Uncertainty and Economic Activity: Evidence from Business Survey Data*

Rüdiger Bachmann Steffen Elstner Eric R. Sims†

June 20, 2012

Abstract

This paper uses survey expectations data from both Germany and the United States to construct empirical proxies for time-varying business-level uncertainty. Access to the confidential micro data from the German IFO Business Climate Survey permits construction of uncertainty measures based on both ex-ante disagreement and on ex-post forecast errors. Ex-ante disagreement is strongly correlated with dispersion in ex-post forecast errors, lending credence to the widespread practice of proxying for uncertainty with disagreement. Surprise movements in either measure are associated with 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 administered by the Federal Reserve Bank of Philadelphia. In contrast to the German case, surprise increases in forecast dispersion lead to large and persistent reductions in production and employment.

*We thank seminar participants at RWTH Aachen University, the Federal Reserve Bank of Atlanta, Bank of Canada, Bundesbank, IAB Nuremberg, Université de la Méditerranée Aix-Marseille II, University of Michigan, 2010 Midwest Macro Meetings (Lansing), 2010 NBER-SI-ME, NYU Stern, Rochester, 2010 SED meeting (Montreal), 2010 World Congress of the Econometric Society in Shanghai, Yale and ZEW Mannheim as well as Robert Barsky, Eduardo Engel, Giuseppe Moscarini, Steven Davis, and four anonymous referees for helpful comments that have substantially improved the paper. We are grateful to Kai Carstensen and Sigrid Stallhofer from the IFO Institute as well as Holly Wade from the NFIB for providing us with their data and introducing us to the institutional backgrounds.

†Author affiliations and contact information, respectively: Bachmann: RWTH-Aachen University, NBER, IFO Institute, and CESifo, ruediger.bachmann@rwth-aachen.de; Elstner: IFO Institute, elstner@ifo.de; Sims: University of Notre Dame, NBER, and IFO Institute, esims1@nd.edu.

1 Introduction

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 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 ex-

[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 Soederlin (2003), Bond and Cummins (2004), Fuss and Vermeulen (2004), Clements (2008), Popescu and Smets (2010), and Baker et al. (2012).

cluded 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 2 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 3 we analyze the dynamic, conditional responses of economic activity to surprise movements in our survey-based uncertainty measures for both Germany and the US using structural vector autoregressions (SVARs).[2] There are 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

[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 et al. (2009) and Gilchrist and Zakrajsek (2011), who look at the dynamic effects of movements in corporate bond spreads; Alexopolous and Cohen (2009), who look at the effects of movements in an index based on the incidence of the words "uncertainty" and "economy" in the *New York Times*; and Baker et al. (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 (1999); Fuss and Vermeulen (2004); Bloom et al. (2007); and Bontempi et al. (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.

Bloom, et al (2011). The basic idea is that the interaction between high uncertainty and non-smooth 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 et al. (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 et al. (2011) show that firms downsize investment projects to avoid default when faced with higher risk. Christiano et al. (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 et al. (2008) and Chugh (2011).

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. Fernandez-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 Papanikolau (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 re-establishment of which

[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 (2012), 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 (2011).

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 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 US. 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 US is quite different from the one in Germany. In particular, the response of output to an innovation in uncertainty in the US 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 US, 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.

2 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 US 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.

2.1 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; towards 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 towards the end of the sample. In terms of firm size, the IFO-BCS contains all categories. About 9.4% of firms in our sample had less than 20 employees, roughly 32.0% had more than 20 but less than 100 employees, 47.3% employed between 100 and 1000 people, and 11.3% had a workforce of more than 1000.

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

Q 1 *"Expectations for the next three months: Our domestic production activities with respect to product X will (without taking into account differences in the length of months or seasonal fluctuations) increase, roughly stay the same, decrease."*

Q 2 *"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."*

[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), p. 18.

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]

$$FDISP_t = \sqrt{Frac_t^+ + Frac_t^- - \left(Frac_t^+ - Frac_t^-\right)^2}$$

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 nine combinations with five 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).

There is an obvious complication that arises because Q1 asks about production change ex-

[6] To ensure representativeness of the sample, for our baseline results we weight each firm observation with the gross valued added of the 2-digit sector to which the firm belongs relative to the gross valued added in manufacturing. Denote this weight by $\omega_{i,t}$. Then $Frac_t^+ \equiv \sum_i \omega_{i,t} * \mathbf{1}_{\text{"increase" response}}$ and $Frac_t^- \equiv \sum_i \omega_{i,t} * \mathbf{1}_{\text{"decrease" response}}$. 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.

pectations 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. Denote this firm-specific variable by $REALIZ_{i,t}$. It 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. Dividing by three is a normalization. $error_{i,t}$ then ranges from $\left[-\frac{4}{3},\frac{4}{3}\right]$. Intuitively, 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 $REALIZ_{i,t}$. 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 2-digit gross-value added weights, of the observed forecast errors:

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

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.

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 2-digit gross value added weighted average:

$$MEANABSFE_t = meanw(|error_{i,t+3}|)$$

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 US. 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 5/1968 to 12/2011.

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.[8] The small number of respondents is a drawback. Because of its broad scope ("general business activity"), the main question of interest is:

Q 3 *"General Business Conditions: What is your evaluation of the level of general business activity six months from now vs. [CURRENT MONTH]: decrease, no change, increase?"*

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 which is more specifically geared towards firm-specific conditions, Q4:

[8] In Appendix D, 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.

Q 4 *"Company Business Indicators: Shipments six months from now vs. [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 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 US.

2.2 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 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 12/1991 and an implied volatility index from 1/1992 onwards (see details in Appendix A). Shaded regions depict recessions as dated by the Sachverständigenrat, the so-called "Economic Wise Men" (see Sachverständigenrat, 2009, p. 261).

The upper plot shows how closely survey disagreement and dispersion in forecast errors track one another. Table 4, row 8 and 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 US. 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 the 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, 2011b) show for a large multi-sector firm-level data set that firm-level changes in value added, employment, and productivity display countercyclical dispersion.[9]

Switching gears, Figure 2 plots four different uncertainty proxies for the US. 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 News based economic uncertainty index recently constructed by Baker et al. (2012) (dashed line).[10] 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 NBER.

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 stronger and somewhat after the BOS series, especially in the latter part of the sample. The latter feature is

[9] 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.

[10] We thank Scott Baker, Nick Bloom and Steven Davis for providing us with their Google News subindex that is based on economic uncertainty (as opposed to economic policy uncertainty) only. They count the number of articles in a given month mentioning "uncertainty" and phrases related to the economy and divide it by the number of articles containing the word "today" to account for the overall increasing volume of news.

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 towards 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 US 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.[11]

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

[11] We will show in Section 3.2, 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.

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 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.

2.3 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.[12] The cross-sectional "within" variance amounts to over 98% of the observed total cross-sectional variance on average. Over time, fluctuations in the "within" variance explain roughly 92% of the fluctuations in the total variance; the "between" variance explains less than 1%, 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 quar-

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

terly 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 the Online Appendix B 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.

3 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 US.

3.1 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 1/1980 - 12/2010. 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 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 one 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 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 C. 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 1 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.

3.2 US

Our benchmark VAR for the US is also a bivariate system with a survey-based measure of uncertainty and a measure of economic activity. Our primary uncertainty measure for the US 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 5/1968 - 12/2011.

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 one percent, occurring at a horizon roughly two 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 five year horizon, production is still about one 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 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. At a three year forecast horizon, for example, innovations in BOS dispersion explain 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 three year horizon, while stock volatility explains about ten 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.[13]

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 manufactur-

[13]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 et al. (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 C 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.

ing 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 Appendix A. 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.

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 one to five 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 five 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 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 C conducts the same robustness checks for the US 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 D presents results using an alternative but similar survey for the US – 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.

3.3 Discussion

What can explain the qualitatively different impulse response functions of economic activity to innovations in business uncertainty in Germany compared to the US? 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 US 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 US 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 US 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."[14] 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. It thus stands to reason that "wait and see" dynamics might be an important driving force behind the conditional relationship between surprise increases in uncertainty and production in Germany. Though there is

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

some evidence consistent with "wait and see" dynamics in the US, particularly with stock market volatility and the corporate bond spread in a large dimensional VAR system, these effects seem to be weak in comparison to what obtains when focusing on the survey-based uncertainty measure from the BOS or the Google News uncertainty index.

The persistent, prolonged negative response of production to a surprise increase in the survey and news-based uncertainty measures in the US 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 US. A number of recent papers have brought attention to such alternative channels. Arellano et al. (2011) 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 et al. (2010) develop a larger scale New Keynesian model with financial 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 US 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 US (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 ($STOCK$).[15] 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.[16]

[15] 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.

[16] 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

4 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 US.

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.

at least partially uncertainty innovations may be driven by first-moment shocks.

References

[1] Alexopoulos, M. and J. Cohen (2009). "Uncertain *Times*, Uncertain Measures." University of Toronto Working Paper 352.

[2] Arellano, C., Bai, Y. and P. Kehoe (2011). "Financial Markets and Fluctuations in Uncertainty." Federal Reserve Bank of Minneapolis Research Department Staff Report.

[3] Bachmann, R. and C. Bayer (2011a). "Investment Dispersion and the Business Cycle. " NBER WP 16861.

[4] Bachmann, R. and C. Bayer (2011b). "Uncertainty Business Cycles - Really?" NBER WP 16862.

[5] Bachmann, R. and G. Moscarini (2011). "Business Cycles and Endogenous Uncertainty." Mimeo, Yale University.

[6] Baker, S., and N. Bloom (2012). "Does Uncertainty Reduce Growth? Using Natural Disasters as Natural Experiments." Mimeo, Stanford University.

[7] Baker, S., Bloom, N., and S. Davis (2012). "Measuring Economic Policy Uncertainty." Mimeo, Stanford University.

[8] Basu, S. and B. Bundick (2011). "Uncertainty Shocks in a Model of Effective Demand." Mimeo, Boston College.

[9] Becker, P. and K. Wohlrabe (2008). "Micro Data at the Ifo Institute for Economic Research - The 'Ifo Business Survey' Usage and Access." *Schmollers Jahrbuch*, 128, 307–319.

[10] Berger, D. and J. Vavra (2011). "Dynamics of the U.S. Price Distribution." Mimeo, Yale University.

[11] Bernanke, B. (1983)."Irreversibility, Uncertainty, and Cyclical Investment." *The Quarterly Journal of Economics*, 98(1), 85–106.

[12] Bloom, N. (2009). "The Impact of Uncertainty Shocks." *Econometrica*, 77(3), 623–685.

[13] Bloom, N., S. Bond, J. Van Reenen (2007). "Uncertainty and investment dynamics." *Review of Economic Studies*, 74, 391–415.

[14] Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten and S. Terry (2011). "Really Uncertain Business Cycles." Mimeo, Stanford University..

[15] Bomberger, W. (1996)."Disagreement as a Measure of Uncertainty." *Journal of Money, Credit and Banking*, 28(3), 391–415.

[16] Bond, S. and J. Cummins (2004). "Uncertainty and Investment: an Empirical Investigation Using Data on Analysts' Profits Forecasts." Mimeo, Federal Reserve Board.

[17] Bontempi, L., R. Golinelli and G. Parigi (2010). "Why demand uncertainty curbs investment: Evidence from a panel of Italian manufacturing firms." *Journal of Macroeconomics*, 32(1), 218–238.

[18] Christiano, L., Eichenbaum, M., and C. Evans (1999). "Monetary Policy Shocks: What Have We Learned and to What End?" In *Handbook of Macroeconomics*, eds. J. Taylor and M. Woodford. Amsterdam: Elsevier.

[19] Christiano, L., Eichenbaum, M., and C. Evans (2005). "Nominal Rigidites and the Dynamic Effects of a Shock to Monetary Policy." *Journal of Political Economy*, 113(1), 1–45.

[20] Christiano, L., R. Motto and M. Rostagno (2010). "Financial Factors in Economic Fluctuations." ECB Working Paper 1192.

[21] Chugh, S. (2011). "Firm Risk and Leverage-Based Business Cycles." Mimeo, Boston College.

[22] Clements, M. (2008)."Consensus and Uncertainty: Using Forecast Probabilities of Output Declines." *International Journal of Forecasting*, 24, 76–86.

[23] D'Erasmo, P., and H. Moscoso Boedo (2012). "Intangibles and Endogenous Firm Volatility over the Business Cycle." Mimeo, University of Maryland.

[24] Dixit, A. and R. Pindyck (1994)."Investment under Uncertainty." Princeton University Press: Princeton, New Jersey.

[25] Dorofeenko, V., G. Lee, and K. Salyer (2008). "Time-Varying Uncertainty and the Credit Channel." *Bulletin of Economic Research*, 60(4), 375–403.

[26] Federer, P. (1993)."Does Uncertainty Affect Investment Spending?" *Journal of Post Keynesian Economics*, 16(1), 19–35.

[27] Fernandez-Villaverde, J., P. Guerron-Quintana, J. Rubio-Ramirez and M. Uribe (2011). "Risk Matters: The Real Effects of Volatility Shocks." *The American Economic Review*, 101(6), 2530–2561.

[28] Fostel, A. and J. Geanakoplos (2012). "Why Does Bad News Increase Volatility and Decrease Leverage?" *Journal of Economic Theory*, 147(2), 501-525.

[29] Fuss, C. and P. Vermeulen (2004). "Firm's Investment Decisions in Response to Demand and Price Uncertainty." *Applied Economics*, 40(18), 2337-2351.

[30] Gilchrist, S., J. Sim and E. Zakrajsek (2010). "Uncertainty, Credit Spreads and Aggregate Investment." Mimeo, Boston University.

[31] Gilchrist, S., V. Yankov and E. Zakrajsek (2009). "Credit Market Shocks and Economic Fluctuations: Evidence from Corporate Bond and Stock Markets." *Journal of Monetary Economics*, 56(4),471–493.

[32] Gilchrist, S., and E. Zakrajsek (2011). "Credit Spreads and Business Cycle Fluctuations." NBER WP 17021.

[33] Giordano, P. and P. Soederlind (2003)."Inflation Forecast Uncertainty." *European Economic Review*, 47, 1037–1059.

[34] Goldrian, G. (2004)."Handbuch der umfragebasierten Konjunkturforschung." ifo Beträge zur Wirtschaftsforschung, München.

[35] Guiso, L. and G. Parigi (1999)."Investment and Demand Uncertainty." *The Quarterly Journal of Economics*, 114(1), 185–227.

[36] Kilian, L. (1998). "Small Sample Confidence Intervals for Impulse Response Functions." *Review of Economics and Statistics*, 80(2), 218–230.

[37] Leahy, J.V. and T.M. Whited (1996)."The Effect of Uncertainty on Investment: Some Stylized Facts." *Journal of Money, Credit and Banking*, 28(1), 64–83.

[38] Lee, J. (2011). "Uncertainty, the Liquidity Trap, and Social Insurance." Mimeo, Harvard University.

[39] Mericle, D. (2011). "Does an Aggregate Increase in Idiosyncratic Volatility Cause a Recession?" Mimeo, University of Chicago.

[40] Narita, F. (2011). "Hidden Actions, Risk-Taking and Uncertainty Shocks." Mimeo, University of Minnesota.

[41] Panousi, V. and D. Papanikolaou (2012), "Investment, Idiosyncratic Risk, and Ownership." forthcoming, *Journal of Finance*.

[42] Popescu, A. and F. Smets (2010). "Uncertainty, Risk-Taking and the Business Cycle in Germany." *CESifo Economic Studies*, 56(4), 596–626.

[43] Sachverständigenrat (2009). "Die Zukunft nicht aufs Spiel setzen - Jahresgutachten 2009/10." Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung.

[44] Schaal, E. (2011). "Uncertainty, Productivity and Unemployment in the Great Recession." Mimeo, Princeton University.

[45] Tian, C. (2012). "Technology Choice and Endogenous Productivity Dispersion over the Business Cycles." Mimeo, University of Pennsylvania.

[46] Trebing, M. (1998). "What's Happening in Manufacturing: 'Survey Says...''' *Federal Reserve Bank of Philadelphia Business Review*, September/October 1998, 15–29.

[47] Uhlig, H. (2005). "What are the effects of monetary policy on output? Results from an agnostic identification procedure." *Journal of Monetary Economics*, 52(2), 381-419.

[48] Van Nieuwerburgh, S. and L. Veldkamp (2006). "Learning Asymmetries in Real Business Cycles." *Journal of Monetary Economcs*, 53(4), 753-772.

[49] Vavra, J. (2012). "Inflation Dynamics and Time-Varying Uncertainty: New Evidence and an Ss Interpretation." Mimeo, Yale University.

[50] Zarnovitz, V. and L. Lambros (1987). "Consensus and Uncertainty in Economic Prediction." *The Journal of Political Economy*, 95(3), 591–621.

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.

Table 2: POSSIBLE EXPECTATION ERRORS – THREE MONTHS 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: $REALIZ_{i,t} = \#(Increase_{i,t-k})_{k=0,...,2} - \#(Decrease_{i,t-k})_{k=0,...,2}$. In words: $REALIZ_{i,t}$ 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-a-vis a three-month production change expectation uttered in month $t-3$.

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. & Regio. Empl.	0.55	0.59	0.55
Philadelphia FED Coincident Index	0.72	0.72	0.56
NIPA Yearly Sect. & 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.

Table 4: BASIC DATA ANALYSIS: GERMANY

	PRODCHANGE	*FDISP*	*FEDISP*	*MEANABSFE*	*STOCKVOL*
Volatility	3.71%	7.27%	5.83%	8.97%	39.97%
Skewness	-0.49	0.17	0.08	0.11	1.67
Kurtosis	3.61	3.42	3.32	3.09	5.97
1^{st} 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.

Table 5: BASIC DATA ANALYSIS: US

	FDISP	$FDISP_{SHIP}$	*GOOGLE*	*STOCKVOL*	*SPREAD*
Volatility	8.95%	8.00%	63.75%	34.89%	39.57%
Skewness	-0.25	-0.05	2.07	2.52	1.73
Kurtosis	2.80	3.09	8.38	12.53	7.94
1^{st} Order Autocorr.	0.70	0.63	0.91	0.96	0.89
Corr w/ $\Delta \ln MP$ - Monthly	-0.25	-0.25	-0.41	-0.49	-0.29
Corr w/ $\Delta \ln MP$ - Quarterly	-0.32	-0.34	-0.64	-0.72	-0.45
Corr w/ BOS General Conditions	-0.44	-0.47	-0.47	-0.52	-0.43
Corr w/ BOS Shipments	-0.26	-0.28	-0.55	-0.53	-0.43
Corr w/ *FDISP*	1	0.83	-0.09	0.22	0.19
Corr w/ $FDISP_{SHIP}$		1	-0.05	0.23	0.25
Corr w/ *GOOGLE*			1	0.62	0.58
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 et al. (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.

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 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.

Table 7: MP FORECAST VARIANCE DUE TO UNCERTAINTY: US

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%

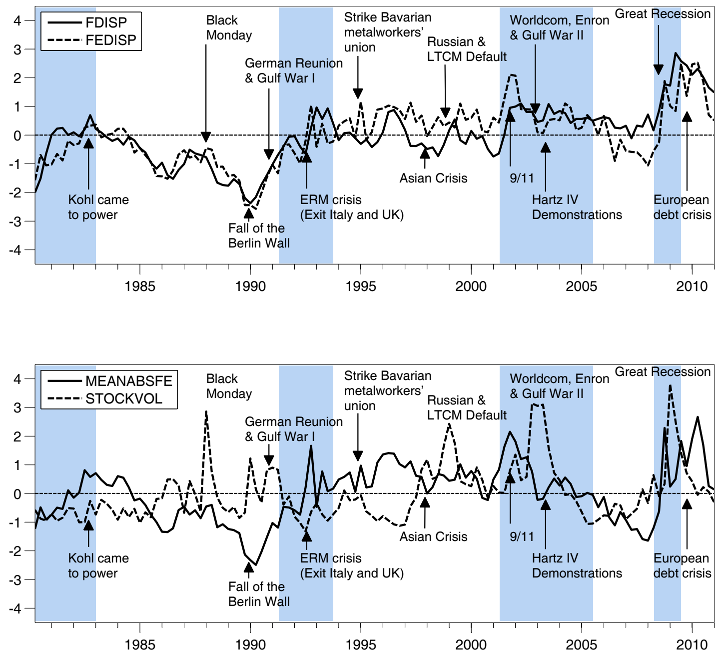
Notes: The columns correspond to different measures of uncertainty used in the bivariate VAR system for the US. The rows show the fraction of the total forecast error variance of log manufacturing production due to innovations in uncertainty, where the uncertainty proxy is ordered first in a recursive 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 et al. (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.

Table 8: MP FORECAST VARIANCE DUE TO UNCERTAINTY: US, 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%

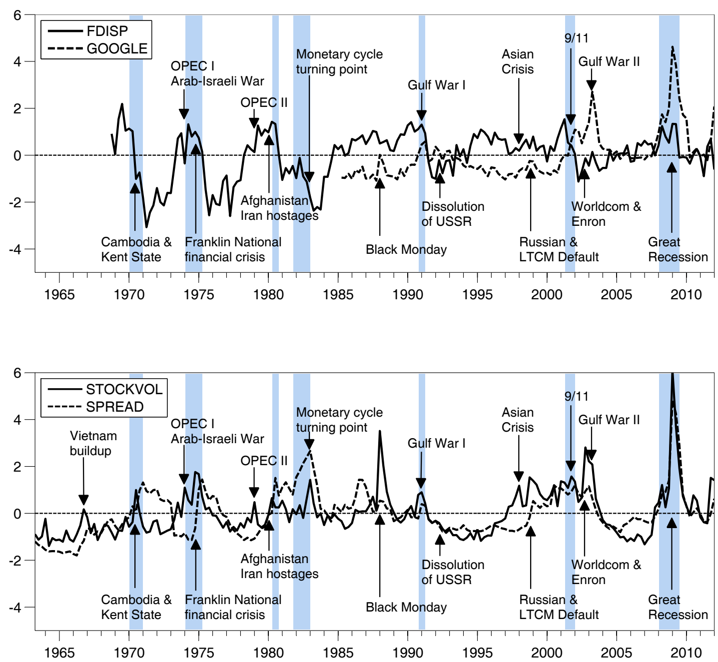
Notes: see notes to Table 7. The VARs feature the log level of the S&P 500 stock index, log manufacturing production, log manufacturing employment, log average hours worked in manufacturing, the log wage in manufacturing, the log aggregate CPI, the Federal Funds rate, and a measure of uncertainty. The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

Figure 1: UNCERTAINTY MEASURES: GERMANY



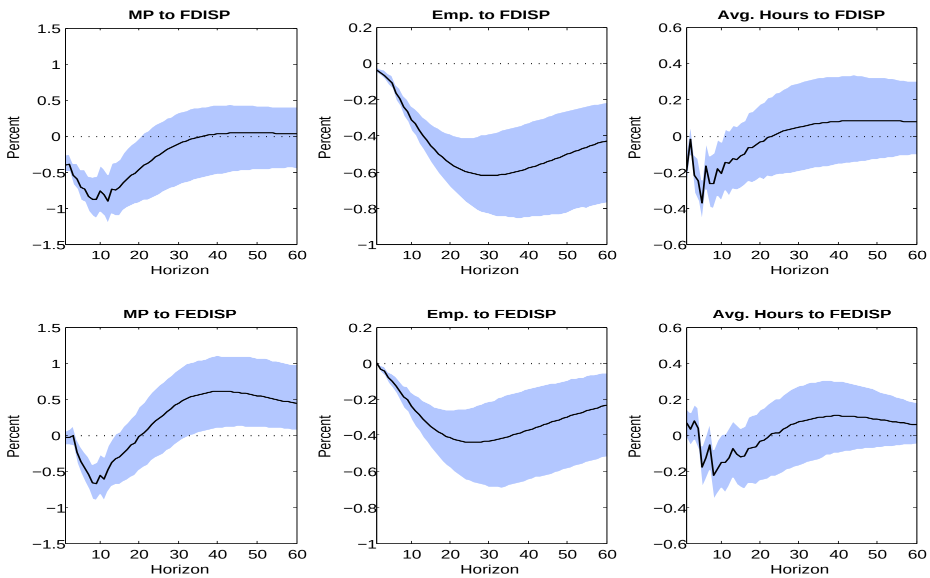
Notes: The upper panel shows the quarterly averages of the monthly time series of the IFO-BCS ex-ante forecast dispersion $FDISP$ and of the standard deviation of ex-post forecast errors $FEDISP$. The lower panel plots the quarterly averages of the average absolute ex-post forecast errors, $MEANABSFE$, 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, p. 261): I/1980 - IV/1982, I/1991 - III/1993, I/2001 - II/2005 and I/2008 - II/2009.

Figure 2: UNCERTAINTY MEASURES: US



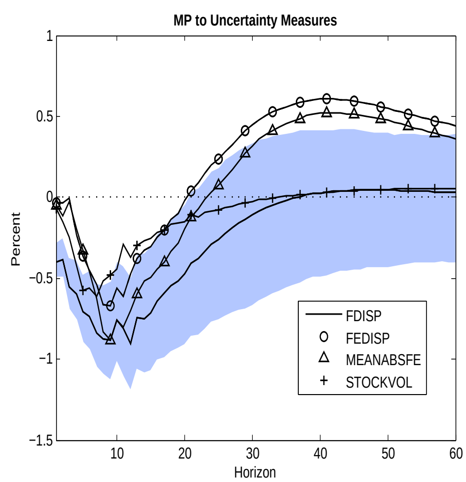
Notes: The upper panel shows the quarterly average of the BOS ex-ante forecast dispersion $FDISP$ and the quarterly average of the Google News uncertainty index $GOOGLE$. The lower panel plots the quarterly averages of stock market volatility $STOCKVOL$ and the corporate bond spread $SPREAD$. The sample for $FDISP$ is II/1968 - IV/2011, for $GOOGLE$ it is I/1985 - IV/2011, and for $STOCK-VOL$ 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.

Figure 3: IRFS TO UNCERTAINTY: GERMANY



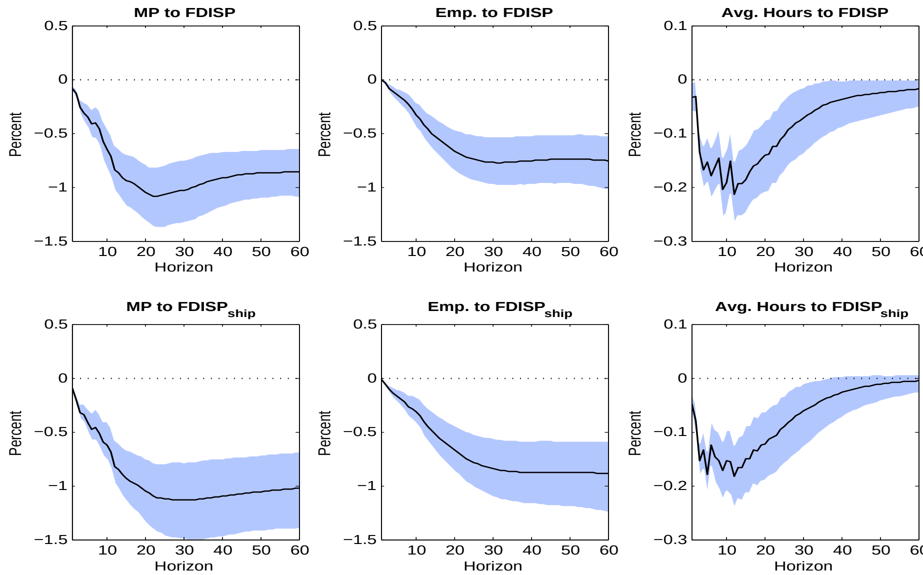
Notes: The upper row plots impulse responses of manufacturing production, manufacturing employment, and manufacturing average hours worked for West Germany (all in logs) to innovations in $FDISP$, obtained from separately estimating bivariate VARs with the IFO-BCS forecast dispersion index (ordered first) 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: IRFS WITH DIFFERENT UNCERTAINTY MEASURES: GERMANY



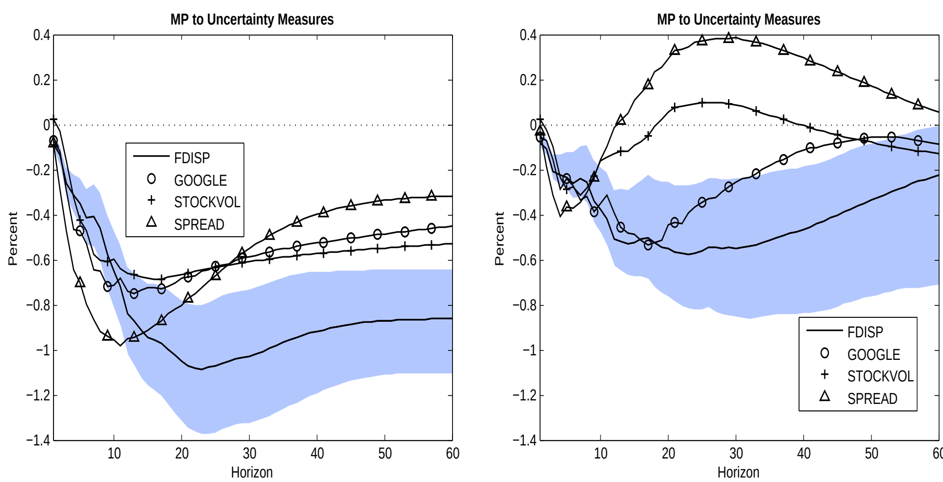
Notes: This figure plots impulse responses of West German manufacturing production to innovations in various uncertainty measures. The responses are obtained from separately estimating a bivariate system with each different uncertainty measure and log manufacturing production. The frequency of the series 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 $FDISP$.

Figure 5: IRFs to Uncertainty: US



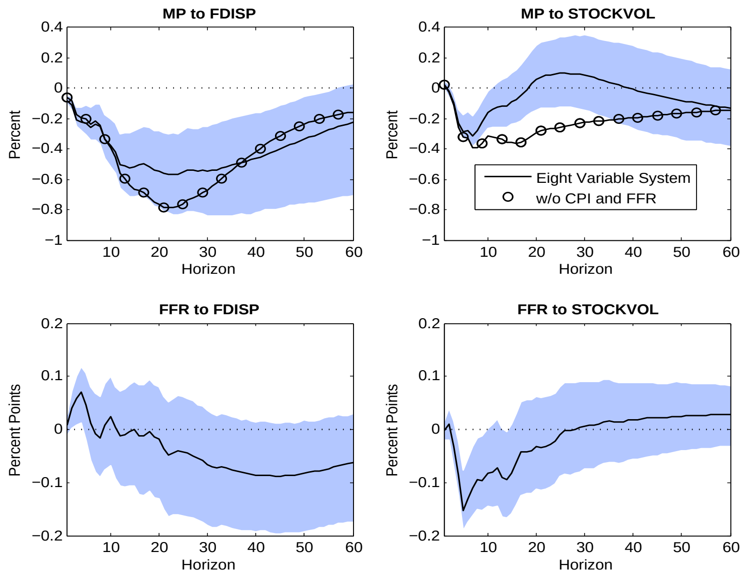
Notes: The upper row plots impulse responses of manufacturing production, manufacturing employment, and manufacturing average hours worked (all in logs) to innovations in $FDISP$, obtained from separately estimating bivariate VARs with the BOS forecast dispersion index (ordered first) and the different 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: IRFs with Different Uncertainty Measures: US



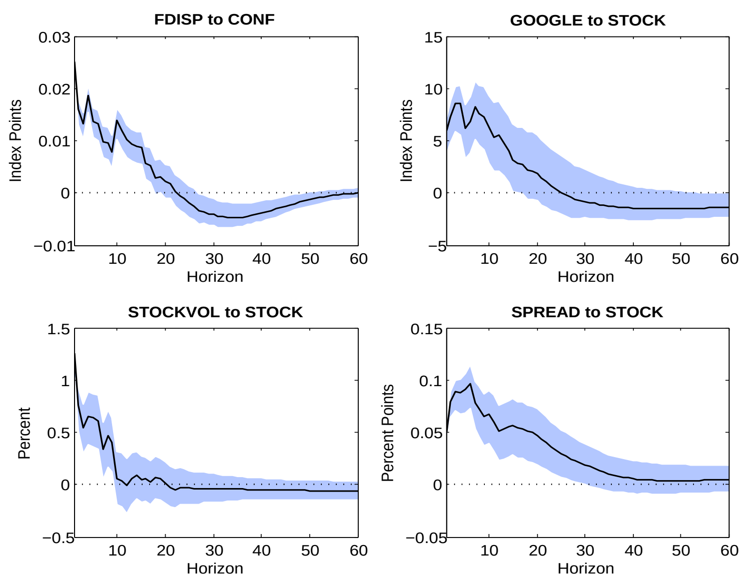
Notes: This figure plots in the left panel the response of log manufacturing production to various uncertainty measures. The responses are obtained from separately estimating a bivariate system with each uncertainty measure. The frequency of the series in the VARs is monthly, the VARs are estimated with 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 et al. (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.

Figure 7: IRFs with and Without Nominal Variables: US



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.

Figure 8: IRFs of Uncertainty Measures to First Moment Shocks: US



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 et al. (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.

A Data Description

Germany

Table 9: DATA SOURCES: GERMANY

Variable	Description	Source
PRODCHANGE	2-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	2-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	2-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	2-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

United States

Table 10: DATA SOURCES: US

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. & 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. & 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 SP500 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 ($STOCK$)	SP500 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

B A Simple Model - For Online Publication Only

To illustrate the relationship between concepts such as disagreement, uncertainty, and cross-sectional variance, we use the following simple two-period model: tomorrow's business situation of firms is unknown today. It can move in three directions. Business situations can improve $(+1)$, stay the same (0) or deteriorate (-1). For each firm, nature draws the change in business situation from the following probability distribution: $[0.5 \times (1-p), p, 0.5 \times (1-p)]$, which is assumed to be known to the firms. The cross-sectional variance of the future business situation is obviously $(1-p)$, a decreasing function of p. Furthermore, we assume that businesses receive a signal about the change in their business situation, with a structure illustrated in Table B.1. For instance, if tomorrow's true state is $+1$, the signal can be $+1$ (with probability q) and 0 with probability $(1-q)$. q thus measures the informativeness of the signal.

Table B.1: A SIMPLE TWO-PERIOD MODEL OF FIRMS' BUSINESS SITUATIONS

State Tomorrow

$0.5 \times (1-p) \swarrow$			$\downarrow p$			$\searrow (1-p) \times 0.5$
+1			0			-1
$q \swarrow$	$\searrow (1-q)$	$0.5 \times (1-q) \swarrow$	$q \downarrow$	$\searrow (1-q) \times 0.5$	$(1-q) \swarrow$	$\searrow q$
+1	0	+1	0	-1	0	-1

Signal

Using Bayes' Law we can compute the probabilities of the true state, conditional on a signal:

1. (a) $Prob(state = 1|signal = 1) = \frac{q \times 0.5 \times (1-p)}{q \times 0.5 \times (1-p) + 0.5 \times (1-q) \times p}$

   (b) $Prob(state = 0|signal = 1) = \frac{0.5 \times (1-q) \times p}{q \times 0.5 \times (1-p) + 0.5 \times (1-q) \times p}$

   (c) $Prob(state = -1|signal = 1) = 0$

2. (a) $Prob(state = 1|signal = 0) = \frac{(1-q) \times 0.5 \times (1-p)}{(1-q) \times 0.5 \times (1-p) + q \times p + (1-q) \times 0.5 \times (1-p)}$

   (b) $Prob(state = 0|signal = 0) = \frac{q \times p}{(1-q) \times 0.5 \times (1-p) + q \times p + (1-q) \times 0.5 \times (1-p)}$

   (c) $Prob(state = -1|signal = 0) = \frac{(1-q) \times 0.5 \times (1-p)}{(1-q) \times 0.5 \times (1-p) + q \times p + (1-q) \times 0.5 \times (1-p)}$

3. (a) $Prob(state = 1|signal = -1) = 0$

   (b) $Prob(state = 0|signal = -1) = \frac{0.5\times(1-q)\times p}{q\times 0.5\times(1-p)+0.5\times(1-q)\times p}$

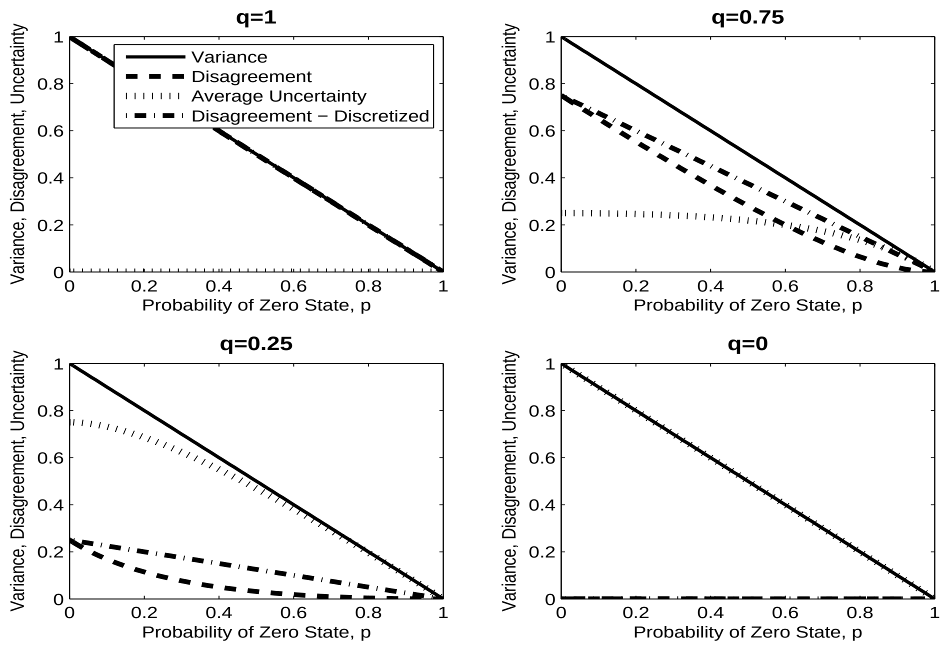
   (c) $Prob(state = -1|signal = -1) = \frac{q\times 0.5\times(1-p)}{q\times 0.5\times(1-p)+0.5\times(1-q)\times p}$

From these conditional probabilities, conditional expectations and variances can be computed. And these, in turn, allow us to calculate (i) the variance of the conditional expectations over the change in business situations, which is a measure of disagreement; and (ii) the average conditional variance over the change in the business situation of a firm, which is a measure of the average (subjective) uncertainty in the population of firms.

We begin with the case of perfectly informative signals: $q = 1$. In this case, obviously, survey disagreement moves one for one with the variance of tomorrow's state, but firms do not experience any subjective uncertainty about the change in their business situation. With $q = 1$ and in a two period set up disagreement and uncertainty do not comove. The fact that we find substantial forecast errors in the IFO-BCS suggests that this extreme case may not be realistic. But even if we assumed $q = 1$ and thus certainty for the immediate future, higher disagreement today indicates a higher cross-sectional variance in business situations tomorrow and thus higher uncertainty about business situations for periods beyond the immediate future, as long as the variance of future innovations to the business situation of firms has some persistence beyond the immediate period and signals are not perfectly informative about this farther future. Tables 4 and 5 in the main text show that all uncertainty measures are highly autocorrelated.

Next, we look at the cases with imperfectly informative signals, i.e. $q < 1$. We know from the conditional variance decomposition formula that if the variance of tomorrow's state increases either the variance of the conditional expectations over tomorrow's state (disagreement) or the average conditional variance over tomorrow's state (average subjective uncertainty) has to increase. Both may increase. The following Figure B.1 shows for various levels of the signal precision, q, that the latter is indeed the case in this model. The actual cross-sectional variance of tomorrow's state is a (linearly declining) function of the probability of drawing the intermediate business state tomorrow, p, as depicted by the solid line; the variance of the conditional expectations over tomorrow's state (disagreement) is shown by the dashed line and the average conditional variance over tomorrow's state (subjective uncertainty) is the dotted line.

Figure B.1: Cross-sectional Variance, Disagreement and Uncertainty



Notice that for intermediate signal qualities ($q = 0.75$ and $q = 0.25$), both disagreement and uncertainty decline in p, and move in the same direction as the actual variance of the state tomorrow. In short, in this simple example cross-sectional variance, disagreement and subjective uncertainty comove with each other, and, given a signal quality q are all determined by p, the probability of drawing the intermediate business state tomorrow. Since p and the cross-sectional variance are linearly and negatively related, we can equivalently say that both disagreement and subjective uncertainty comove with the actual cross-sectional variance. Of course, if the signal was such that it left everybody with the same conditional expectation, i.e. completely uninformative ($q = 0$), then disagreement would always be zero. Only subjective uncertainty would then be affected by p and equal the actual cross-sectional variance, which is seen in the right lower panel of Figure B.1. In this case, disagreement and its fluctuations would not be a good measure of either subjective uncertainty or cross-sectional variance and their fluctuations. Since in the IFO-BCS disagreement and cross-sectional error variance are highly correlated, the case of a completely uninformative signal is unlikely to hold.

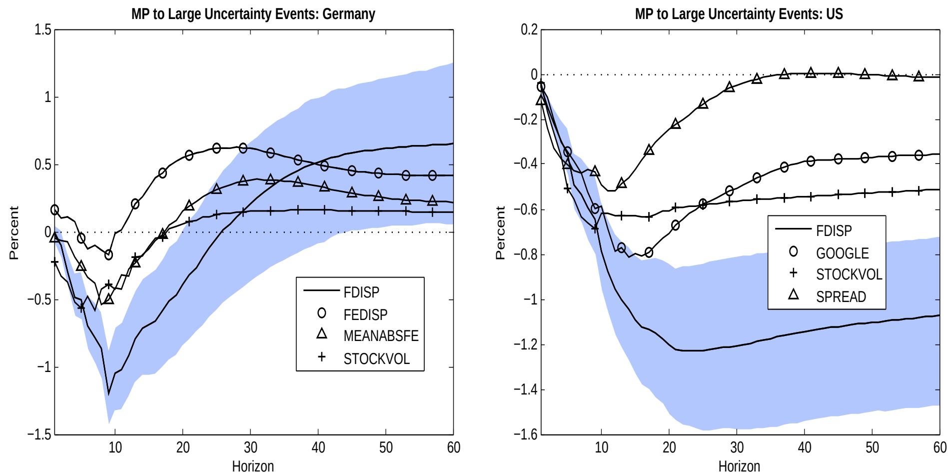
Finally, in order to translate the continuous disagreement measure – the variance of the conditional expectations over the change in business situations – into discrete disagreement in survey answers, where only $[-1,0,1]$ as an answer are possible, we assume that if the firm receives zero as a signal, it will answer zero, simply because the conditional expectation is zero in this case (by the symmetry of the model). Furthermore, if it receives a signal equal to 1, the probability of answering 1 in the survey equals the expectation conditional on the signal being 1, which ranges from 1 (if $p = 0$) to 0 (if $p = 1$). This conditional expectation, $E[state|signal = 1]$, is computed from the conditional probabilities above. This means that the closer the conditional expectation is to unity, the more likely firms are going to respond with 1 in the survey. Symmetrically this is also true for the case of receiving a signal that equals -1. With these assumptions, the variance of the survey answers is given by ($E[answer]$ is computed analogously):

$$\begin{aligned}
VAR[answer] = \quad & (1 - E[answer])^2 E[state|signal = 1] \times Prob(signal = 1) + \\
& (0 - E[answer])^2 (1 - E[state|signal = 1]) \times Prob(signal = 1) + \\
& (0 - E[answer])^2 Prob(signal = 0) + \\
& (0 - E[answer])^2 (1 - E[state|signal = -1]) \times Prob(signal = -1) + \\
& (-1 - E[answer])^2 (E[state|signal = -1]) \times Prob(signal = -1)
\end{aligned}$$

This discretized version of disagreement is also shown in Figure B.1, by the dashed-dotted line. It closely follows the continuous disagreement measure, which gives us confidence that the discretized disagreement measure in the IFO-BCS and its fluctuations are good approximations to both the underlying continuous disagreement and subjective uncertainty and their fluctuations.

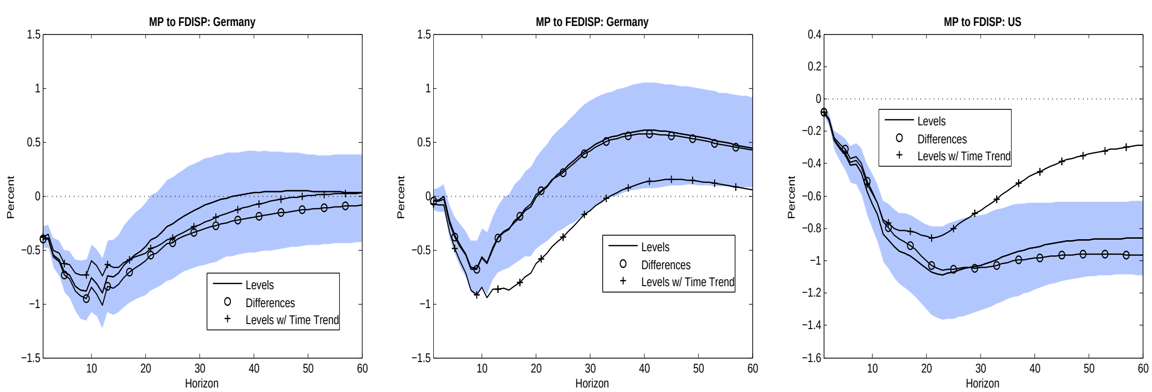
C Robustness Checks - For Online Publication Only

Figure C.1: IRFs to "Large" Uncertainty Events



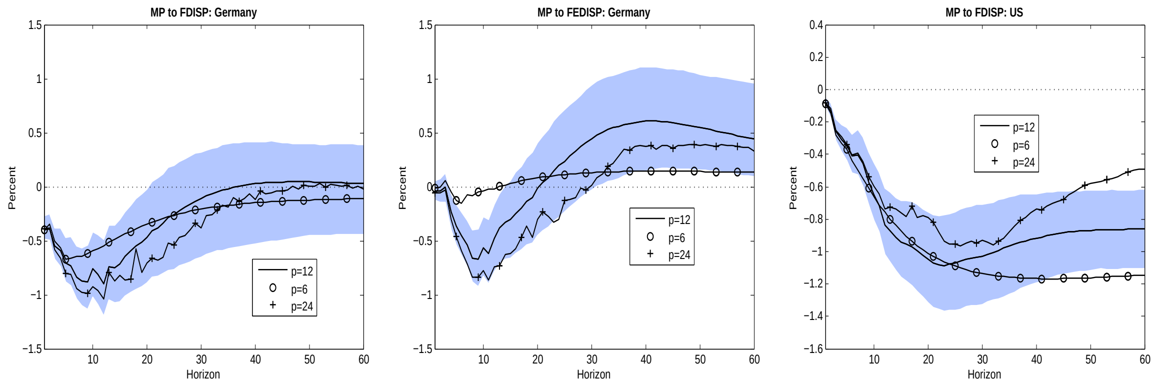
Notes: This figure plots in the left panel impulse responses of West German manufacturing production to innovations in various uncertainty measures. The responses are obtained from separately estimating a bivariate system with each different uncertainty measure and log manufacturing production. The frequency of the series in the VARs is monthly, the VARs are estimated with 12 lags, and manufacturing production enters the systems in levels. Instead of using the actual uncertainty measures in the VAR, we replaced them with a derived uncertainty series that takes on 1 in the months where the underlying uncertainty measure was one or more time series standard deviations above the mean of the underlying uncertainty series. $FDISP$ stands for the forecast disagreement index, based on Q1. $FEDISP$ stands for dispersion in forecast errors, constructed as described in the text. $MEANABSFE$ stands for the mean of the absolute value of forecast errors. $STOCKVOL$ stands for 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 Kilian's (1998) bootstrap-after-bootstrap from the system using $FDISP$. The right panel does the same for the US uncertainty measures. $FDISP$ stands for the forecast disagreement index, based on Q3. $GOOGLE$ stands for the Google News subindex that is based on economic uncertainty from Baker et al. (2012). $STOCKVOL$ stands for 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. $SPREAD$ stands for 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 from the system using $FDISP$.

Figure C.2: Robustness to Trend Assumptions



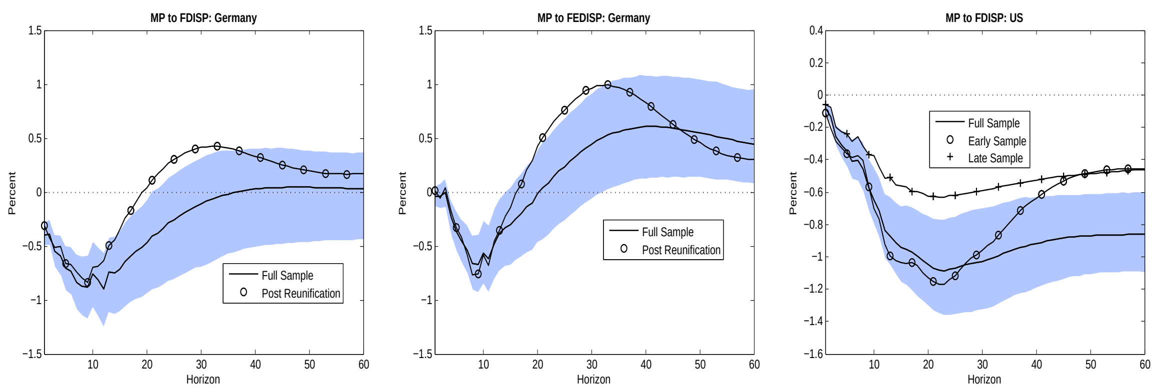
Notes: The VARs for $FDISP$ and $FEDISP$ in Germany and $FDISP$ for the US here are estimated from bivariate VARs with an uncertainty measure and log manufacturing production, with the uncertainty series ordered first, under alternative trend assumptions: the solid lines show responses where production enters in levels, the lines with circles show cumulated responses when log production enters the VAR in first differences, and the lines with squares when a deterministic linear time trend is included in the VAR. The shaded gray regions are the +/- one standard error confidence bands from the system that is estimated in levels.

Figure C.3: Robustness to Lag Lengths



Notes: The VARs for *FDISP* and *FEDISP* in Germany and *FDISP* for the US here are estimated from bivariate VARs with an uncertainty measure and log manufacturing under alternative lag structures. The shaded gray regions are the +/- one standard error confidence bands from the system that is estimated with 12 lags.

Figure C.4: Robustness: Subsamples



Notes: The VARs for *FDISP* and *FEDISP* in Germany and *FDISP* for the US here are estimated from bivariate VARs with an uncertainty measure and log manufacturing on different samples. For Germany we show results for both *FDISP* and *FEDISP* for the full sample, 1/1980-12/2010, as well as for a post-reunification sample, 1/1992-12/2010. For the US three sets of responses are shown: one for the full sample, 5/1968-12/2011; one for the pre "Great Moderation" sample, 5/1968-12/1983; and one for the period after the conventional dating of the "Great Moderation," 1/1984-12/2011. The shaded gray regions are the +/- one standard error confidence bands from the system that is estimated on the full sample.

D Small Business Economic Trend Survey (SBETS) - For Online Publication Only

The Small Business Economic Trends Survey (SBETS) is a monthly survey conducted by the National Foundation of Independent Businesses (NFIB), which focuses on small companies across the US and across all sectors. Thus the SBETS is a good complement to the BOS which focuses on larger manufacturing firms in the Third FED District. To the extent that the SVAR results are similar this section lends additional support to our findings. The SBETS's monthly part starts in 1986. The survey on a quarterly basis is available since the mid 1970s. We prefer the highest possible frequency. None of our results depend on that choice of frequency. In terms of participation, the October 2009 issue of the SBETS (see Dunkelberg and Wade, 2009) reports that from January 2004 to December 2006 roughly 500 business owners responded, and that the number has subsequently increased to approximately 750.[17] Almost 25% of respondents are in the retail sector, 20% in construction and 15% in manufacturing, followed by services, which ranges well above 10%. All other one-digit sectors are represented with a single digit fraction. In terms of firm size, the sample contains much smaller enterprises than the BOS: the modal bin for the number of employees is "three to five", to which over 25% of respondents belong, followed by the "six to nine"-category with roughly 20%. The highest category is "forty or more", which contains just under 10% of firms.

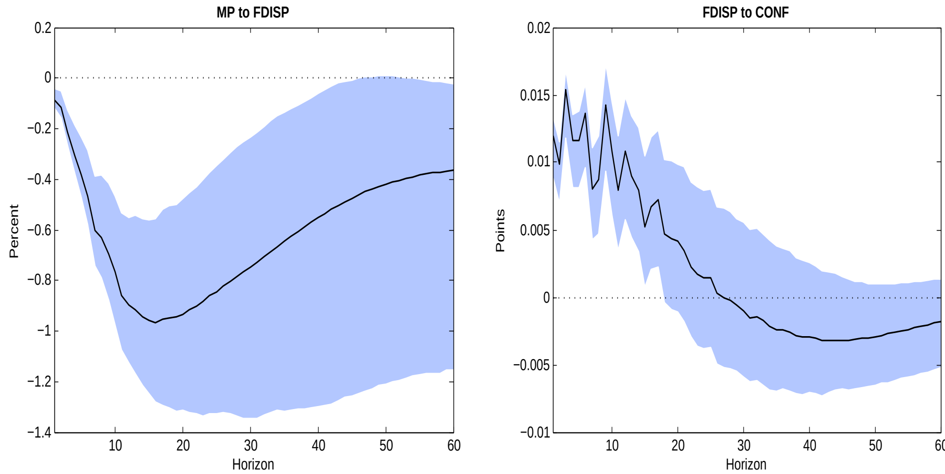
Our uncertainty index is based on an $FDISP$ index derived from a question about general business conditions just like in the BOS (the box and the bold font are also used in the original):

Q *"About the* $\boxed{\textit{economy in general,}}$ *do you think that* ***six months from now*** *general business conditions will be better than they are now, about the same, or worse?:* $\boxed{1}$ *Much better,* $\boxed{2}$ *Somewhat better,* $\boxed{3}$ *About the same,* $\boxed{4}$ *Somewhat worse,* $\boxed{5}$ *Much worse,* $\boxed{6}$ *Don't know. "*

One advantage of this question over its BOS cousin is that it is slightly more nuanced because it allows for two "increase" and two "decrease" categories. We quantify the extreme categories with -2 and 2, respectively.

[17] The participation in the quarterly survey is higher, 1200 on average before January 2007 and 1750 thereafter.

Figure D.1: SBETS RESULTS



Notes: The left panel plots an impulse response of log manufacturing production to an innovation in $FDISP$, obtained from estimating a bivariate VAR with the SBETS forecast dispersion index (**Q**, ordered first) and US manufacturing production. The frequency of the series in the VAR is monthly, the VAR is estimated with 12 lags, and log manufacturing production enters the systems in levels. The sample period for the VAR is from 1/1986 - 9/2009. Shaded regions are +/- one standard error confidence bands from Kilian's (1998) bootstrap-after-bootstrap. The right panel estimates a similar VAR, as in the left panel, augmented by a measure of "confidence" – based on the relative score, $Frac_t^+ - Frac_t^-$, from **Q** ($CONF$). It shows the response of $FDISP$ to a *negative* innovation in $CONF$, where the latter is ordered first.

Figure D.1 displays the analogue of our results from Figures 5 and 8 in the main text. The left panel of Figure D.1 plots the impulse response of log manufacturing production to an innovation in the SBETS-based $FDISP$ uncertainty measure. We use manufacturing production as the activity variable for comparability reasons with our main results, even though the SBETS covers more sectors than manufacturing. While somewhat less persistent than the results for the BOS-based $FDISP$ uncertainty measure, they are nevertheless qualitatively similar: the peak negative response is reached after well over a year and there is limited evidence of a strong rebound or even overshooting effect. The right panel of Figure D.1 plots the impulse response of the SBETS-based $FDISP$ uncertainty measure to a negative innovation in a measure of "confidence" – based on the relative score, $Frac_t^+ - Frac_t^-$, from **Q**. This impulse response was obtained from the VAR that we used for the results in the left panel, augmented by this measure of confidence, ordered first. Similarly to what we find in Figure 8, uncertainty and confidence are negatively correlated in the SBETS, which is consistent with the "by-product" hypothesis.

REFERENCES

Dunkelberg, W. and H. Wade (2009). "NFIB Small Business Economic Trends." October.