Uncertainty and Economic Activity: Evidence from Business Survey Data

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Abstract

What is the impact of time-varying business uncertainty on economic activity? We construct empirical measures of uncertainty based on business survey data from the U.S. and Germany. We show that measured uncertainty is robustly negatively correlated with economic activity far into the future. In particular, adverse "supply" shocks lead to large increases in measured uncertainty. In contrast, innovations in measured uncertainty uncorrelated with shocks identified as having a permanent impact on production have quantitatively small impacts on economic activity. Our results are consistent with two economic environments: uncertainty shocks cause rather low-frequency negative effects on activity, or high uncertainty events are mainly a by-product of bad economic times – recessions breed uncertainty.

JEL Codes: E30, E32, E37.

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1 Introduction

What is the impact of time-varying business uncertainty on economic activity? The seminal contribution in Bloom (2009) has renewed interest in the aggregate effects of time-varying uncertainty and influenced a growing literature in macroeconomics, which we will discuss in detail below. In this paper we use (partly confidential) data from business surveys to investigate the relationship between uncertainty and economic activity within a structural vector autoregressions (SVAR) framework.

These business surveys contain, on a monthly basis, qualitative information on the current state of, and expectations regarding, firms' business situations. In particular, we use disagreement in business expectations for the Third Federal Reserve District Business Outlook Survey (BOS) to measure business uncertainty. Using dispersion of expectations as a measure of uncertainty has a long tradition in the literature: Zarnovitz and Lambros (1987) show with the NBER-ASA expert forecasts of output growth and inflation that disagreement and intrapersonal uncertainty are positively correlated.[1] While we do not have probabilistic forecasts of individual business situations, the confidential micro data of the German IFO Business Climate Survey (IFO-BCS) allow us to compare the disagreement-based measure of uncertainty with a qualitative index of the forecast error variance of production expectations. We find that the two uncertainty measures are positively correlated and that their impact on economic activity is qualitatively and quantitatively similar and statistically often indistinguishable.

High-frequency business survey data from narrowly defined segments of the economy are well-suited to measure the impact of uncertainty on economic decision-making for several reasons. First, business survey data capture a subjective element of uncertainty for actual decision makers, as opposed to outside experts. Second, we will show that our business uncertainty measure explains a higher fraction of the total forecast error variance of economic activity variables than volatility measures based on stock market returns. Third, the recent literature (Bloom, 2009, and Bloom, et al., 2010) has highlighted the so-called "wait-and-see" effect of uncertainty: if firms find themselves in a more uncertain environment, they stop hiring and the economy slips into a recession. Positive shocks to uncertainty can thus lead to short run fluctuations, starting with a rapid decline in economic activity, then a rebound phase and prolonged overshoot after approximately six months. As discussed more in Section 2, "wait-and-see" dynamics are thus rather short-run and rely on adjustment frictions, which render high-frequency data the best candidate to detect these dynamics. Readily available at a monthly frequency, business survey data have an advantage over balance sheet data, which are only available at

[1] Other examples in the literature that either find significant positive correlations between these two measures or use disagreement as a proxy for uncertainty are: Federer (1993), Bomberger (1996), Giordano and Soederlind (2003), Bond and Cummins (2004), Fuss and Vermeulen (2008), Clements (2008), Popescu and Smets (2010) and Bloom et al. (2010).

lower frequencies. Fourth, our use of dispersion in survey responses 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 makes this assumption more likely to hold. Finally, the confidential micro data allow us to compare expectations and realizations of economic variables and thus to construct two complementary proxies for uncertainty: ex ante disagreement and ex post forecast error variance.

We begin by estimating low-dimensional SVARs featuring the survey-based uncertainty indices and measures of economic activity within a sector. We order uncertainty first, so that innovations to uncertainty can affect economic activity immediately. We find that positive innovations to uncertainty have protracted negative effects on economic activity. The effect on impact and at high frequencies is small. This is a robust result across specifications and surveys. While they do not appear to be consistent with the aforementioned high-frequency "wait-and-see"-effect, "wait-and-see"-dynamics could be combined with an endogenous growth mechanism – R&D investment, for example – to generate the observed protracted negative implications for economic activity. In addition, we also suggest a new interpretation: the "by-product"-hypothesis. In this view, high uncertainty events are merely reflective of bad economic times, rather than their cause.

To investigate further, we then impose more structure and change the identification strategy. In systems featuring uncertainty, a measure of sectoral economic activity, and a measure of the aggregate unemployment rate, we identify three structural shocks. In the spirit of Shapiro and Watson (1988), Blanchard and Quah (1989), and Gali (1999), we use a long-run restriction to identify a shock which affects the level of sectoral economic activity in the long-run from the other two shocks, which can only have a transitory effect on output. We identify the uncertainty shock from the other "demand" shock by imposing that our measure of uncertainty not respond within period to the other shock. This identification "shuts down" the long-run influence of uncertainty in the hope of making its short-run impact shine through, while at the same time allowing uncertainty to have a strong temporary, short-lived effect on activity. In point of fact, however, shocks to uncertainty so identified have small effects on production and unemployment. Rather, consistent with the "by-product"-hypothesis, empirical measures of uncertainty appear to be largely driven by the long-run shock. Shocks which permanently lower economic activity give rise to significantly higher measured uncertainty on impact. This is true for survey-based uncertainty measures, as well as uncertainty measures based on the corporate bond spread over treasuries and uncertainty measures based on stock market volatility.

This conclusion is consistent with a general view of recessions as times of destroyed business practices and relationships, the reestablishment of which generates uncertainty. It accords with empirical work by Hamilton and Lin (1996), who find that high stock market volatility is driven mainly by bad economic times. It is also consistent with the theoretical models of Bachmann and Moscarini (2011) as well as Fostel and Geanakoplos (2011), who argue that bad economic times incentivize risky behavior – in the former through price experimentation, in the latter through increased leverage – and therefore endogenously lead to increased uncertainty.

Related Literature

There is a growing literature that studies the effects of uncertainty shocks in fully specified dynamic general equilibrium models. Bachmann and Bayer (2011), exploring data from a German firm-level panel, argue that the effects in Bloom (2009) and Bloom et al. (2010) are small and do not substantially alter unconditional business cycle dynamics. Chugh (2011), who explains the dynamics of leverage with shocks to micro-level uncertainty, also finds only a small business cycle impact of uncertainty shocks. Using a model with financial frictions, Gilchrist et al. (2009) argue that increases in uncertainty lead to an increase in bond premia and the cost of capital which, in turn, triggers a decline in investment activity. Arellano et al. (2011) show that firms downsize investment projects to avoid default when faced with higher uncertainty. Schaal (2010) uses a directed search model with uncertainty shocks to understand the recent labor market behavior. Basu and Bundick (2011) study uncertainty shocks in a sticky price environment. Fernandez-Villaverde et al. (2011) argue that positive shocks to interest rate volatility depress economic activity in several Latin American economies.

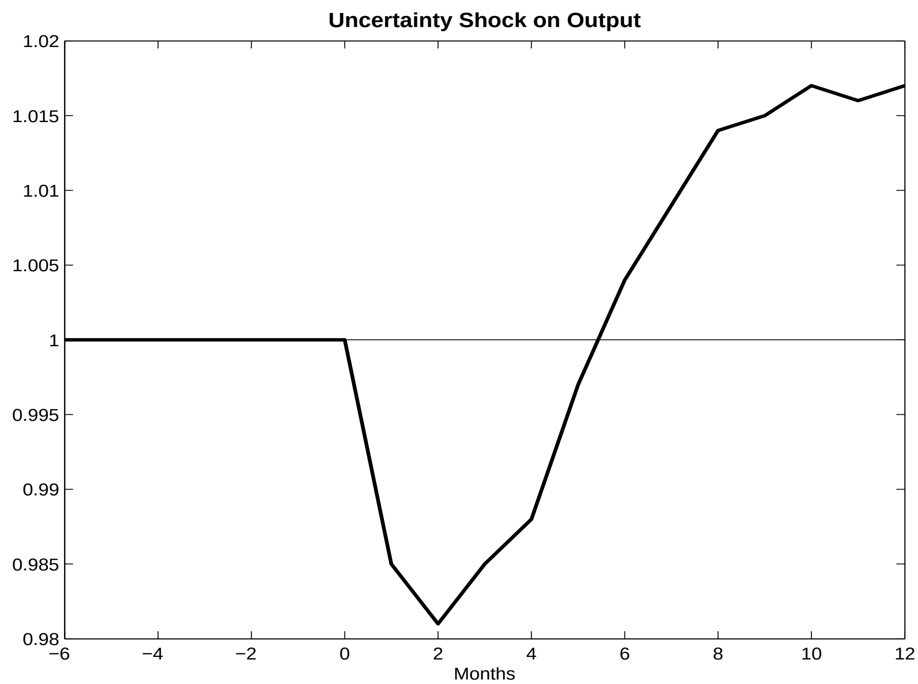
There is another literature that, like this paper, estimates the impacts of various uncertainty proxies on economic activity. Leahy and Whited (1996) is one of the first papers to document empirically a negative relationship between uncertainty and firms' investment. Bond and Cummins (2004) use data on publicly traded U.S. companies to show that various measures of uncertainty predict prolonged declines of firms' investment activities. Gilchrist et al. (2009) find a similar result for increases in the dispersion of firms' sales growth. Christiano et al. (2010), in a large-scale DSGE context, also find a strong low-frequency impact of the identified risk shock. Alexopolous and Cohen (2009) use a narrative approach in a structural VAR framework (the incidence of the words "uncertainty" and "economy" in *New York Times* articles) and find high-frequency decline-rebound-overshoot dynamics. Popescu and Smets (2010) show, again with structural vector autoregressions and for German expert survey data, that it is shocks to risk aversion rather than innovations to uncertainty that explain roughly 10%-15% of output fluctuations.

The remainder of the paper is organized as follows. The next section discusses the "wait-and-see"-mechanism and delivers a benchmark against which we compare our empirical results. The third section describes the business survey data we use. The fourth section presents the main results and interprets them. Details and additional results are relegated to various appendices.

2 Uncertainty and Activity: "Wait-and-See"

In this section we give a brief overview of the "wait-and-see"mechanism that might give rise to uncertainty-driven short-run fluctuations. In addition to providing a benchmark against which we can compare our empirical results, this exercise will also serve to motivate the use of high-frequency data in examining the impact of uncertainty on economic activity.

Figure 1: Replication of Wait-and-See in Bloom (2009)



Notes: This graph is a replication of the simulated model IRF of output to an uncertainty shock, see Figure 12 in Bloom (2009).

Time-varying uncertainty at the firm level may have economic consequences when there is a degree of irreversibility to firm actions (see Bernanke, 1983, as well as Dixit and Pindyck, 1994). For a concrete example, suppose that a firm faces fixed costs to adjusting the size of its labor force and/or physical capital stock. Suppose further that there is a mean-preserving spread on the distribution of future demand for the firm's product. With fixed adjustments costs, higher uncertainty over future demand makes new hiring and investment less attractive. If a large fixed cost must be paid to adjust the firm's labor or capital, then there is reason to minimize the number of times this cost must be paid. If the future is very uncertain (in the sense that demand could be either very high or very low relative to the present), then it makes sense to wait until the uncertainty is resolved to undertake new hiring and investment. Why pay a large fixed cost now when a highly uncertain future means that one will likely have to pay the fixed cost again?

An increase in uncertainty thus makes inaction relatively more attractive. Given a reduction in hiring, employment, and hence output, will fall through exogenous separations. As the future begins to unfold, demand or productivity conditions are, in expectation, unchanged. There will be pent up demand for labor and capital. Inaction today moves firms closer to their adjustment triggers in subsequent periods, leading to expected increases in hiring, investment and a general rebound and even overshoot in economic activity, followed by a return to steady state. Figure 1 provides an example of an impulse response of output to an increase in uncertainty, replicated from the model in Bloom (2009).

This theoretical impulse response highlights an important aspect as pertains to our empirical work. The economic implications of uncertainty shocks in a model with "wait-and-see"-effects are decidedly high-frequency in nature. Thus, an empirical study of uncertainty that wants to detect "wait-and-see"-effects should make use of high-frequency data, which is one of the reasons why we use monthly surveys in this paper.

3 Measuring Business Uncertainty

We construct uncertainty measures from the Third FED District Business Outlook Survey (BOS) and the German IFO Business Climate Survey (IFO-BCS). In the next subsection we briefly describe the characteristics of each and list the main survey questions we use to measure business uncertainty. We then define the variables used in the empirical analysis, followed by a subsection on the cyclical properties of these variables.

3.1 Data Description

3.1.1 BOS

The Business Outlook Survey is a monthly survey conducted by the Federal Reserve Bank of Philadelphia since 1968. The survey design has essentially been unaltered since its inception. It is sent to large manufacturing firms in the Third FED District, which comprises the state of Delaware, the southern half of New Jersey, and the eastern two thirds of Pennsylvania. The survey questionnaire is of the "box check" variety. It asks about firms' general business expectations as well as their expectations and actual realizations for various firm-specific variables such as shipments, workforce and work hours. Respondents indicate whether the value of each economic indicator has increased, decreased, or stayed the same over the past month. They are also asked about their expectations for each indicator over the next six months. Whenever possible, the survey is sent to the same individual each month, typically the chief executive, a financial officer or other person "in the know". Participation is voluntary. 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. Each month 100-125 firms respond. As noted by Trebing (1998), occasional telephone interviews are used to verify the accuracy of the survey responses.

The advantages of the BOS are its long time horizon, its focus on one consistent, economically relatively homogenous class of entities – large manufacturing firms in one region –, an unparalleled number of questions that are useful for our research question and the fact that for each question there is a "current change" and an "expectation" version. Its main drawback is the relatively small number of respondents. Nevertheless, given its advantages, we use the BOS for our baseline results.[2] We focus on the following two questions (the other questions we use from the BOS are documented in Appendix B.1):

Q 1 *"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?"*

Q 2 *"General Business Conditions: What is your evaluation of the level of general business activity [LAST MONTH] vs. [CURRENT MONTH]: decrease, no change, increase?"*

Both questions are phrased, somewhat ambiguously, about general business conditions. Trebing (1998) notes, however, that answers to these questions are highly correlated with responses to the shipments question, which is phrased as explicitly company specific. He concludes that both series are essentially indicators of firm-specific business conditions.

In addition, in order to construct an employment turnover indicator, we use the following question:

Q 3 *"Company Business Indicators: Number of Employees [LAST MONTH] vs. [CURRENT MONTH]: decrease, no change, increase?"*

[2] Appendix D supplements the baseline results with an analysis of the U.S. Small Business Economic Trends Survey (SBETS). There is a concern that if adjustment costs grow less than proportionally with firm size the firms in the BOS may be sufficiently large that adjustment costs do not matter for them, and therefore "wait-and-see"cannot be detected in the BOS. The SBETS also has larger cross-sections of firms compared to the BOS. We find essentially the same results.

3.1.2 IFO-BCS

The German IFO Business Climate Survey is one of the oldest and broadest monthly business confidence surveys available (see Becker and Wohlrabe, 2008, for more detailed information). However, due to longitudinal consistency problems and availability of micro data in a processable form only since 1980, we limit our analysis to the manufacturing sector from 1980 until the present. From 1991 on, the sample includes East-German firms as well.

One of the IFO-BCS's main advantages is the high number of survey participants. 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 2,500.[3] 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 on and this allows us to construct a measure of ex post forecast error uncertainty. Our final sample of continuing firms comprises roughly 4,000 respondents at the beginning and 2,000 towards the end of the sample. In terms of firm size, the IFO-BCS contains all categories. In the survey for January 2009, for example, about 12% of respondents had less than 20 employees, roughly 39% had more than 20 but less than 100 employees, 43% of the participants employed between 100 and 1000 people and less than 7% had a workforce of more than 1000 people.

The two main questions that allow us to construct a qualitative index of ex-post forecast errors are:[4]

Q 4 *"Expectations for the next three months: Our domestic production activities with respect to product XY will (without taking into account differences in the length of months or seasonal fluctuations) increase, roughly stay the same, decrease."*

Q 5 *"Trends in the last month: Our domestic production activities with respect to product XY have (without taking into account differences in the length of months or seasonal fluctuations) increased, roughly stayed the same, decreased."*

3.2 Variable Definitions

Survey answers fall into three main categories, $Increase$, $Decrease$, and a neutral category. We use these categories to define our expectation-based index of uncertainty and one index of current economic activity. Define $Frac_t^+$ as the fraction of "increase"-responses to a survey ques-

[3] The IFO-BCS is a survey at the product level, so that these numbers do not exactly correspond to firms.

[4] Here we provide a translation, for the German original see Appendix C.1.

tion at time t; $Frac_t^-$ is defined analogously. We start with the uncertainty index, constructed for questions like Q 1 and Q 4:

$$Uncertainty_t \equiv sqrt\left(Frac_t^+ + Frac_t^- - \left(Frac_t^+ - Frac_t^-\right)^2\right).$$

Notice that $Uncertainty_t$ so defined is the cross-sectional standard deviation of the survey responses, if the $Increase$-category is quantified by $+1$ and the $Decrease$-category by -1 and the residual categories by 0. This is a standard quantification method for qualitative survey data. Next, we define a current index of economic activity for questions like Q 2 and Q 5. Summing up variables that essentially measure changes is intended to capture a qualitative measure of the level of economic activity:

$$Activity_t \equiv \sum_{\tau=1}^{t} (Frac_\tau^+ - Frac_\tau^-).$$

3.3 Is Cross-sectional Dispersion a Good Proxy for Uncertainty?

Measuring the (subjective) uncertainty of decision makers 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. With this probability distribution it is straightforward to compute a measure of intrapersonal uncertainty for firms' decision makers. However, to the best of our knowledge such probability distributions are not available repeatedly and over long time horizons.[5] Researchers have to rely on proxies instead. Although frequently done in the literature, using the cross-sectional dispersion of firms' expectations as a proxy for firms' uncertainty is not without potential problems. First, time-varying cross-sectional dispersion in firms' survey responses might be due to different firms reacting differently to aggregate shocks even with constant uncertainty. Notice that for relatively homogenous samples such as the BOS this is likely to be less of a problem. Secondly, time variation in the dispersion of expectations might be the result of time variation in the heterogeneity of said expectations, without these expectations reflecting a higher degree of uncertainty on the part of the business managers.

We address the first concern – different firms having different factor loadings to aggregate shocks – by a variance decomposition of the IFO-based (based on Q 4, to be specific) uncertainty measure, $(Uncertainty_t^{IFO})^2$, into the average within-variance and the between-variance of the 13 manufacturing subsectors contained in the IFO-BCS (see Appendix C.2 for details). The idea behind this decomposition is that such differences in factor loadings to aggregate

[5] Bontempi et al. (2010), using the same Italian data sets as Guiso and Parigi (1999), construct eight years of annual uncertainty measures from the max-min range of firms' one-year ahead sales forecasts.

shocks might be due to industry-specific production and adjustment technologies. Figure 20 in Appendix C.2, however, shows that the time series of $(Uncertainty_t^{IFO})^2$ is not explained by the between-variance of the manufacturing subsectors. This means it is not explained by the manufacturing subsectors getting more or less different over the business cycle.

To address the second concern – the relationship between (time-varying) dispersion, uncertainty and cross-sectional shock variance – we present in Appendix A 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.

Furthermore, the confidential micro data in the IFO-BCS and its panel structure allow us to construct a qualitative index of the ex post forecast error standard deviation, which by construction excludes heterogeneous, but certain, changes in expectations.[6] The basic idea is that we can compare firms' answers about their production expectations, Q 4, with their answers on past production realizations, Q 5, and thus construct a measure of firm-specific production expectation errors. The cross-sectional standard deviation of these expectation errors, $Uncertainty_t^{fe^{IFO}}$, is a dispersion index for the ex post forecast errors. In Appendix C.3 we describe the construction of $Uncertainty_t^{fe^{IFO}}$ in detail.

The advantage of $Uncertainty_t^{fe^{IFO}}$ over $Uncertainty_t^{IFO}$ is that it is based on actual "uncertain-at-time-t" innovations, as opposed to potentially heterogeneous expectations about the future, which could be certain. However, the raw correlation coefficient between $Uncertainty_t^{fe^{IFO}}$ and $Uncertainty_t^{IFO}$ is reasonably high for monthly data, 0.73, and when we aggregate both series up to the quarterly level the correlation is 0.77. The fact that both conceptually different proxies for uncertainty are reasonably close to each other lends some support to the widespread practice of proxying uncertainty with survey disagreement. Most importantly, the impulse responses on economic activity look qualitatively and quantitatively similar and are statistically often indistinguishable (see Section 4.2).

3.4 Cyclicality of Business Survey Variables

In this subsection, we report basic cyclical properties of the survey-based variables introduced in Sections 3.2 and 3.3: $Uncertainty_t$, $Uncertainty_t^{fe}$ and $Activity_t$. They have been seasonally adjusted with the SAS X12 procedure, an adaptation of the U.S. Bureau of the Census

[6] Whereas the aggregate survey responses, $Frac_t^+$ and $Frac_t^-$, are publicly available for both the BOS and the IFO-BCS, individual firm responses are not. In the case of the IFO-BCS they are available to researchers on-site.

X-12-ARIMA seasonal adjustment method. Table 1 displays the contemporaneous correlations of the various survey-based monthly uncertainty measures with, respectively, manufacturing industrial production and the corresponding survey-based activity measures. The uncertainty indices are all countercyclical. This confirms previous findings by Bloom (2009), Bloom et al. (2010), Chugh (2011) and Bachmann and Bayer (2011), who find, using different data sources, that stock market volatility and balance-sheet-based cross-sectional measures of uncertainty are all countercyclical.[7] The correlation is even more negative when we aggregate up to the quarterly frequency.

Table 1: CYCLICAL PROPERTIES OF $Uncertainty_t$ AND $Uncertainty_t^{fe}$

	Monthly		Quarterly	
	Correlation with		Correlation with	
Uncertainty Measure	IP_t	$Activity_t$	IP_t	$Activity_t$
General Conditions-$Uncertainty_t^{BOS}$	-0.28	-0.47	-0.33	-0.51
Shipments-$Uncertainty_t^{BOS}$	-0.27	-0.29	-0.31	-0.32
Production-$Uncertainty_t^{IFO}$	-0.10	-0.61	-0.23	-0.62
Production-$Uncertainty_t^{fe^{IFO}}$	-0.05	-0.54	-0.24	-0.59

Notes: This table displays the unconditional contemporaneous correlations between the survey-based uncertainty variables in the rows and the month-over-month/quarter-over-quarter differences of two different activity measures in the columns. Industrial production (IP) measures are logged. The General Conditions-$Uncertainty_t^{BOS}$ measure, based on Q 1, is paired with the corresponding difference of the (seasonally adjusted) manufacturing industrial production index from the OECD main economic indicators and the General Conditions-$Activity_t^{BOS}$ measure based on Q 2. The Shipments-$Uncertainty_t^{BOS}$ measure, based on Q 6 (see Appendix B.1), is paired with the corresponding difference of the (seasonally adjusted) manufacturing industrial production index from the OECD main economic indicators and the Shipments-$Activity_t^{BOS}$ measure based on Q 9 (see Appendix B.1). The Production-$Uncertainty_t^{IFO}$ measure, based on Q 4, is paired with the corresponding difference of the (seasonally adjusted) manufacturing industrial production index from the German Federal Statistical Agency and the $Activity_t^{IFO}$-measure based on Q 5. Production-$Uncertainty_t^{fe^{IFO}}$ is paired with the same activity measures as the Production-$Uncertainty_t^{IFO}$ measure.

Table 2 displays the contemporaneous correlations of the survey-based (differenced) activity measures we constructed in Section 3.2 with manufacturing industrial production. These activity measures are, not surprisingly, procyclical.

[7]We also find that both uncertainty measures from the IFO-BCS, $Uncertainty_t^{IFO}$ and $Uncertainty_t^{fe^{IFO}}$, are countercyclical, separately for each of the 13 manufacturing subsectors. This excludes composition effects as an explanation for the countercyclicality of the overall uncertainty measure. The numbers are available on request.

Table 2: CYCLICAL PROPERTIES OF $Activity_t$

Activity Measure / Correlation with	Monthly IP_t	Quarterly IP_t
General Conditions-$Activity_t^{BOS}$	0.55	0.79
Shipments-$Activity_t^{BOS}$	0.46	0.70
Production-$Activity_t^{IFO}$	0.25	0.53

Notes: This table displays the unconditional contemporaneous correlations between the differenced survey-based variables in the rows and the month-over-month/quarter-over-quarter differences of industrial production indices. Industrial production (IP) measures are logged. The General Conditions-$Activity_t^{BOS}$ measure, based on Q 2, is paired with the corresponding difference of the manufacturing industrial production index from the OECD main economic indicators. The Shipments-$Activity_t^{BOS}$ measure, based on Q 9 (see Appendix B.1), is paired with the corresponding difference of the manufacturing industrial production index from the OECD main economic indicators. The Production-$Activity_t^{IFO}$ measure, based on Q 5, is paired with the corresponding difference of the manufacturing industrial production index from the German Federal Statistical Agency.

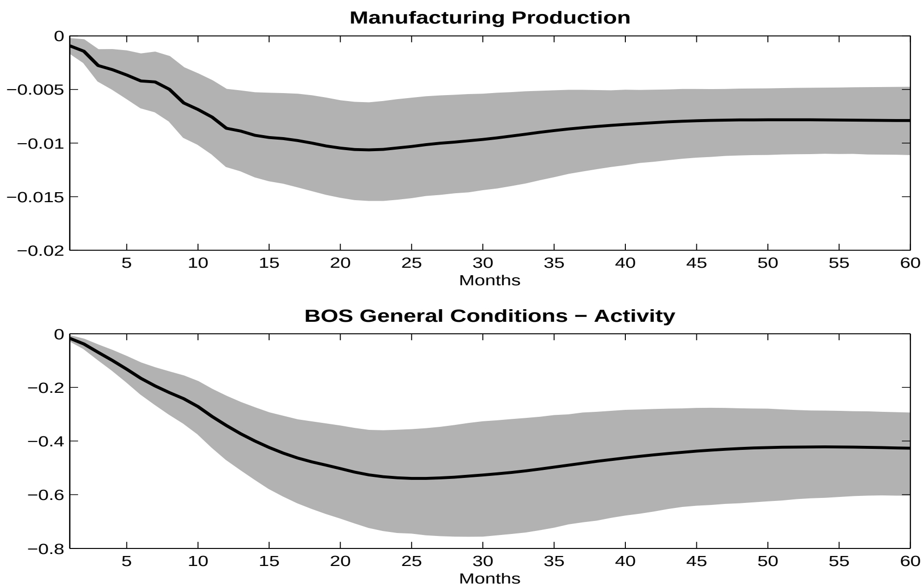
4 Results

In this section we present and discuss our main empirical results. In Choleski-identified SVARs with uncertainty ordered before economic activity variables, we robustly find that innovations to business uncertainty are associated with initally small, but slowly-building reductions in economic activity. Imposing the restriction that uncertainty shocks have no long-run effects on activity renders the responses of economic activity to uncertainty statistically and economically insignificant. Both findings are difficult to reconcile with an important “wait-and-see”-channel from uncertainty to aggregate dynamics. Rather, we find that shocks adversely impacting the economy are important drivers of various empirical uncertainty measures, suggesting that uncertainty is a consequence of bad shocks.

4.1 Third FED District Business Outlook Survey

We begin the analysis with the Federal Reserve Bank of Philadelphia Third District Business Outlook Survey and low-dimensional Choleski-identified SVARs containing the General Conditions-$Uncertainty_t^{BOS}$ index and various economic activity variables. We order the uncertainty index first. This gives uncertainty its “best shot” of being quantitatively important for economic activity dynamics. Figure 2 shows impulse responses for U.S. manufacturing industrial production (upper panel) and General Conditions-$Activity_t^{BOS}$ (based on Q 2; lower panel) to an innovation in business uncertainty.[8] Both variables enter the system in levels and we include 12 lags.[9]

Figure 2: Uncertainty Innovations on Manufacturing Activity



Notes: Both IRFs are based on General Conditions-$Uncertainty_t^{BOS}$, which derives from Q 1 in the BOS. The upper panel shows the response of manufacturing production to a positive uncertainty innovation in a two-variable SVAR with $Uncertainty$ ordered first. Manufacturing production is the natural logarithm of the (seasonally adjusted) monthly manufacturing production index from the OECD main economic indicators. The lower panel shows the response of General Conditions-$Activity_t^{BOS}$ (based on Q 2) to a positive uncertainty innovation in a two-variable SVAR with $Uncertainty$ ordered first. All VARs are run with 12 lags, the confidence bands are at the 95% significance level using Kilian's (1998) bias-corrected bootstrap.

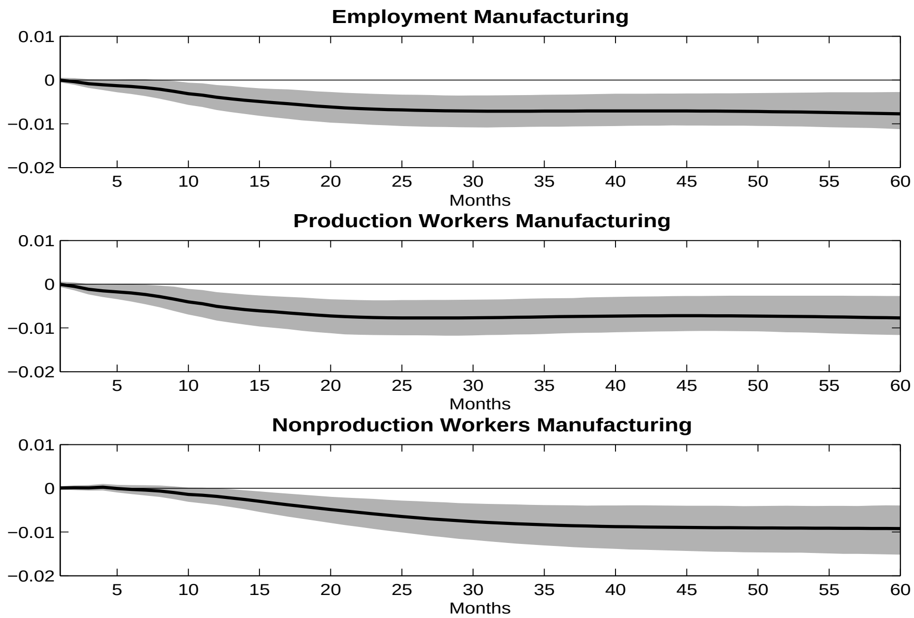
The impulse response of manufacturing production to an innovation in business uncertainty is slightly negative on impact with effects that build over time. The peak decline is at about 1 percent, occurring about two years after impact, with no tendency to revert. The lower panel of Figure 2 provides corroborating evidence with a different measure of sectoral economic activity. The BOS in Q 2 asks about current business conditions relative to the recent past. The impulse response of General Conditions-$Activity_t^{BOS}$ is strikingly similar to that using overall manufacturing production as the activity measure. This is particularly important, as we do

[8]One might be worried that uncertainty should not affect economic activity on impact because of various information or decision lags. For instance, one might assume that companies learn the uncertainty of their business environment only through the published surveys themselves, when they see a lot of disagreement there. Figure 14 in Appendix B.3 presents the impulse response with economic activity ordered first. It is clear that the Choleski ordering does not drive our results.

[9]Our results are robust to alternative assumptions about how the variables enter the VAR (i.e. levels vs. differences) as well as to alternative assumptions about lag length.

not have monthly industrial production data disaggregated at the regional and sectoral level that would allow us to construct a quantitative activity measure that corresponds exactly to the BOS. The fact that the results are nearly identical across two related, but different activity measures lends credence to our finding: neither impulse response function seems to be consistent with the "wait-and-see"-dynamics as shown in Figure 1.[10]

Figure 3: Uncertainty Innovations on Manufacturing Employment



Notes: see notes to Figure 2. Uncertainty is ordered first. The employment measures are seasonally adjusted and logged and are taken from the BLS-CES data base.

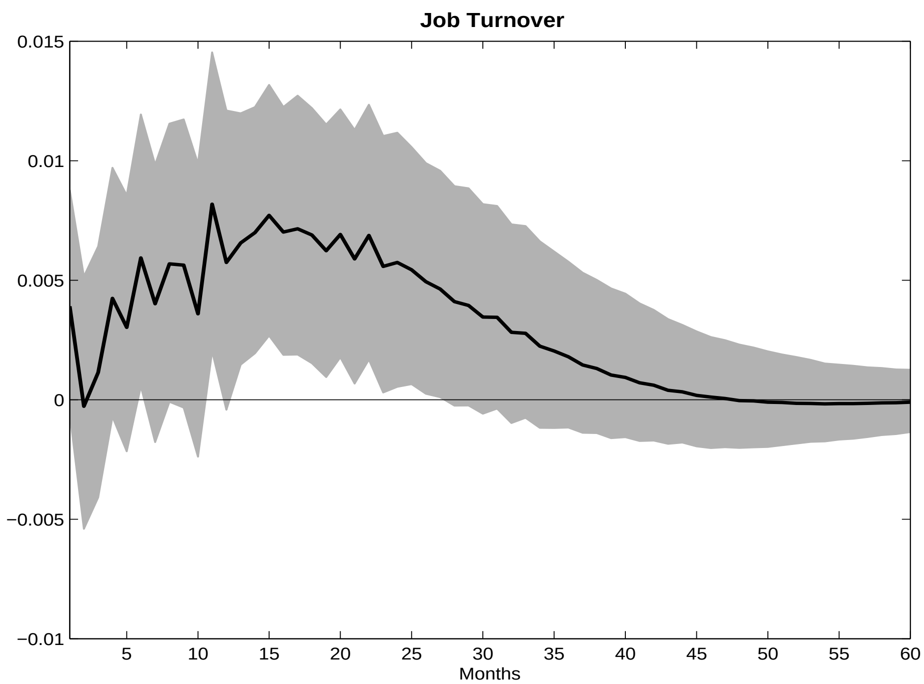
In Figure 3 we show impulse responses from bivariate SVARs featuring our BOS baseline uncertainty measure and various manufacturing employment measures. The responses shown are that of employment to uncertainty, with uncertainty ordered first. The "wait-and-see"-theory of the transmission from uncertainty shocks to business cycles emphasizes hiring and firing frictions. With these we should observe a large reduction in employment followed by a quick recovery in response to an uncertainty shock, similarly to the output response in Figure 1 in Section 2.

[10]In Table 7 in Appendix B.2 we display contemporaneous correlations of various BOS activity measures with the monthly Third FED district BLS manufacturing employment data available from 1990 on. Running the same two-variable SVAR with this employment measure as the activity variable on data from 1990 onwards results in very similar point estimates for the impulse response functions. We also compare the monthly BOS activity measures with the monthly coincident index from the Philadelphia FED, which measures overall economic, not merely manufacturing activity for the Third FED district. Using this index as the activity variable in the two-variable SVAR would yield identical results. Finally, we compare yearly averages of the BOS activity measures with the yearly NIPA manufacturing production index for the Third FED district. The BOS activity measures are positively correlated with all these other imperfect activity measures from official statistics, which shows that the BOS depicts the dynamics of real economic activity in the manufacturing sector of the Third FED district reasonably accurately.

However, the response of manufacturing employment is rather consistent with our results for production: it moves little on impact, followed by a period of sustained reductions, with no obvious tendency for reversion, even at very long horizons. Production and non-production workers, who might be subject to different adjustment costs, are affected similarly.

Another direct and related prediction of the "wait-and-see"-theory is that job turnover – defined as the sum of job creation and job destruction – should decline following an increase in uncertainty: wait and do nothing. Yet again, the survey data do not seem to support this prediction. Figure 4 shows the response of the extensive margin of job turnover to an innovation in uncertainty. The point estimate on and near impact is positive and insignificant from zero, turning more significant at horizons well beyond one year.

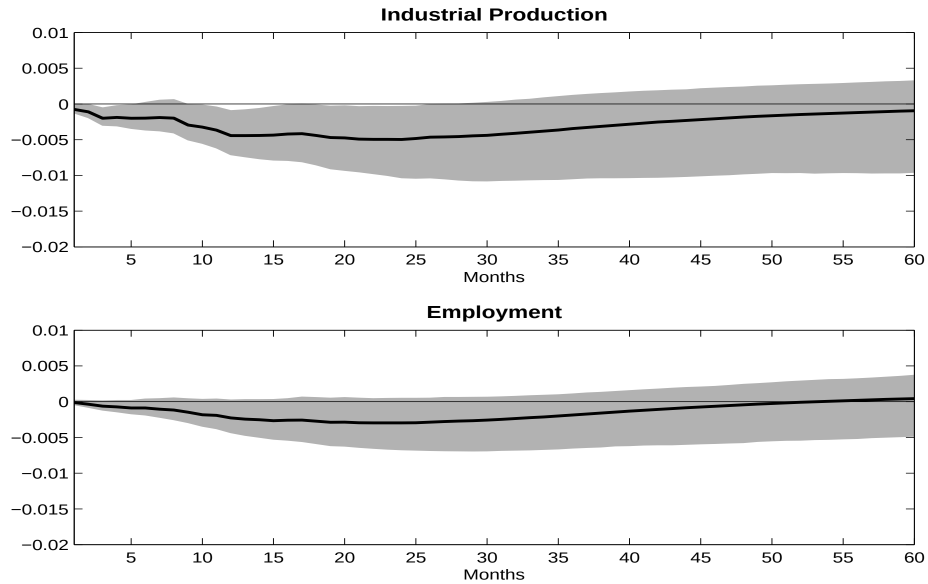
Figure 4: Uncertainty Innovation on BOS Job Turnover Index



Notes: see notes to Figure 2. $Turnover_t \equiv Frac_t^+ + Frac_t^-$. $Turnover_t$ is based on Q 3.

For a comparison of our results with the SVAR evidence in Bloom (2009), we estimate exactly the same high-dimensional system, but replace the high uncertainty dummy variable based on stock market volatility with our General Conditions-$Uncertainty_t^{BOS}$ index. The VAR otherwise includes the S&P500 stock market index, the Federal Funds Rate, average hourly earnings, the consumer price index, hours, employment and industrial production. Uncertainty is ordered second in a recursive identification. Figure 5 shows the impulse response of production and employment to an innovation in General Conditions-$Uncertainty_t^{BOS}$. Although with reduced statistical significance, the pattern remains: slowly-building declines and slow recoveries of economic activity variables.

Figure 5: Uncertainty Innovations in the Bloom (2009) SVAR



Notes: see notes to Figure 2. The S&P500 stock market index has been logged and is ordered first. Then follows the General Conditions-$Uncertainty_t^{BOS}$ index. Hourly Earnings, the CPI, employment and industrial production have been logged.

We also conduct a forecast error variance decomposition in this high-dimensional SVAR with uncertainty based on the BOS and compare it to the forecast error variance decomposition in the SVAR with uncertainty based on stock market volatility. On impact, the variation in production that is explained by either proxy for uncertainty is almost zero. Interestingly, the forecast error variance in production that is explained by our survey-based General Conditions-$Uncertainty_t^{BOS}$ index rises steadily to 8% at the one-year horizon, 16% at the two-year horizon and 20% at the five-year horizon. Similarly, the forecast error variance in employment that is explained by our survey-based General Conditions-$Uncertainty_t^{BOS}$ index rises steadily to 4% at the one-year horizon, 11% at the two-year horizon and 12% at the five-year horizon. In contrast, the uncertainty innovation from the high-uncertainty dummy based on stock market volatility explains never more than 3% of the forecast error variance in production at any horizon, and at most 3% of the forecast error variance in employment. These numbers are even lower when the actual volatility series is used instead of the dummy. We take this as evidence that our uncertainty measure has more explanatory power for economic activity than uncertainty measures based on stock market volatility.

We conduct many more robustness checks to our result that in Choleski-identified SVARs uncertainty innovations trigger prolonged declines in economic activity. For example, we vary the economic activity variable used in the baseline SVAR, while keeping General Conditions-$Uncertainty_t^{BOS}$ (based on Q 1) as the uncertainty measure: the BOS shipments, employment and "work hours" based activity indices and overall labor productivity in manufacturing. We also vary the uncertainty measure: an indicator variable for high uncertainty to capture uncertainty spikes as opposed to general uncertainty fluctuations, an uncertainty measure based on entropy, and uncertainty measures derived from other expectation questions in the BOS. The results are depicted in Appendix B.3, Figures 15 to 19. The basic qualitative patterns of these impulse responses are the same as in our benchmark systems.

There are two main results from our analysis thus far – one negative and one positive. The negative result is that there is little evidence supporting the high-frequency "wait-and-see"-mechanism with a rebound, described in Section 2. On the positive side we have that innovations to uncertainty contain significant predictive information for the future path of sectoral economic activity.

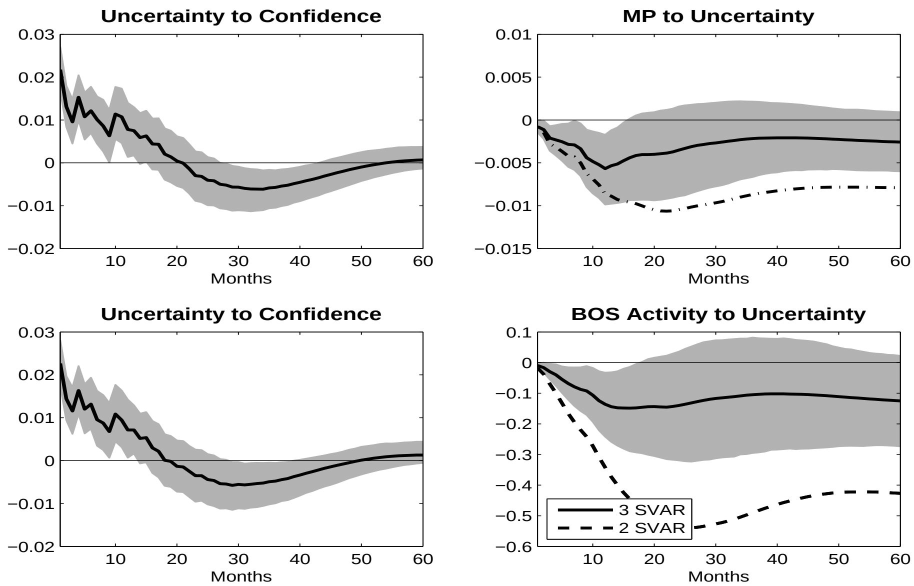
This, in turn, leaves open two interpretations: for one, autonomous shocks to uncertainty have long-run or even permanent effects. This would be consistent with a "wait-and-see"-story where the R&D-sector is particularly heavily hit, so that persistent, but transitory uncertainty shocks could lead to permanent effects on economic activity.[11] In this case, it could well be that the high-frequency "wait-and-see"-dynamics are simply swamped by low-frequency effects, and we need to attempt to "control" for the latter.

In any event, another interpretation opens up: uncertainty could itself be generated by bad news about the future. Under this interpretation, uncertainty events are merely a by-product of bad economic times. Figure 6 shows results from the Choleski-identified baseline SVAR, augmented by a measure of business confidence, ordered first. We define business confidence as the difference between the fraction of positive responses and the negative responses in the business survey. As in Figure 2, the two upper panels use manufacturing production as the activity variable, and the two lower panels use the survey-based activity measure General Conditions-$Activity_t^{BOS}$. The two left panels show the impulse response of the uncertainty index to a negative innovation in business confidence. They are strongly and significantly positive. Bad news increase uncertainty. On the right hand side, we see the impulse responses of economic activity to a positive innovation in business uncertainty, orthogonalized to business confidence innovations. The impulse responses from Figure 2 are also depicted for comparison. While the impulse responses remain small on impact and protracted over time, albeit much less so, their

[11] The increase of measured uncertainty to an uncertainty innovation lasts about 12 months in our baseline SVAR displayed in Figure 2 and then dies out.

permanence vanishes once uncertainty innovations are orthogonalized to confidence innovations and the responses are quantitatively much smaller.

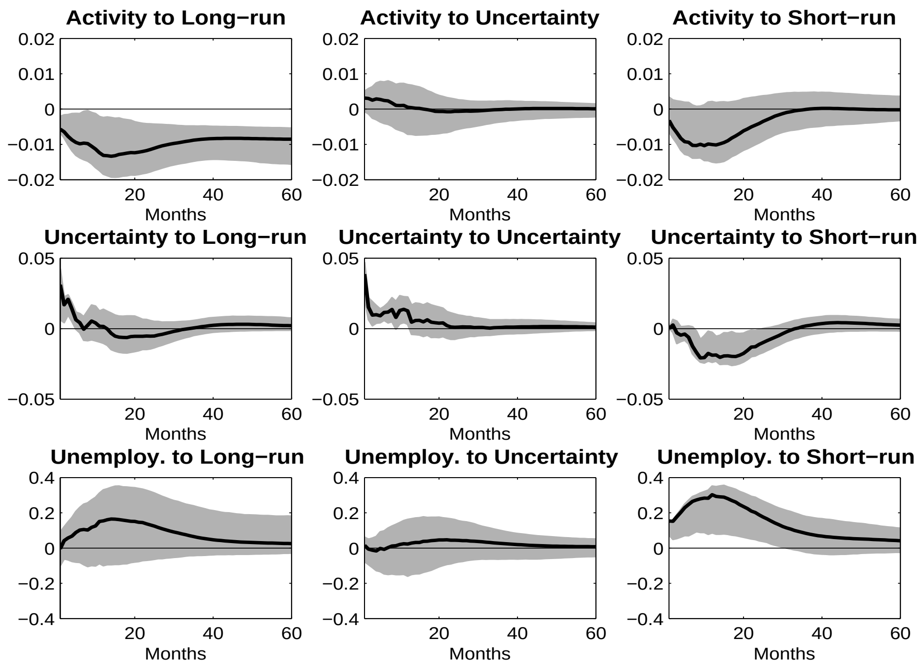
Figure 6: Uncertainty Innovations Orthogonalized to Confidence Innovations



Notes: see notes to Figure 2. The two upper panels feature results from an SVAR with (in this ordering) General Conditions-$Confidence_t^{BOS}$, General Conditions-$Uncertainty_t^{BOS}$ and manufacturing production. General Conditions-$Confidence_t^{BOS}$ is a business confidence indicator, defined as $Confidence_t \equiv Frac_t^+ - Frac_t^-$. It is based on Q 1. In the lower panels General Conditions-$Activity_t^{BOS}$ index replaces manufacturing production as the activity variable. The two left panels show the impulse responses of the uncertainty index to a negative innovation in business confidence. The two right panels show impulse responses of economic activity to a positive innovation in business uncertainty. The dashed lines reproduce the impulse responses of activity from Figure 2.

To explore the "by-product"-hypothesis further, as well as to give uncertainty a better chance of leading to high-frequency "wait-and-see"-type dynamics, we now attempt to "control" for any information about long-run economic activity contained in the uncertainty measures. We do so by adopting an identification approach in the spirit of Shapiro and Watson (1988) as well as Blanchard and Quah (1989) in a three-variable VAR with General Conditions-$Uncertainty_t^{BOS}$, manufacturing production as a sectoral activity measure and the aggregate unemployment rate. We identify three structural shocks – one which can have a long-run effect on production and two which cannot. Notice that the corresponding long-run shock in our case, unlike in Blanchard and Quah (1989) who use aggregate and not sectoral production, need not literally be a productivity shock. Rather, it is any shock that permanently affects sectoral output. We identify the uncertainty shock as a shock that does not impact activity in the long-run, but can influence uncertainty and unemployment. The long-run impact of uncertainty is shut down by construction to let short-run effects of uncertainty shine through. Third, we identify a more conventional aggregate demand shock separately from the short-run uncertainty shock, where we assume that the conventional demand shock does not affect uncertainty on impact.[12]

Figure 7: A Three-Variable Blanchard-Quah-Type SVAR



Notes: see notes to Figure 2. We use manufacturing production as the activity measure, and the General Conditions-$Uncertainty_t^{BOS}$ index as the uncertainty measure. The unemployment rate is the (seasonally adjusted) monthly civilian unemployment rate from the BLS. The uncertainty innovation and the conventional short-run shock are identified as shocks that do not impact manufacturing production in the long-run. The conventional short-run shock is identified as the shock that does not affect the uncertainty index on impact. The long-run shock and the conventional short-run shock have a negative sign.

Figure 7 shows the impulse responses in such a three-variable SVAR, and Table 3 the corresponding forecast error variance decomposition for horizons ranging from one month to five years. Two results are important: first, once the long-run impact of uncertainty is "controlled" for, there is little significant impact of uncertainty on output or unemployment left. The forecast error variance for activity is mainly driven by the long-run and the conventional short-run shock, whereas the contribution of the uncertainty shock after three months drops below 10 percent. The contribution of the uncertainty shock to the fluctuations of the unemployment rate is even smaller. Secondly, a shock which permanently lowers sectoral production is associated with an increase in uncertainty. This is consistent with the Choleski-identified results in

[12]We also tried an alternative specification which identifies the uncertainty shock as the shock leading to no long-run impact on output which maximally explains variation in our uncertainty measure over various horizons (as opposed to just on impact, which is what the recursive assumption does). The results are very similar.

Figure 6 and precisely what our "by-product"-hypothesis with respect to uncertainty implies. The forecast error variance decomposition shows that the long-run shock accounts for a significant fraction of the fluctuations in the uncertainty index, particularly in the first six months.

Table 3: FORECAST ERROR VARIANCE DECOMPOSITION - BOS

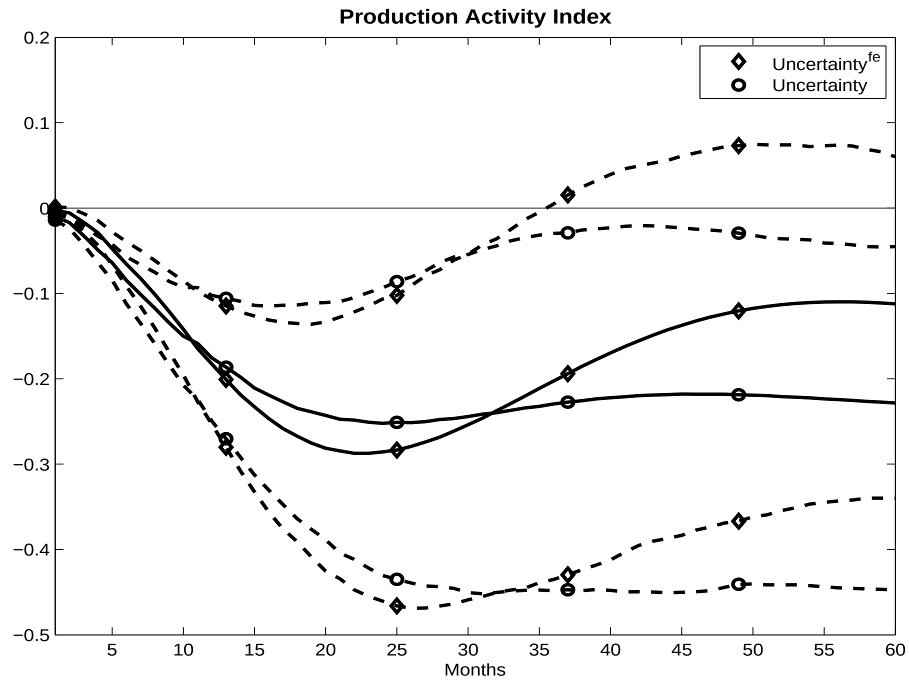
	Shock	1M	3M	6M	1Y	2Y	5Y
Activity	Long-run	62%	55%	52%	53%	64%	77%
	Uncertainty	19%	10%	6%	3%	1%	1%
	Short-run	20%	34%	42%	44%	34%	22%
Uncertainty	Long-run	39%	48%	47%	28%	21%	21%
	Uncertainty	61%	52%	51%	43%	29%	27%
	Short-run	0%	0%	2%	30%	51%	52%
Unemployment Rate	Long-run	0%	6%	11%	15%	21%	23%
	Uncertainty	1%	1%	0%	0%	1%	2%
	Short-run	99%	93%	89%	85%	77%	75%

Notes: see notes to Figure 7.

4.2 IFO Business Climate Survey

We now turn to results using the IFO Business Climate Survey, which gives us the advantage of being able to compare uncertainty measures based on ex-ante disagreement with uncertainty measures based on ex-post forecast error variance. Figure 8 shows the activity responses for the Choleski-identified baseline SVAR to the innovations in the two types of uncertainty we are considering: uncertainty based on the ex post forecast error standard deviation – $Uncertainty_t^{fe^{IFO}}$ – and uncertainty based on ex ante disagreement – $Uncertainty_t^{IFO}$. The activity variable is based on Q 5, the IFO current production question. The SVARs here include a dummy variable from 1991 on to account for structural breaks associated with the German reunification, though our results are insensitive to alternative ways of dealing with that event. There are two important results: first, the responses of activity to the two different measures of uncertainty are quite similar to each other, in fact statistically indistinguishable. This serves as support for our use of a disagreement measure as an uncertainty proxy. Second, the results are also similar to those from the BOS, with somewhat more evidence of reversion at longer horizons when $Uncertainty_t^{fe^{IFO}}$ is used. The impact effects on activity are small, with the trough of the negative response occurring roughly two years subsequent to the shock. This provides corroboration of the results from U.S. data in another country.

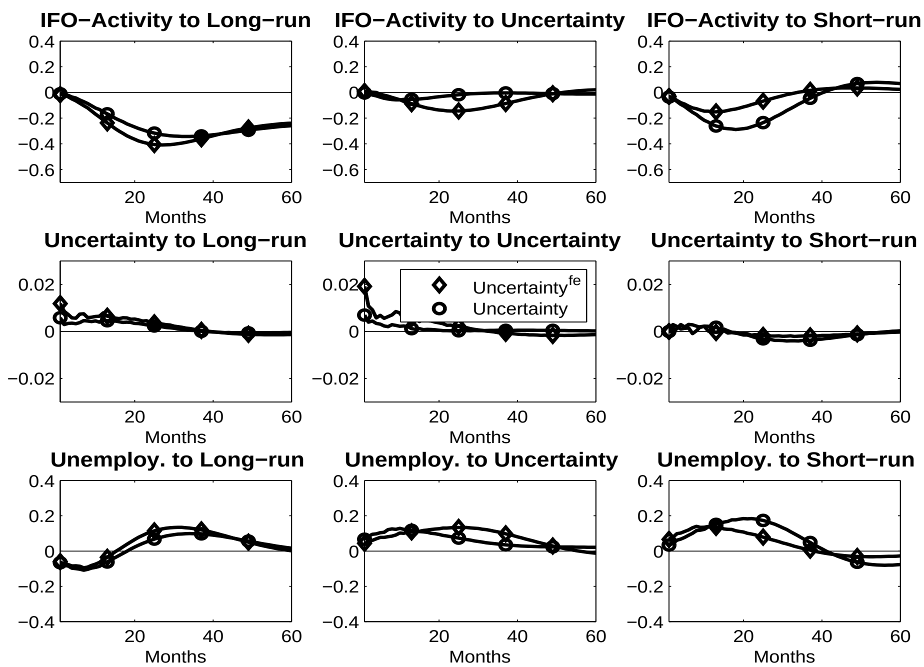
Figure 8: Uncertainty Innovations on Production-$Activity_t^{IFO}$



Notes: $Uncertainty_t$ is based on Q 4. $Uncertainty_t^{fe}$ is based on Q 4 and Q 5. The activity variable is based on Q 5. Uncertainty is ordered first. We include a dummy variable from 1991 to account for the German reunification. We run the VARs with 12 lags. All confidence bands are at the 95% significance level using Kilian's (1998) bias-corrected bootstrap.

We conclude by also confirming the BOS results from the three-variable Blanchard-Quah-type SVAR with Production-$Activity_t^{IFO}$, $Uncertainty_t$ and $Uncertainty_t^{fe}$, and the unemployment rate in Figure 9 and Table 4 (for the sake of readabililty, we leave out the confidence bands). We find that uncertainty measured either way has a lower impact on sectoral economic activity than in the BOS and somewhat more impact on the unemployment rate, especially for the disagreement measure $Uncertainty_t$. The impulse response to either uncertainty measure does not look like high-frequency "wait-and-see"-dynamics. We again find that a negative long-run shock has a sizeable positive impact on the uncertainty index. The similarity between the BOS and IFO-BCS results suggests that the negative findings in Popescu and Smets (2010) as well as Bachmann and Bayer (2011) with regards to the role of uncertainty shocks as a major driving force of short-run fluctuations are not driven by their use of German data.

Figure 9: A Three-Variable Blanchard-Quah-Type SVAR - IFO-BCS



Notes: see notes to Figure 8. The unemployment rate is the (seasonally adjusted) monthly unemployment rate from the Bundesanstalt für Arbeit. The uncertainty shock and the conventional short-run shock are identified as shocks that do not impact manufacturing production in the long-run. The conventional short-run shock is identified as the shock that does not affect the uncertainty index on impact.

Table 4: FORECAST ERROR VARIANCE DECOMPOSITION - IFO-BCS

	Shock	1M	3M	6M	1Y	2Y	5Y
$Uncertainty_t^{fe}$							
Activity	Long-run	22%	22%	32%	51%	74%	87%
	Uncertainty	5%	1%	2%	6%	10%	7%
	Short-run	73%	77%	66%	43%	16%	6%
Uncertainty	Long-run	28%	31%	36%	40%	45%	44%
	Uncertainty	72%	67%	63%	59%	53%	51%
	Short-run	0%	2%	2%	2%	2%	5%
Unemployment Rate	Long-run	37%	35%	31%	23%	17%	33%
	Uncertainty	19%	19%	21%	25%	37%	39%
	Short-run	45%	45%	48%	52%	46%	28%
$Uncertainty_t$							
Activity	Long-run	8%	8%	13%	21%	40%	73%
	Uncertainty	1%	5%	8%	6%	2%	1%
	Short-run	91%	87%	80%	73%	58%	27%
Uncertainty	Long-run	41%	39%	41%	52%	62%	44%
	Uncertainty	59%	60%	49%	36%	25%	17%
	Short-run	0%	1%	10%	13%	13%	39%
Unemployment Rate	Long-run	44%	40%	38%	28%	14%	23%
	Uncertainty	44%	45%	41%	40%	30%	23%
	Short-run	12%	15%	20%	32%	56%	55%

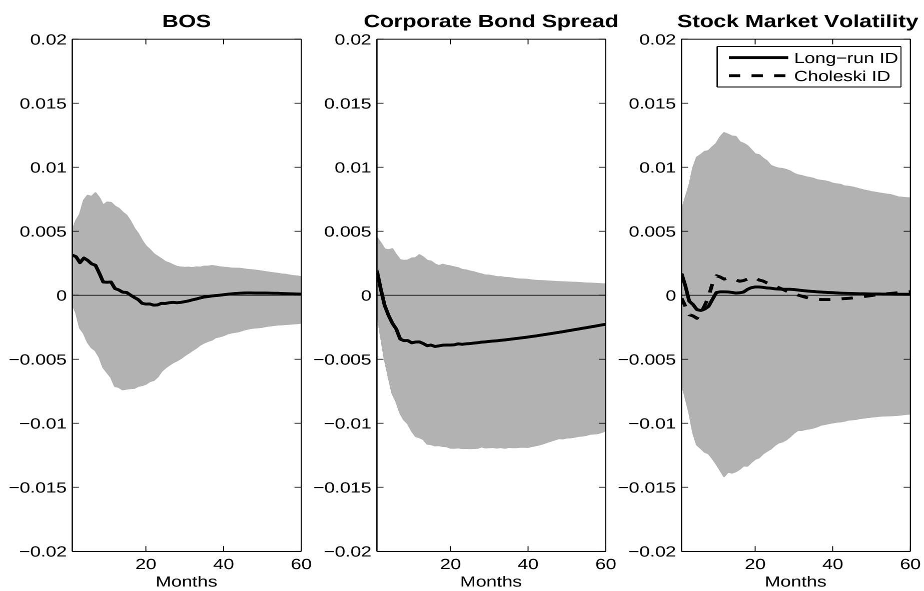
Notes: see notes to Figure 9.

4.3 Discussion

In Choleski-identified SVARs with sectoral business uncertainty and sectoral economic activity variables we find protracted negative impulse responses of activity to uncertainty innovations. Job turnover reacts positively to the same shocks. A different SVAR identification identifies uncertainty shocks as having no long-run effect on production, but affecting production and unemployment on impact. An uncertainty shock so identified has little significant effect on economic activity. In contrast, a shock identified as having a permanent effect on activity is associated with significant increases in uncertainty.

Figures 10 and 11 show both these results from survey based uncertainty measures in a condensed form and compare them to results based on other uncertainty proxies used in the literature. To do so, we replace General Conditions-$Uncertainty_t^{BOS}$ with, respectively, the corporate bond spread as in Gilchrist et al. (2009), and stock market volatility as in Bloom (2009), in the three-variable Blanchard-Quah-type SVAR that leads to Figure 7.

Figure 10: Uncertainty Shock on Activity

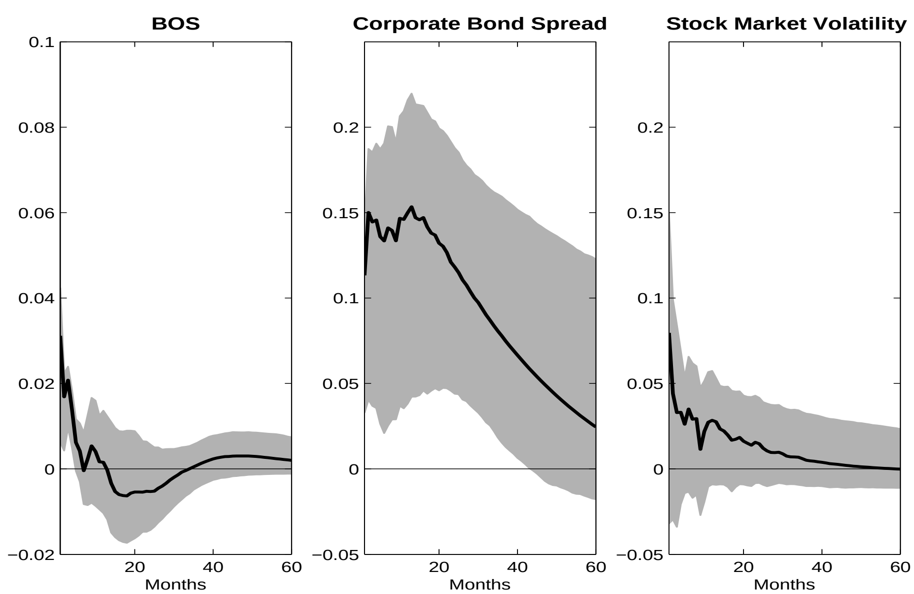


Notes: see notes to Figure 7. The first panel is simply a replication of the 'Activity to Uncertainty' impulse response from Figure 7. The second panel displays the 'Activity to Uncertainty' response of a three-variable Blanchard-Quah-type SVAR with 'Corporate Bond Spread' as the uncertainty measure, total industrial production as the activity measure and the civilian unemployment rate. 'Corporate Bond Spread' refers to the spread of the 30 year Baa corporate bond index over the 30 year treasury bond. Where the 30 year treasury bond was missing we used the 20 year bond. Data source for the bond data is the Federal Reserve Board. The third panel displays the 'Activity to Uncertainty' response of the same SVAR with the stock market volatility dummy from Bloom (2009) as the uncertainty measure. The Choleski-identified impulse response (dashed line) from Bloom (2009) is included for comparison.

Figure 10 compares the effects of surprise movements in various uncertainty proxies on production. The leftmost panel is simply a replication of the result in Figure 7, i.e. where we use the survey-based General Conditions-$Uncertainty_t^{BOS}$-index as the uncertainty measure. The middle panel uses the corporate bond spread and the rightmost panel the "high stock market volatility"-dummy from Bloom (2009). Note that the high-frequency "wait-and-see"-dynamics with a fast rebound more or less survive the long-run idenfication strategy, as far as the point estimate is concerned. This is not too surprising given that the Choleski-identified impulse response is essentially zero in the long-run. But Figure 10 also shows that any high-frequency impact of surprise movements in uncertainty, regardless of how it is measured, is likely to be small – much less than half a percent of production – and statistically indistinguishable from each other as well as from zero.

Figure 11 compares the reaction of various uncertainty indices to an adverse long-run shock. The leftmost panel is again a replication of the result in Figure 7. The point estimates for all three uncertainty measures are positive, signficantly so for General Conditions-$Uncertainty_t^{BOS}$ and the corporate bond spread, which is at least suggestive of the "by-product"-hypothesis.

Figure 11: Long-Run Shock on Uncertainty



Notes: see notes to Figures 7 and 10. The first is a replication of the 'Uncertainty to Long-Run' impulse response from Figure 7. The second panel displays the 'Uncertainty to Long-Run' response of a three-variable Blanchard-Quah-type SVAR with 'Corporate Bond Spread' as the uncertainty measure, total industrial production as the activity measure and the civilian unemployment rate. The third panel displays the 'Uncertainty to Long-Run' response of the same SVAR with stock market volatility from Bloom (2009) as the uncertainty measure. Until 1986 this is realized monthly stock return volatility, and thereafter an implied volatility index.

As has been mentioned before our results leave open two interpretations for the role of uncertainty in economic fluctuations. The first interpretation is that uncertainty is an autonomous source of such fluctuations but has mainly long-run effects. In this case our SVARs show that structural models need a mechanism that transmits rather transitory uncertainty shocks into very persistent or even permanent output and employment declines. Alternatively, uncertainty can be viewed as an epiphenomenon that accompanies bad economic times. While we cannot strictly rule out the former, we believe that the data points in the latter direction: bad times breed uncertainty.

Table 5: RELATION BETWEEN NBER RECESSIONS AND HIGH UNCERTAINTY DATES

Uncertainty Measure	High Uncertainty In Recessions	High Uncertainty Outside of Recessions
$Uncertainty^{BOS}$	7 out of 7	8.5%
Corporate Bond Spread	6 out of 8	11.2%
Stock Market Volatility	7 out of 7	8.3%

Notes: $Uncertainty^{BOS}$ refers to the BOS uncertainty measure, based on Q 1. For 'Corporate Bond Spread' see notes to Figure 10. For 'Stock Market Volatility' see notes to Figure 11. For each uncertainty proxy we construct a high uncertainty dummy, setting it unity, when the value exceeds the time series average by one standard deviation. In the first column we report how many post 1960 recessions coincide with high uncertainty events. We do not have BOS or stock market volatility data available for the 1961 recession. There are no high corporate bond spread-uncertainty events during the 1961 and the 1991 recessions. In the second column we report the fraction of months where high uncertainty events occur outside of NBER recessions.

Table 5 shows that almost all NBER-dated recessions were periods of high uncertainty – whether it is measured as cross-sectional forecast dispersion from business survey data, the corporate bond spread or stock market volatility. We define high uncertainty events as months when either uncertainty measure was one standard deviation above its time series average. That almost all US recessions have been times of high uncertainty is consistent with causality running in either direction – from uncertainty to economic activity or from activity to uncertainty. It is therefore interesting to note that there is a considerable fraction of months – close to 10 percent – where uncertainty spikes but the economy was not in a recession, nor did a period of economic distress soon follow. This is particularly true in the mid-late 1980s (around the time of the 1987 stock market crash) and the mid-late 1990s, well before the downturn of 2001. That such large increases in uncertainty did not lead to economic contractions is at least suggestive evidence that uncertainty is a concomitant factor of bad economic times rather than a causal factor for them.

It is beyond the scope of this paper to fully specify a model of intrinsic uncertainty as an endogenous result of bad first moment shocks. Bachmann and Moscarini (2011) do so using price experimentation as a mechanism; Fostel and Geanakoplos (2011) point to leverage. More generally, we think of recessions as times of severed business and customer relationships and of failing business models. Business and customer relationships have to be reestablished and business models altered when the economy is at trough. This generates uncertainty. In booms, in contrast, businesses have little incentive (or opportunity) to substantially change their operating practices. Customers stay with their preferred business.

As a highly stylized example, suppose there are three businesses in an economy each producing the same product, with total demand equal to 2 units of the product. Suppose initially that all three businesses have an equal share of two-thirds. In a boom demand becomes 2.5. With costs to establishing new business relationships, the customers of each business stick around and demand more. There is no uncertainty. In a recession demand becomes $2x$, where $x < 1$. Assume that one of the businesses goes under and business relations are severed. The existing customers at the two remaining businesses now demand $\frac{2}{3}x$ each. What happens to the customers whose business partner vanished? Let us assume there is some uncertainty over where they are going to go, as in a location model where businesses do not know the spatial distribution of customers. On the one extreme, the allocation might be $\left[\frac{4}{3}x, \frac{2}{3}x\right]$, i.e. one business gets all the free customers, on the other extreme it might be an equal split: $[x, x]$. It is obvious that there exists a range for x, namely $\left(\frac{1}{2}, \frac{2}{3}\right)$, where even in the most equal distribution both businesses are worse off than before, but with an unequal split one business might even come out better than before in this recession. The important point is this: there is an intrinsic uncertainty due to recessions, because business structures and practices have to be re-arranged.

5 Final Remarks

Using two different measures of business uncertainty from high-frequency, sectoral business surveys in Choleski-identified structural vector autoregressions we find that positive innovations to business uncertainty have protracted negative implications for sectoral economic activity. This appears to be inconsistent with a high-frequency "wait-and-see"-channel being the dominant effect of suprise movements in business uncertainty. This contrasts with the results in the literature for suprise movements in stock market volatility, which trigger short-run collapses of activity and quick rebounds. We confirm this result from Bloom (2009) also in a long-run identification strategy.

This can mean two things, which are not necessarily mutually exclusive. On the one hand, perhaps stock market volatility really measures a different type of uncertainty than survey-based uncertainty and the corporate bond spread – say aggregate uncertainty versus idiosyncratic uncertainty – and these types of uncertainty have different impacts on businesses' behavior. The second possibility is that the low-frequency impact of the survey-based uncertainty measures swamps the high-frequency "wait-and-see"-dynamics. However, we show in this paper that any high-frequency impact of surprise movements in uncertainty is likely to be small, regardless of how uncertainty is measured and how its high-frequency impact is identified. This leaves open the possibility that "wait-and-see"-dynamics can be combined with an endogenous growth mechanism – R&D investment or embodied technological change – to generate the observed protracted negative implications for economic activity in Choleski-identified structural vector autoregressions. Finally, structural vector autoregression studies, by their very nature, can only make statements about the *average* effect of uncertainty shocks, which leaves open the possibility that high uncertainty events in certain episodes may have severely adverse high-frequency consequences.

But this paper also opens up another possibility, the "by-product"-hypothesis, for which we find evidence both in Choleski-identified as well as Blanchard-Quah-type structural vector autoregressions. Under this interpretation negative long-run shocks lead to high uncertainty events. Uncertainty is a concomitant phenomenon of negative first moment events in the economy. Bad times breed uncertainty. Of course, this leaves open the possibility that uncertainty and the resulting "wait-and-see" are an important *propagation and amplification* mechanism for other shocks. Businesses may invest and hire less when the outlook is bleak, but they may even be more reluctant to invest and hire when, in addition, the outlook is uncertain.

Our results suggest that research in the following three areas may prove fruitful: "wait-and-see"-mechanisms in endogenous growth environments; fully specified mechanisms that endogenously generate uncertainty in bad economic times; and the role of uncertainty as a propagation and amplification mechanism.

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A Appendix - A Simple Model

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 into 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: $[0.5*(1-p), p, 0.5*(1-p)]$, 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 6. 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 6: A SIMPLE TWO-PERIOD MODEL OF FIRMS' BUSINESS SITUATIONS

State Tomorrow

	$0.5*(1-p)\swarrow$			$\downarrow p$			$\searrow (1-p)*0.5$	
	+1			0			-1	
$q\swarrow$		$\searrow (1-q)$	$0.5*(1-q)\swarrow$	$q\downarrow$	$\searrow (1-q)*0.5$	$(1-q)\swarrow$		$\searrow q$
+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) $Prob(state=1|signal=1) = \frac{q*0.5*(1-p)}{q*0.5*(1-p)+0.5*(1-q)*p}$

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

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

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

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

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

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

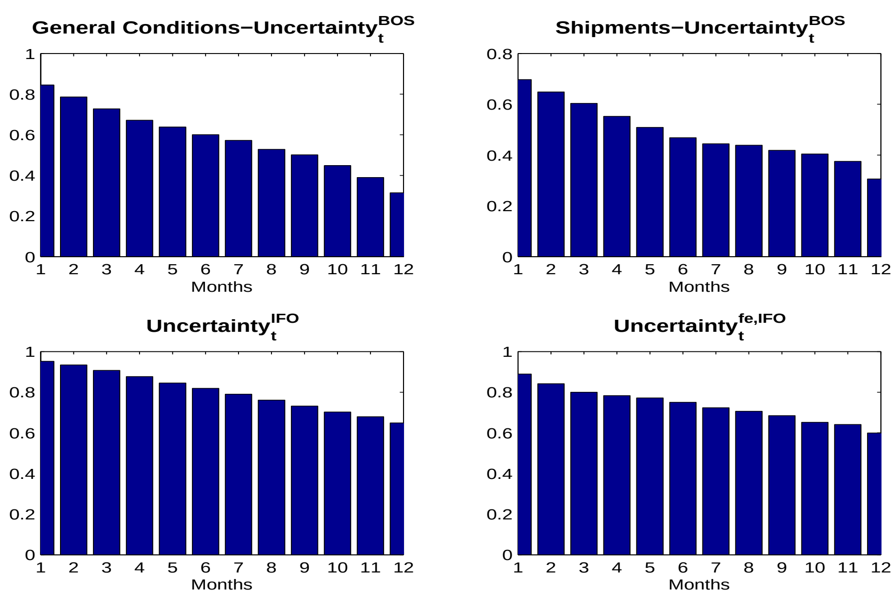
   (b) $Prob(state=0|signal=-1) = \frac{0.5*(1-q)*p}{q*0.5*(1-p)+0.5*(1-q)*p}$

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

From these conditional probabilities, conditional expectations and variances can be computed. And these, in turn, allow us to calculate 1) the variance of the conditional expectations over the change in business situations, which is a measure of disagreement; and 2) 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. Figure 12 plots the autocorrelograms for General Conditions-$Uncertainty_t^{BOS}$, Shipments-$Uncertainty_t^{BOS}$, Production-$Uncertainty_t^{IFO}$ and Production-$Uncertainty_t^{fe^{IFO}}$, showing that uncertainty is very persistent.

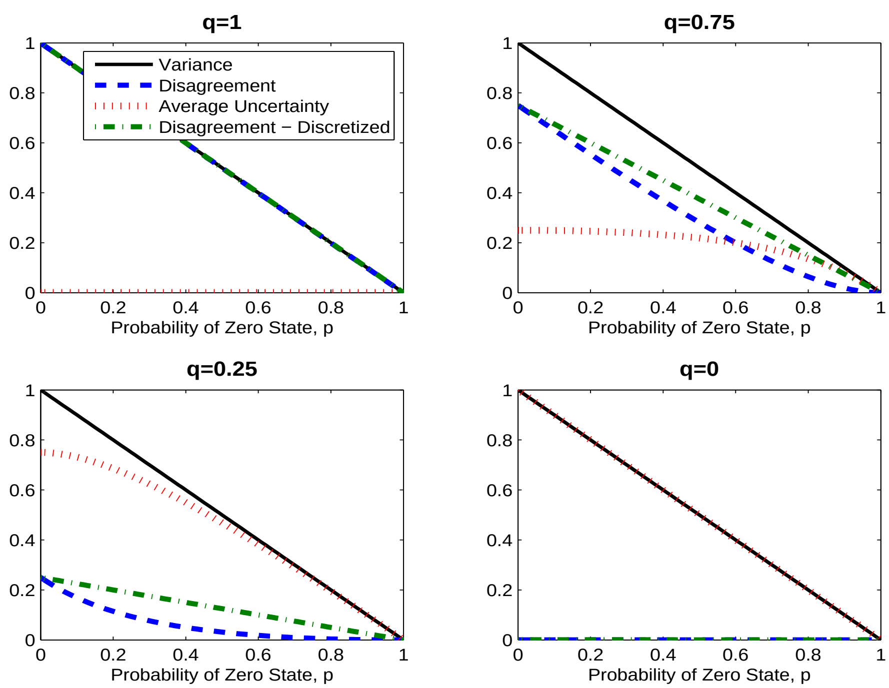
Figure 12: Autocorrelograms of Various Uncertainty Measures



Notes: General Conditions-$Uncertainty_t^{BOS}$ is based on Q 1. Shipments-$Uncertainty_t^{BOS}$ is based on Q 6. Production-$Uncertainty_t^{IFO}$ is based on Q 4. For the construction of Production-$Uncertainty_t^{fe^{IFO}}$, based on Q 4 and Q 5, see Section 3.3.

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 13 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 given by the black solid line, the variance of the conditional expectations over tomorrow's state (disagreement) by the blue dashed line and the average conditional variance over tomorrow's state (subjective uncertainty) by the red dotted line.

Figure 13: Cross-sectional Variance, Disagreement and Uncertainty



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, the closer the conditional expectation is to unity, the more likely firms are going to respond with 1 in the survey. Symmetrically 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):

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

This discretized version of disagreement is also shown in Figure 13, by the green dashed-dotted line. It follows closely the continuous disagreement measure. Notice that for intermediate signal qualities, both disagreement and uncertainty move in the same direction as the variance of the state tomorrow. In particular, for high values of p subjective uncertainty varies significantly with the cross-sectional variance of the change in business situations. If the signal was such that it left everybody with the same conditional expectation ($q = 0$), then of course disagreement would always be zero. Only the subjective uncertainty would then be affected.

B Appendix - Third FED District Business Outlook Survey (BOS)

B.1 Additional BOS Questions

Q 6 *"Company Business Indicators: Shipments six months from now vs. [CURRENT MONTH]: decrease, no change, increase?"*

Q 7 *"Company Business Indicators: Number of Employees six months from now vs. [CURRENT MONTH]: decrease, no change, increase?"*

Q 8 *"Company Business Indicators: Average Employee Workweek six months from now vs. [CURRENT MONTH]: decrease, no change, increase?"*

Q 9 *"Company Business Indicators: Shipments [LAST MONTH] vs. [CURRENT MONTH]: decrease, no change, increase?"*

Q 10 *"Company Business Indicators: Average Employee Workweek [LAST MONTH] vs. [CURRENT MONTH]: decrease, no change, increase?"*

B.2 Additional Information on BOS Variables

Table 7: Correlation between BOS-$Activity_t$ Variables and Official Statistics

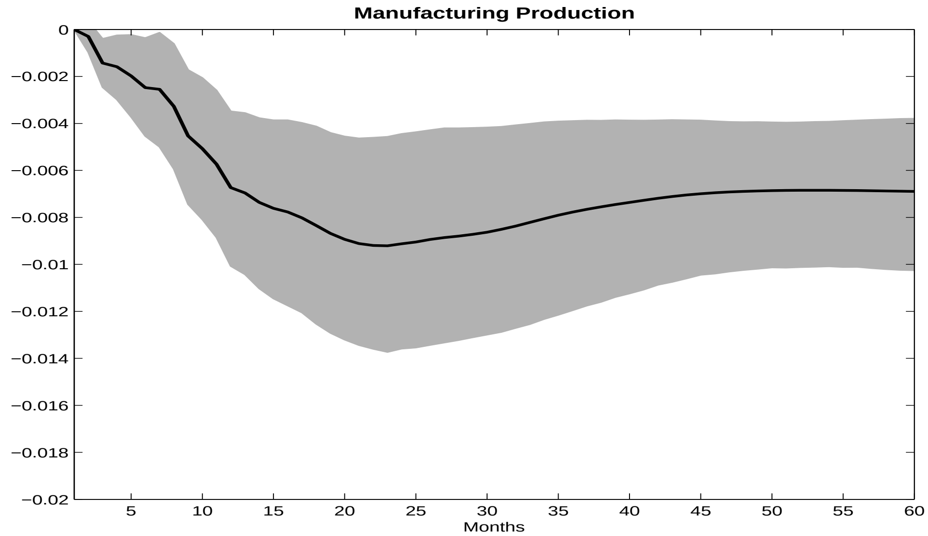
	General Conditions	Shipments	Employment
BLS Monthly Sect. & Regio. Empl.	0.54	0.60	0.63
Philadelphia FED Coincident Index	0.71	0.68	0.60
NIPA Yearly Sect. & Regio. Prod.	0.39	0.41	-

Notes: This table displays the unconditional contemporaneous correlations of BOS-$Activity_t$ Variables, based, in column order, on Q 2, Q 9 and Q 3, with log-differences of three different measures of sectoral and regional activity measures from official statistics (in row order): 'BLS Monthly Sect. & Regio. Empl.' refers to the sum of the seasonally adjusted monthly manufacturing employment series for Pennsylvania, Delaware and New Jersey, available from the BLS from 1990 on. 'Philadelphia FED Coincident Index' refers to the GDP-weighted sum of the Philadelphia FED Coincident Indices for Pennsylvania, Delaware and New Jersey (notice that this index is regionally, but not sectorally coinciding with the coverage of the BOS). It is available from 1979 on. 'NIPA Yearly Sect. & Regio. Prod.' refers to the GDP-weighted sum of the yearly NIPA quantity indices for the manufacturing sector for Pennsylvania, Delaware and New Jersey.

B.3 Additional BOS Results

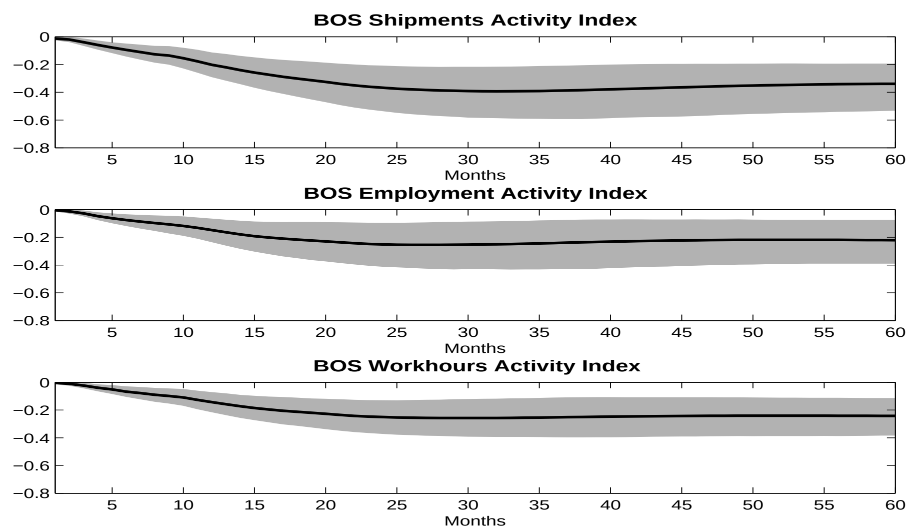
This appendix provides various robustness checks to the results in Section 4.1. Figure 14 shows that the ordering between uncertainty and activity variables is irrelevant for the result that uncertainty innovations in two-variable SVARs trigger prolonged declines in sectoral economic activity. Figures 15 and 16 vary the economic activity variable used in our baseline two-variable SVAR, while keeping General Conditions-$Uncertainty_t^{BOS}$ (based on Q 1) as the uncertainty measure: the BOS shipments, employment and workhours based activity indices, and labor productivity. Figures 17 to 19, in turn, vary the uncertainty measure used: an indicator variable for high uncertainty, an entropy-based uncertainty measure and uncertainty measures derived from other expectation questions in the BOS.

Figure 14: Uncertainty Innovation on Manufacturing Production - Reverse Ordering



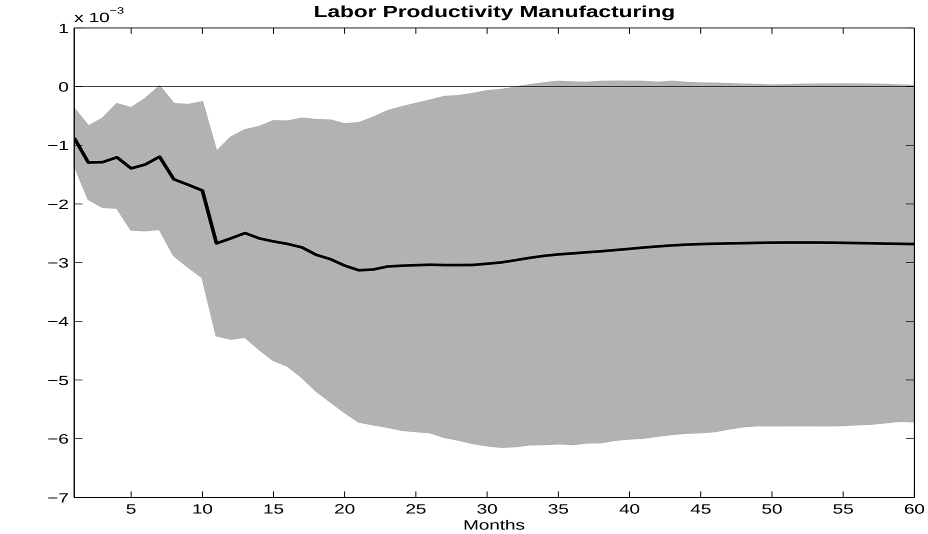
Notes: The IRF is based on a two-variable SVAR with General Conditions-$Uncertainty_t^{BOS}$ (based on Q 1 of the BOS) ordered second and 12 lags. Manufacturing production is the natural logarithm of the (seasonally adjusted) monthly manufacturing production index from the OECD main economic indicators. All confidence bands are at the 95% significance level using Kilian's (1998) bias-corrected bootstrap.

Figure 15: Uncertainty Innovations on Various BOS Activity Indices



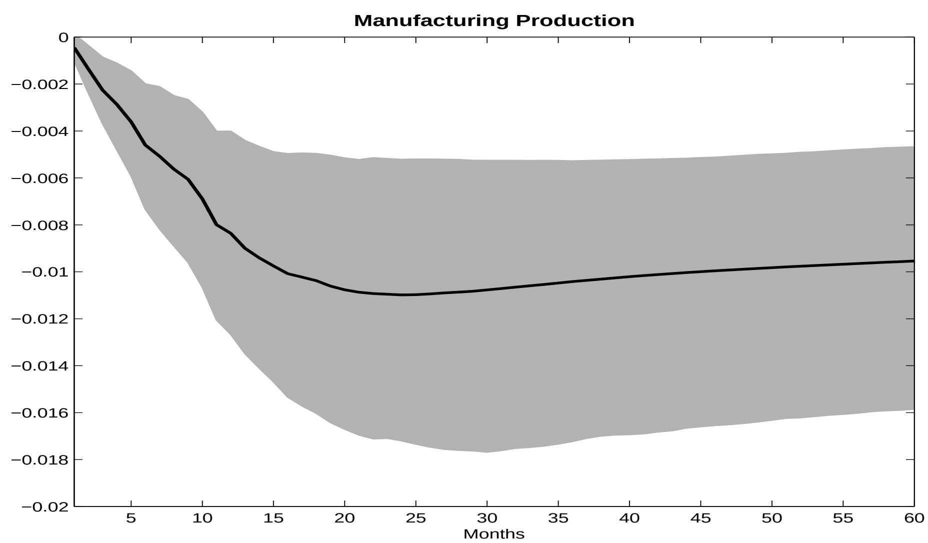
Notes: see notes to Figure 14. Uncertainty is ordered first. The activity indices for the three panels are based on Q 9, Q 3 and Q 10, respectively.

Figure 16: Uncertainty Innovation on Manufacturing Labor Productivity



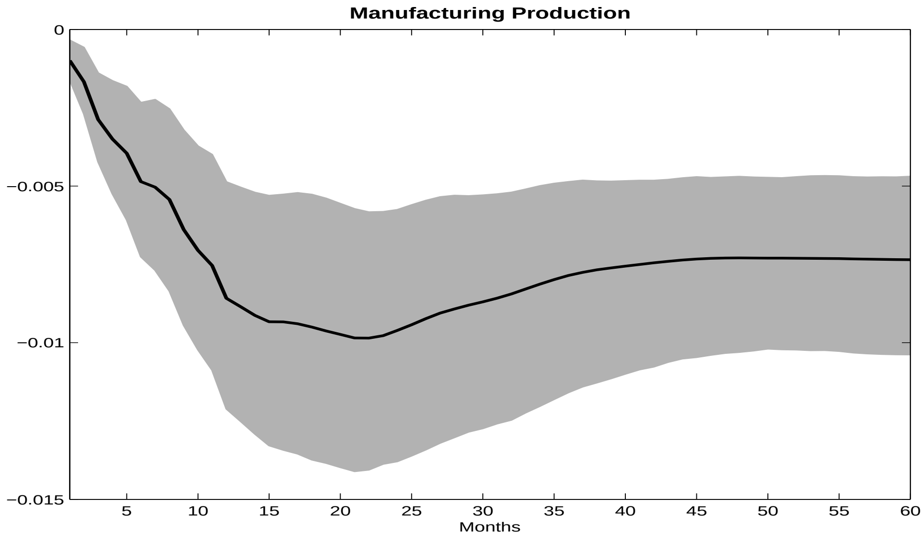
Notes: see notes to Figure 14. Uncertainty is ordered first. Labor productivity is the log-difference between the (seasonally adjusted) monthly manufacturing production index from the OECD main economic indicators and the (seasonally adjusted) monthly manufacturing total hours series, which is itself based on the manufacturing employment and weekly hours per worker series from the BLS-CES data base.

Figure 17: Uncertainty Innovation (Indicator Variable) on Manufacturing Production



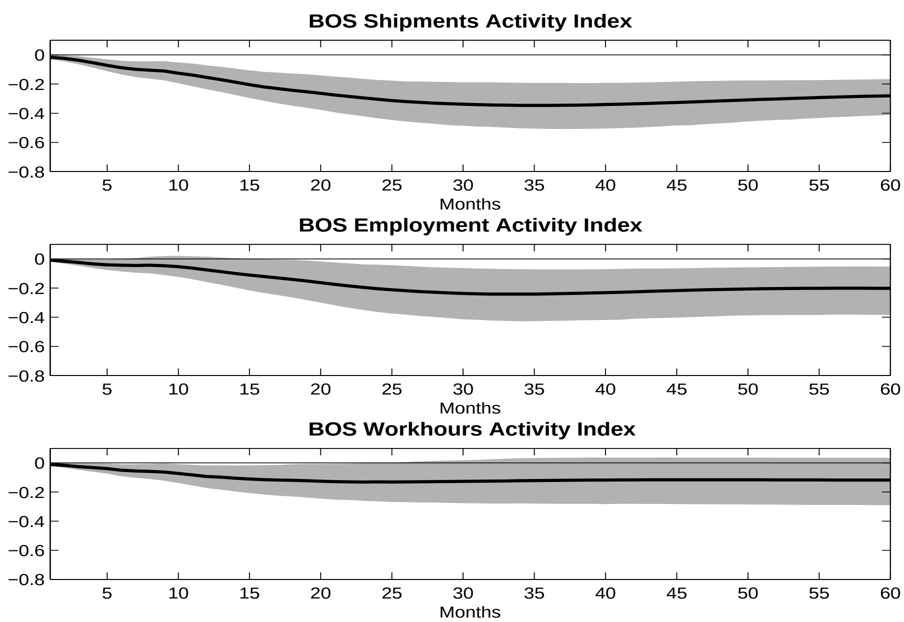
Notes: see notes to Figure 14. Uncertainty is ordered first. The uncertainty variable here is an indicator variable that takes on a value of one, if General Conditions-$Uncertainty_t^{BOS}$, the measure of uncertainty which is based on Q 1, is one standard deviation above its mean, and zero otherwise. There are 60 high-uncertainty observations, or about 12% of the sample.

Figure 18: Uncertainty Innovation on Manufacturing Production - Entropy



Notes: see notes to Figure 14. Uncertainty is ordered first. It is measured as $Uncertainty_t^{Entrop} \equiv Frac_t(\text{Increase})\log(1/Frac_t(\text{Increase})) + Frac_t(\text{Decrease})\log(1/Frac_t(\text{Decrease})) + Frac_t(\text{Neutral})\log(1/Frac_t(\text{Neutral}))$.

Figure 19: Uncertainty Innovations from Other BOS Activity Indices



Notes: see notes to Figure 14. The uncertainty variables for the three panels are based on Q 6, Q 7 and Q 8, respectively. The activity indices for the three panels are based on Q 9, Q 3 and Q 10. Uncertainty is ordered first.

C Appendix - IFO Business Climate Survey (IFO-BCS)

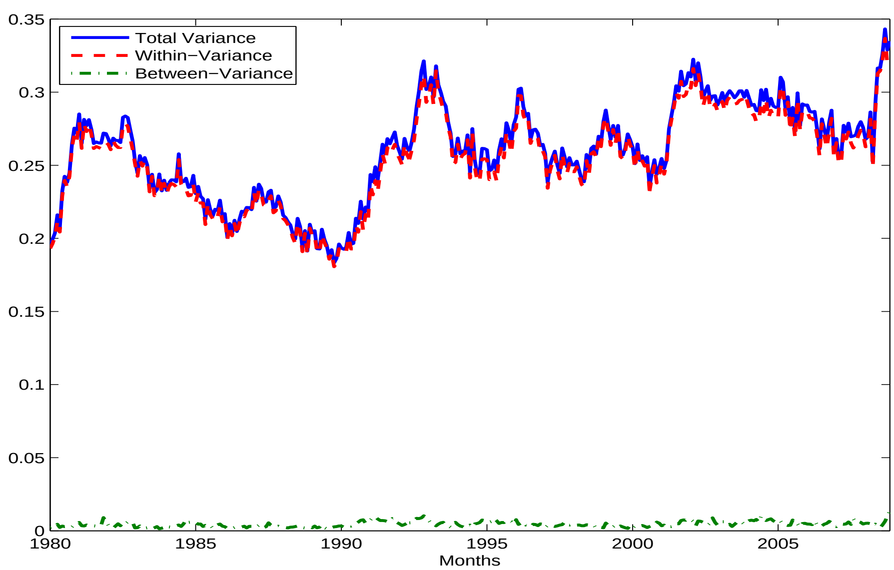
C.1 Original German IFO-BCS Questions

Q 11 *"Erwartungen für die nächsten 3 Monate: Unsere inländische Produktionstätigkeit – ohne Berücksichtigung unterschiedlicher Monatslängen und saisonaler Schwankungen – bezüglich XY wird voraussichtlich: steigen, etwa gleich bleiben, abnehmen."*

Q 12 *"Tendenzen im vorangegangenen Monat: Unsere inländische Produktionstätigkeit – ohne Berücksichtigung unterschiedlicher Monatslängen und saisonaler Schwankungen – bezüglich XY ist: gestiegen, etwa gleich geblieben, gesunken."*

C.2 Variance Decomposition of $(Uncertainty_t^{IFO})^2$

Figure 20: Variance Decomposition of $(Uncertainty_t^{IFO})^2$



Notes: 'Total Variance' refers to $(Uncertainty_t^{IFO})^2$. 'Within-Variance' is the cross-sectional average of the industry analogs of $(Uncertainty_t^{IFO})^2$ for the following 13 manufacturing industries: transportation equipment (*Fahrzeugbau*), machinery and equipment (*Maschinenbau*), metal products (*Metallerzeugung*), other non-metallic mineral products (*Glas, Keramik, Verarbeitung von Steinen und Erden*), rubber and plastic products (*Gummi und Kunststoff*), chemical products (*Chemische Industrie*), electrical and optical equipment (*Elektrotechnik, Feinmechanik und Optik*), pulp, paper, publishing and printing (*Papier, Verlage, Druck*), furniture and jewelery (*Möbel und Schmuck*), cork and wood products except furniture (*Holz ohne Möbel*), leather (*Leder*), textiles and textile products (*Textil und Bekleidung*), food, beverages and tobacco (*Ernährung und Tabak*). We leave out the oil industry, because it has only very few observations. 'Between-Variance' refers to the cross-sectional variance of the industry-specific $Frac_t^+ - Frac_t^-$-indicators.

C.3 Construction of $Uncertainty_t^{fe^{IFO}}$

In this section we describe the construction of the $Uncertainty_t^{fe^{IFO}}$-index. To fix ideas, we proceed at first as if the production expectation question in IFO-BCS, Q 4, was asked only for the next month instead of the following three months. In this case, when comparing the expectation in month t with the realization in month $t+1$, nine possibilities arise: the company could have predicted an increase in production and realized one, in which case we would count this as zero forecast error. It could have realized a no change, in which case, we would quantify the expectation error as -1 and, finally, it could have realized a decrease, which counts as -2.

Table 8: POSSIBLE EXPECTATION ERRORS - ONE MONTH CASE

	$Increase_{t+1}$	$Unchanged_{t+1}$	$Decrease_{t+1}$
Expected $Increase_t$	0	-1	-2
Expected $Unchanged_t$	+1	0	-1
Expected $Decrease_t$	+2	+1	0

Notes: Rows refer to qualitative production expectations in month t. Columns refer to qualitative production realizations in month $t+1$.

Table 8 summarizes the possible expectation errors. Of course, the production expectation question in IFO-BCS is for three months ahead. Suppose that a firm stated in month t that its production will increase in the next three months. Suppose that in the next three months one observes the following sequence of outcomes: production increased in $t+1$, remained unchanged in $t+2$ and finally decreased in $t+3$. Due to the qualitative nature of the IFO-BCS we have to make some assumptions about the definition of the expectation error at the micro level. As a baseline we adopt the following steps. First, we define for every month t a firm-specific activity variable over the next three months, $t+3$, by the sum of the $Increase$-instances minus the sum of the $Decrease$-instances over that time period.[13] Denote this variable by $REALIZ_t$. It can obviously range from $[-3,3]$. Then the expectation errors are computed as:

[13] We also experiment with a weighted sum approach: we weight realizations in $t+1$ one half, realizations in $t+2$ one third and realizations in $t+3$ one sixth. Naturally, when asked in t about the next three months, the firm may bias its answer towards the immediate future. None of our results depends on the precise weighting scheme.

Table 9: POSSIBLE EXPECTATION ERRORS - THREE MONTH CASE

		$Expectationerror_{t+3}$
Expected $Increase_t$	$REALIZ_t > 0$	0
Expected $Increase_t$	$REALIZ_t \leq 0$	$(REALIZ_t - 1)/3$
Expected $Unchanged_t$	$REALIZ_t > 0$	$REALIZ_t/3$
Expected $Unchanged_t$	$REALIZ_t = 0$	0
Expected $Unchanged_t$	$REALIZ_t < 0$	$REALIZ_t/3$
Expected $Decrease_t$	$REALIZ_t < 0$	0
Expected $Decrease_t$	$REALIZ_t \geq 0$	$(REALIZ_t + 1)/3$

Notes: Rows refer to the qualitative production expectations in IFO-BCS in month t (Q 4).

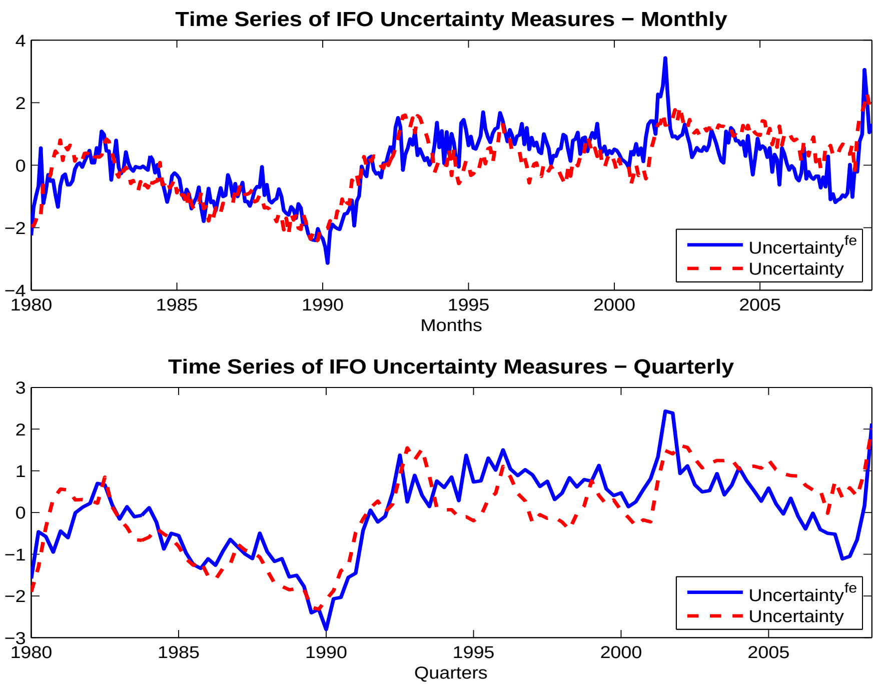
Notice that the procedure in Table 9 is analogous to the one month case. Dividing by three is simply a normalization. $Expectationerror_{t+3}$ ranges from $[-\frac{4}{3}, \frac{4}{3}]$, where for instance $-\frac{4}{3}$ indicates a strongly negative forecast error: the company expected production to increase over the next three months, yet every single subsequent month production actually declined.

Computing the cross-sectional standard deviations of the expectation errors at each month, t, gives us a qualitative series of forecast error standard deviations. Specifically:

$$Uncertainty_t^{fe} \equiv STD(Expectationerror_{t+3}).$$

Notice the timing in the definition of $Uncertainty_t^{fe}$, which is the same as in Bloom (2009) for stock market volatility: the standard deviation of *realized* expectation errors in $t+3$ does not constitute uncertainty in $t+3$. It is the knowledge (at time 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. Figure 21 depicts $Uncertainty_t^{fe^{IFO}}$ and $Uncertainty_t^{IFO}$, both at the monthly and the quarterly frequency, and shows that they strongly comove.

Figure 21: Comparison of $Uncertainty_t^{IFO}$ and $Uncertainty_t^{fe^{IFO}}$



Notes: The upper panel shows the monthly time series of $Uncertainty_t^{IFO}$ and $Uncertainty_t^{fe^{IFO}}$, demeaned and standardized by their standard deviation. Their correlation is 0.73. The lower panel shows the quarterly averages of the monthly $Uncertainty_t^{IFO}$ and $Uncertainty_t^{fe^{IFO}}$ time series, demeaned and standardized by their standard deviation. Their correlation is 0.77.

D Appendix - Small Business Economics Trends Survey (SBETS)

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 U.S. 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 to give the "wait-and-see"-dynamics the best possible chance to appear in the data. 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.[14] Almost 25% of respondents are in the retail sector,

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

20% in construction and 15% in manufacturing, followed by services, which ranges well above 10%. All other one-digit sectors have a single digit representation 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.

We use three questions from the SBETS. The uncertainty index is based on a question about general business conditions just like in the BOS (the box and the bold font are also used in the original):

Q 13 *"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. To measure activity in the SBETS we use:

Q 14 *"During the* ***last calendar quarter****, was your dollar sales volume higher, lower, or about the same as it was for the quarter before?* $\boxed{1}$ *Much higher* $\boxed{2}$ *Higher* $\boxed{3}$ *About the same,* $\boxed{4}$ *Lower* $\boxed{5}$ *Much lower. "*

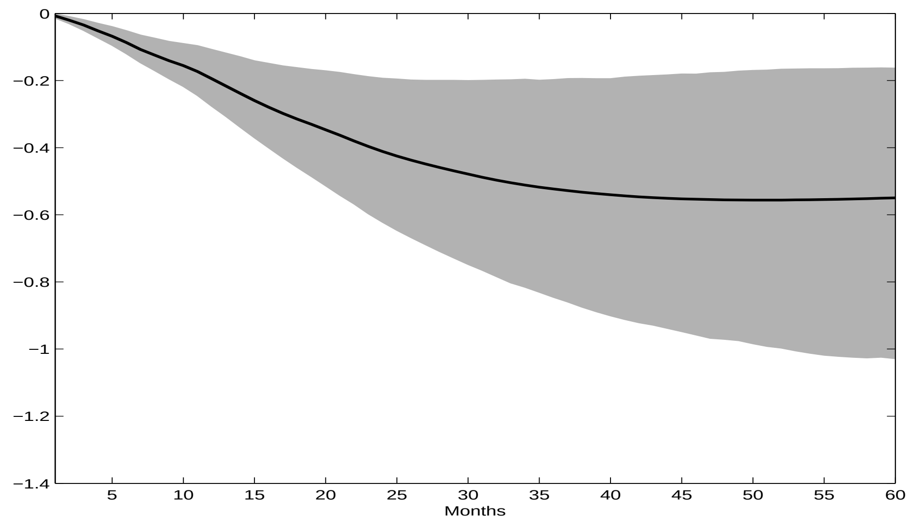
And as with the BOS we construct a turnover index for employment from an actual employment change question:

Q 15 *"During the* ***last three months****, did the* ***total*** *number of employees in your firm increase, decrease or stay about the same?* $\boxed{1}$ *Increased* $\boxed{2}$ *Decreased* $\boxed{3}$ *Stayed the same. "*

Figure 22 displays the analog of Figure 2 in Section 4.1. Positive business uncertainty innovations lead to long and protracted negative reactions of the economic activity of small firms. Similarly to the BOS, there is little or no high-frequency impact followed by a strong rebound of economic activity.

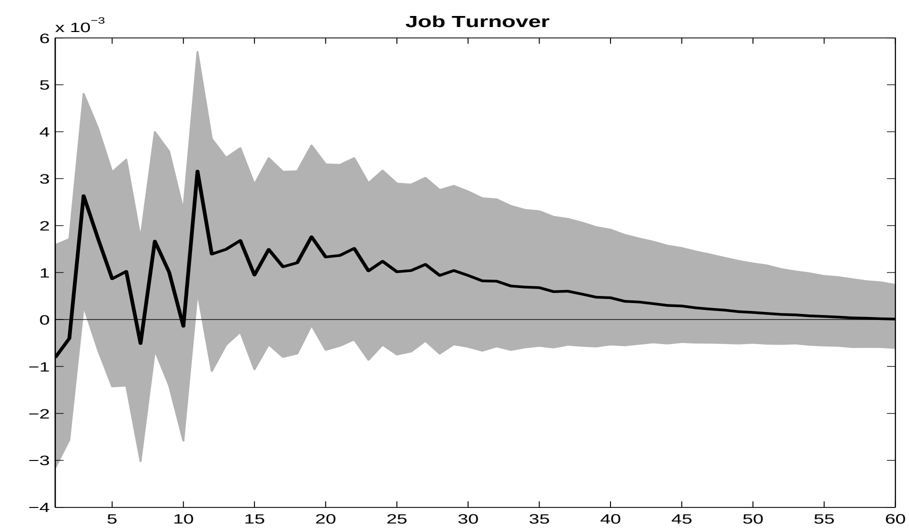
Figure 23 is similar to Figure 4 in Section 4.1. It shows the impulse response of the job turnover measure to an innovation to uncertainty. As before, to the extent to which job turnover reacts to business uncertainty at all, it rises (at least the point estimate), which appears to be inconsistent with the "wait-and-see"-theory of uncertainty shocks.

Figure 22: Uncertainty Innovations on SBETS Sales Activity Index



Notes: The uncertainty index is based on Q 13. The activity variable is based on Q 14. The impulse response is based on a two-variable SVAR with uncertainty ordered first, then activity, and 12 lags. It displays the response of the SBETS Sales Activity Index to a positive uncertainty innovation. All confidence bands are at the 95% significance level using Kilian's (1998) bias-corrected bootstrap.

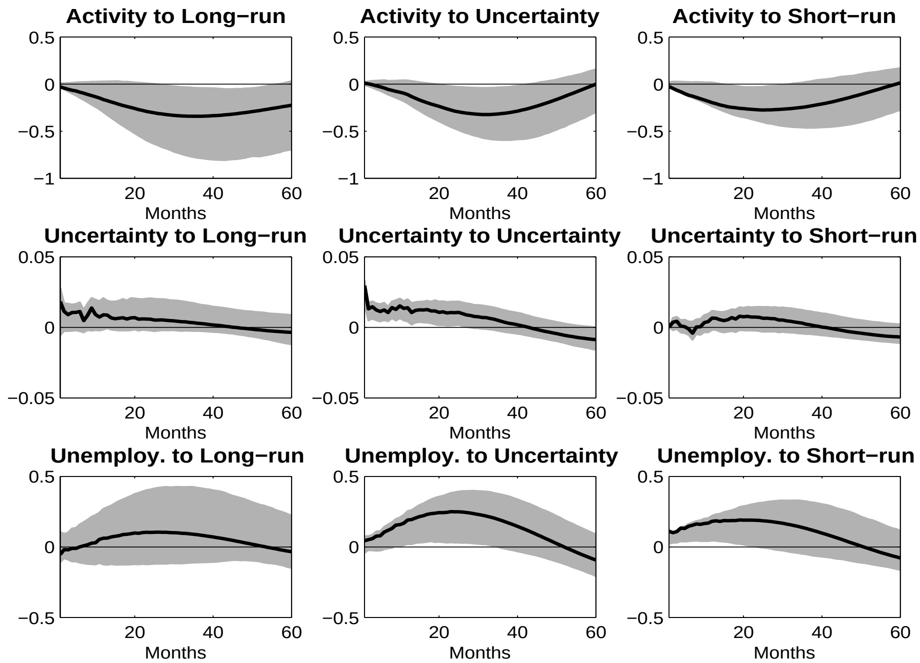
Figure 23: Uncertainty Innovation on SBETS Job Turnover Index



Notes: see notes to Figure 22. The IRF is based on a two-variable SVAR with uncertainty ordered first and then job turnover. Job turnover is based on Q 15.

Finally, Figure 24 and Table 10 display the analogs of Figure 7 and Table 3 in Section 4.1. There is little, albeit compared to the BOS somewhat larger impact of uncertainty innovations to either sectoral economic activity or the economy-wide unemployment rate. There is again some impact of the long-run innovations on the uncertainty index.

Figure 24: A Three-Variable Blanchard-Quah-Type SVAR - SBETS



Notes: see notes to Figure 22. The unemployment rate is the (seasonally adjusted) monthly civilian unemployment rate from the BLS. The uncertainty innovation and the conventional short-run shock are identified as shocks that do not impact manufacturing production in the long-run. The conventional short-run shock is identified as the innovation that does not affect the uncertainty index on impact.

Table 10: FORECAST ERROR VARIANCE DECOMPOSITION - SBETS

	Shock	1M	3M	6M	1Y	2Y	5Y
Activity	Long-run	54%	45%	36%	34%	35%	46%
	Uncertainty	5%	1%	5%	12%	26%	30%
	Short-run	41%	54%	60%	54%	39%	24%
Uncertainty	Long-run	28%	30%	34%	32%	28%	24%
	Uncertainty	72%	69%	65%	65%	63%	61%
	Short-run	0%	2%	1%	3%	10%	15%
Unemployment Rate	Long-run	17%	8%	3%	3%	7%	9%
	Uncertainty	11%	17%	25%	40%	51%	54%
	Short-run	72%	75%	72%	58%	42%	37%

Notes: see notes to Figure 24.