most recent vintage available at that time.

TABLE A2—DATA SOURCES: UNITED STATES

Variable	Description	Source
Manufacturing production (*MP*)	Index (2005=100), monthly, manufacturing, seasonally adjusted; used from 7/1962–12/2011	OECD main economic indicators
BLS monthly sect. and regio. empl.	Sum of the seasonally adjusted monthly, manufacturing employment series for Delaware, New Jersey, and Pennsylvania; available from 1/1990–12/2011	BLS
Philadelphia FED Coincident Index	Weighted sum of the monthly Philadelphia FED Coincident Indices for DE, NJ and PA; the months in a year were weighted by the annual nominal GDP for these states from the BEA; available from 1/1979–12/2010	Philadelphia FED, BEA
NIPA yearly sect. and regio. prod.	Weighted sum of the annual GDP quantity indices from the BEA for DE, NJ, and PA; the years were weighted by the annual nominal GDP for these three states from the BEA; available from 1977 to 2010	BEA
FDISP	Cross-sectional standard deviation for Q3; monthly, manufacturing, third FED district, seasonally adjusted; available 5/1968–12/2011	BOS
$FDISP_{SHIP}$	Cross-sectional standard deviation for Q4; monthly, manufacturing, third FED district, seasonally adjusted; available 5/1968–12/2011	BOS
GOOGLE	Google News subindex based on economic uncertainty (as opposed to political uncertainty) only; count of the number of articles in a given month in Google News mentioning "uncertainty" and phrases related to the economy, divided by the number of articles containing the word "today"; available 1/1985–12/2011	Baker, Bloom, Davis (2012)
STOCKVOL	Concatenated series of the monthly volatility of daily S&P500 returns (from 7/1962 to 12/1985) and the implied volatility index from options (VXO) (from 1/1986 to 12/2011)	Standard and Poor's
SPREAD	Spread of the 30-year Baa-rated corporate bond yield index over the 30-year treasury bond yield; in months where the 30-year treasury bond was missing the 20-year treasury bond was used; used from 7/1962–12/2011	Federal Reserve Board
BOS general conditions	Relative score, $Frac_t^+ - Frac_t^-$, for the one-month retrospective version of Q3; monthly, manufacturing, third FED district, seasonally adjusted; available from 5/1968–12/2011	BOS
BOS shipments	Relative score, $Frac_t^+ - Frac_t^-$, for the one-month retrospective version of Q4; monthly, manufacturing, third FED district, seasonally adjusted; available from 5/1968–12/2011	BOS
Manufacturing employment	All employees, monthly, manufacturing, seasonally adjusted; used from 7/1962–12/2011	BLS
Manufacturing average hours	Production workers, monthly, manufacturing, seasonally adjusted; used from 7/1962–12/2011	BLS
CPI	Index (1982–1984=100), all urban consumers, US city average, monthly, seasonally adjusted; used from 7/1962–12/2011	BLS
Wage	Average hourly earnings of production workers, monthly, manufacturing, seasonally adjusted; used from 7/1962–12/2011	BLS
Federal funds rate	Fed Funds Effective Rate, monthly average, seasonally adjusted; used from 7/1962–12/2011	Federal Reserve Board
Stock index (*STOCK*)	S&P 500 index; used from 7/1962–12/2011	Standard and Poor's
CONF	Relative score, $Frac_t^+ - Frac_t^-$, for Q3; monthly, manufacturing, third FED district, seasonally adjusted; available from 5/1968–12/2011	BOS

Note: All series were downloaded off the Internet from the cited sources in March 2012 at the most recent vintage available at that time.

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