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ABSTRACT

What is the impact of time-varying business uncertainty on economic activity? Using partly confidential business survey data from the U.S. and Germany in structural VARs, we find that positive innovations to business uncertainty lead to prolonged declines in economic activity. In contrast, their high-frequency impact is small. We find no evidence of the "wait-and-see"-effect – large declines of economic activity on impact and subsequent fast rebounds – that the recent literature associates with positive uncertainty shocks. Rather, positive innovations to business uncertainty have effects similar to negative business confidence innovations. Once we control for their low-frequency effect, we find little statistically or economically significant impact of uncertainty innovations on activity. We argue that high uncertainty events are a mere epiphenomenon of bad economic times: recessions breed uncertainty.

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1 Introduction

What is the impact of time-varying business uncertainty on economic activity? Real options theory associates innovations to uncertainty with a "wait-and-see"effect: if firms suddenly find themselves in a more uncertain environment they stop investing and hiring and the economy slips into a recession. This "wait-and-see"-effect has recently attracted attention in the literature: Bloom (2009) and Bloom et al. (2009) use a quantitative RBC model with various adjustment frictions to capital and labor to argue that positive innovations to uncertainty lead to short-run fluctuations, starting with a rapid decline in aggregate activity, then a rebound phase and a prolonged overshoot after approximately six months.[1] Prima facie, uncertainty shocks have appealing properties, chiefly among them that no technological regress is required to generate recessions. All that is needed are autonomous increases in business uncertainty.

Bachmann and Bayer (2009), exploring data from a detailed German firm-level panel, argue that the effects in Bloom (2009) and Bloom et al. (2009) are quantitatively small and do not substantially alter unconditional business cycle dynamics. This is confirmed in Chugh (2009), who explains the dynamics of leverage with innovations to micro-level uncertainty, but also finds a small business cycle impact of uncertainty shocks. Using a model with financial frictions, Gilchrist, Sim and Zakrajsek (2009) argue that increases in uncertainty lead to an increase in the cost of capital through an increase in bond premia which is followed by a decline in investment activity. In a similar framework Arellano et al. (2010) show that increases in uncertainty lead to downsizing of investment projects to avoid default.[2] These papers employ mostly quantitative models and calibration exercises to study the impact of time-varying uncertainty on economic activity. What is missing from the literature are more agnostic studies of the economic effects of innovations in uncertainty.[3]

In this paper we use partly confidential monthly data from business surveys to investigate the relationship between uncertainty and economic activity within a structural vector autoregressions (SVAR) approach. We confirm the sceptical results in Bachmann and Bayer (2009) and Chugh (2009) without relying too strongly on a specific model and calibration. These business surveys contain qualitative information on the current state of, and expectations regard-

[1] Figure 2 in Section 2 provides the impulse response of output to an uncertainty shock from the model in Bloom (2009). The three phases – activity collapse, rebound and overshoot – can be clearly seen in this graph.

[2] In a related, but slightly different context, Fernandez-Villaverde et al. (2009) argue that innovations to the volatility of interest rates depress economic activity in small open Latin American economies.

[3] The two exceptions we know of are: Alexopolous and Cohen (2009) who 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; and Popescu and Smets (2009) who show, again with structural vector autoregressions and for German data, that it is innovations to risk aversion rather than innovations to uncertainty per se that explain roughly 10%-15% of output fluctuations.

ing, firms' business situations. Specifically, we use disagreement in business expectations for the Third FED District Business Outlook Survey (BOS) to estimate the impact of business uncertainty on economic activity.[4] We also take seriously the potential criticisms against using aggregate disagreement measures as proxies of uncertainty. The German IFO Business Climate Survey (IFO-BCS) data allow us to do so. In particular, we use the confidential micro data of the survey 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. This justifies our use of survey disagreement as a proxy for uncertainty when micro data are unavailable.

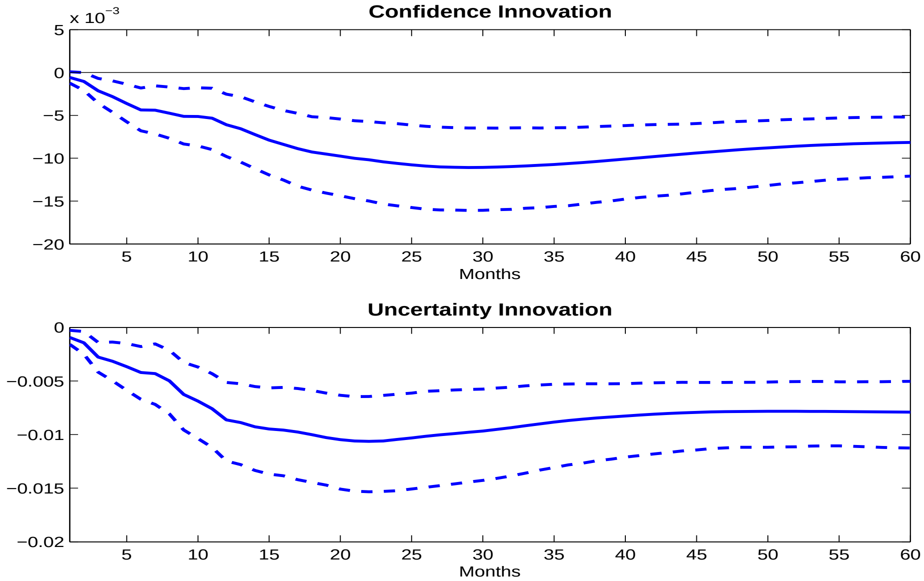
We argue that these high-frequency business survey data are well suited to measure the direct impact of uncertainty on economic decision making. As discussed in the next section, "wait-and-see"-dynamics are rather short-run and rely on adjustment frictions, which render high-frequency data the best candidate to detect these dynamics. *Aggregate* business survey data are also readily available. All this puts qualitative survey data in an advantage over quantitative balance sheet data. *Business* survey data in particular capture the subjective element of uncertainty, viz the mind set of actual decision makers, as opposed to outside experts. Also, the confidential survey *micro* data allow us to compare expectations and realizations of economic variables and thus – as is the case with the IFO-BCS data – construct two complementary proxies of true ex ante uncertainty: ex ante disagreement and ex post forecast error variance.

We consistently find that in two-variable SVARs innovations to uncertainty have very protracted negative effects on economic activity. The effect on impact, in contrast, is small. This is documented in Figure 1, where we show in the lower panel an impulse response from a positive innovation to a measure of business uncertainty from the BOS on U.S. manufacturing industrial production. For comparison, the upper panel shows the impulse response from a negative innovation to a business confidence measure on the same activity variable. They look very similar. This is a robust finding across specifications and surveys.

We then impose more structure in the identification and add measures of business uncertainty to a VAR with sectoral economic activity and the aggregate unemployment rate in the spirit of Blanchard and Quah (1989). Consistent with the implications of "wait-and-see", we identify the uncertainty shock as a shock which does not influence economic activity in the long run but which may influence both activity and unemployment on impact. We thus "shut down" the long-run impact of uncertainty in the hope of making its short-run influence shine through.

[4] Using dispersion indexes of expectations as measures of uncertainty has a long tradition in the literature (mostly in the context of inflation expectations and inflation uncertainty): see, for instance, Zarnovitz and Lambros (1987), Bomberger (1996), Giordano and Soederlind (2003), Fuss and Vermeulen (2004) for a good literature overview, Bloom et al. (2009) and Popescu and Smets (2009).

Figure 1: Confidence and Uncertainty Innovations on Manufacturing Production



Notes: Both IRFs are based on the "general business conditions" question of the BOS. $Confidence_t \equiv Frac_t(\text{Increase}) - Frac_t(\text{Decrease})$ and $Uncertainty_t \equiv sqrt(Frac_t(\text{Increase}) + Frac_t(\text{Decrease}) - (Frac_t(\text{Increase}) - Frac_t(\text{Decrease}))^2)$, where $Frac_t(\text{Increase})$ is the fraction of respondents that say that general business conditions six months from time t will increase. $Frac_t(\text{Decrease})$ is defined analogously. The upper panel shows the response of manufacturing production to a negative confidence innovation in a two-variable SVAR with $Confidence$ ordered first. The lower 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. All VARs are run with 12 lags, the confidence bands are at the 95% significance level using Kilian's (1998) bias-corrected bootstrap.

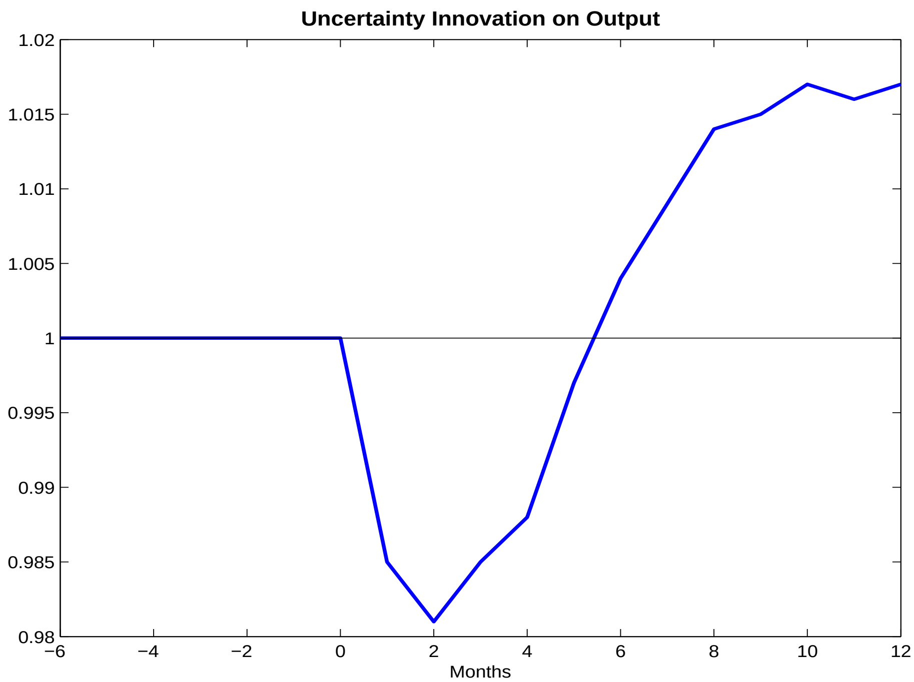
We find that there is little statistically or economically significant impact of uncertainty shocks on economic activity left. Rather, we provide some evidence that negative long-run shocks give rise to higher uncertainty, which leads us to interpret high uncertainty events as a mere epiphenomenon of bad economic times. We interpret this in light of the view of recessions as times of destroyed relationships and practices, the reestablishment of which generates uncertainty for businesses.

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 fluctuations.[5] 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, sectoral data in examining the impact of uncertainty on economic activity.

Figure 2: Replication of Wait-and-See in Bloom (2009)



Notes: this graph is a replication of the simulated model IRF of out to an uncertainty shock, see Figure 12 in Bloom (2009). The overshoot reaches its peak after roughly one year, and, as Figure 9 in Bloom (2009) shows, needs two more years to settle down.

Time-varying uncertainty at the firm level may have economic consequences when there is a degree of irreversibility to firm actions. 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. The reason for this is intuitive – if a large fixed cost must be paid

[5]The literature has highlighted other mechanisms, such as countercyclical default risk in the presence of financial frictions, for instance Arellano et al. (2010), Gilchrist, Sim and Zakrajsek (2009) and Gilchrist, Yankov and Zakrajsek (2009). While default risk is related to firm-level uncertainty, the two concepts of uncertainty are different.

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?[6]

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 2 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. The entire bust-boom cycle in response to increased uncertainty only takes about one year to play out with roughly two more years to revert back to steady state (see for the full impulse response Figure 9 in Bloom, 2009). 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.

An additional advantage of our survey data from specific segments of the economy – specific sectors and/or regions – is that general equilibrium effects are likely to be mitigated. "Wait-and-see"is clearly a partial equilibrium mechanism, which might be dampened by general equilibrium price adjustments.[7] For instance, if in response to an increase in uncertainty, all firms simultaneously want to shut down hiring, wages are likely to adjust in equilibrium so that at least some firms do continue hiring. Our focus on sector level data thus gives the "wait-and-see"mechanism a better chance of shining through.

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).[8] In the next subsection we briefly de-

[6] The argument is equally valid with partial irreversibilities instead of fixed costs.

[7] Note that Bloom (2009) is a partial equilibrium analysis.

[8] Appendix D supplements our baseline results with an analysis of the U.S. Small Business Economic Trends Survey (SBETS).

scribe 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 the cyclical properties of our main 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.[9] 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 Trebin (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[10] –, 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.[11] Nevertheless, given its advantages, we use the BOS for our baseline results. We focus on the following two questions:[12]

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?"*

[9] The Third Federal Reserve District comprises the state of Delaware, the southern half of New Jersey, and the eastern two thirds of Pennsylvania.

[10] 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. To address this issue, we complement the BOS analysis with the SBETS (see Appendix D) and find essentially the same results.

[11] This problem is alleviated in the SBETS.

[12] The other questions we use from the BOS are documented in Appendix B.1.

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 as if they were about general business conditions. Trebin (1998) notes, however, that answers to these questions are highly correlated with responses to the shipments question, which is phrased as explicitly company specific. As such, 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?"*

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.[13] 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, many 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% possessed 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:[14]

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."*

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

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

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."*

Since this survey is the only one where we have access to the micro data, it provides us with an opportunity to compare ex ante uncertainty measures that are derived from cross-sectional disagreement with a qualitative index of ex post forecast error uncertainty. We can compare firms' qualitative predictions about expected changes with their qualitative answers about realized changes.

3.2 Variable Definitions

Survey answers fall into three main categories, $Increase$, $Decrease$, and a neutral category. We use these categories to define two forward-looking indices concerning expectations and two indices of current activity. We start with the forward-looking indices, constructed for questions like Q 1 and Q 4:

$$Confidence_t \equiv Frac_t(\text{Increase}) - Frac_t(\text{Decrease}).$$

$$Uncertainty_t \equiv sqrt\Big(Frac_t(\text{Increase}) + Frac_t(\text{Decrease}) - \big(Frac_t(\text{Increase}) - Frac_t(\text{Decrease})\big)^2\Big).$$

Notice that $Uncertainty_t$ 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, under which $Confidence_t$ simply becomes the cross-sectional average of the survey responses. 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:

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

For the question on actual employment changes, Q 3, we also construct a turnover index, defined as:

$$Turnover_t \equiv Frac_t(\text{Increase}) + Frac_t(\text{Decrease}).$$

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 the 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 subjective uncertainty for firms' decision makers. However, to the best of our knowledge such probability distributions are not available repeatedly and over long time horizons. Therefore, researchers have to rely on proxies. 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 simply be due to different firms reacting differently to aggregate shocks even with constant aggregate and idiosyncratic uncertainty. 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. In this subsection, we briefly address these concerns, summarizing more detailed results from various appendices.

We address the first concern – different firms having different factor loadings to aggregate shocks – by a variance decomposition of $(Uncertainty_t^{IFO})^2$ 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 shocks might be due to industry-specific production and adjustment technologies. Figure 21 in Appendix C.2, however, shows that the time series of $(Uncertainty_t^{IFO})^2$ is clearly 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. While this is an admittedly imperfect test, because it could still be the case that differences in factor loadings to aggregate shocks are generated by differences in production and adjustment technologies below the level of disaggregation that we can study with the IFO survey, these differences would have to emerge equally in all manufacturing subsectors for the between-variance to have such low explanatory power for the overall variance. We view this as highly unlikely.

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.

The micro data in the IFO-BCS allow us to go a step further and specifically address this concern. We construct a qualitative index of the ex post forecast error standard deviation, which by construction excludes heterogeneous, but certain, changes in expectations. To fix ideas, we proceed 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 that 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 1: 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 1 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.[15] Denote this variable by $REALIZ_t$. It can obviously range from $[-3,3]$. Then the expectation errors are computed as:

[15] 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 2: 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 2 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 $Uncertainty_t^{fe}$: 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.[16] The advantage of $Uncertainty_t^{fe}$ over $Uncertainty_t$ is that it is based on actual "uncertain-at-time-t" innovations, as opposed to potentially heterogeneous expectations of the future, which could be certain. However, the raw correlation coefficient between $Uncertainty_t^{fe}$ and $Uncertainty_t$ is reasonably high for monthly data, 0.73, and when we aggregate both series up to the quarterly level the correlation becomes 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. Figure 22 in Appendix C.2 depicts $Uncertainty_t^{fe}$ and $Uncertainty_t$, both at the monthly and the quarterly frequency. Most importantly, the impulse responses on economic activity look qualitatively and quantitatively similar and are statistically often indistinguishable (see Section 4.3).

[16]We follow here Bloom's (2009) timing convention for stock market volatility.

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 X-12-ARIMA seasonal adjustment method. Table 3 displays the cyclical properties of the various survey-based uncertainty measures. They are all countercyclical. This confirms previous findings by Bloom (2009), Bloom et al. (2009), Chugh (2009) and Bachmann and Bayer (2009), who find, using different data sources, that stock market volatility and balance-sheet-based cross-sectional measures of uncertainty are all countercyclical.[17] The discrepancy between the first and second columns for the IFO uncertainty measures is partly, just as for the other surveys, the result of an imperfect representation of the entire population by the survey sample. For Germany, however, we find that the industrial production measure exhibits a lot of high-frequency noise-like movements, which in part contributes to this low correlation. The correlation becomes more negative when we aggregate up to the quarterly frequency.

Table 3: CYCLICAL PROPERTIES OF $Uncertainty_t$ AND $Uncertainty_t^{fe}$

	Monthly		Quarterly	
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 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. For the definition of Production-$Uncertainty_t^{fe^{IFO}}$, see Section 3.3; it is paired with the same activity measures as the Production-$Uncertainty_t^{IFO}$ measure.

[17]See Table 10 in Appendix C.2 for similar results in 13 manufacturing subsectors.

Table 4 displays the cyclical properties of the survey-based (differenced) activity measures we constructed in Section 3.2. They are, not surprisingly, procyclical.

Table 4: CYCLICAL PROPERTIES OF $Activity_t$

Activity Measure	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. We robustly find that innovations to business uncertainty are associated with small and slowly-building reductions in economic activity. Imposing the restriction that uncertainty innovations have no long-run effects on activity, which is consistent with the "wait-and-see"-hypothesis, renders the responses of economic activity to uncertainty insignificant and often essentially zero at all horizons. This finding is difficult to reconcile with the "wait-and-see"channel from uncertainty to aggregate dynamics.

We begin the analysis with the Federal Reserve Bank of Philadelphia Third District Business Outlook Survey and conclude with the German IFO Business Climate Index. In addition to providing verification of our main qualitative findings from data in another country, the IFO micro data allows us to compare our SVAR results when using ex ante survey disagreement versus the ex post forecast error standard deviation as measures of business uncertainty. We show that they are similar using either measure as a proxy for uncertainty.

4.1 Third FED District Business Outlook Survey

We begin our analysis with the Federal Reserve Bank of Philadelphia's Third District Business Outlook Survey. Figure 1 in the Introduction shows impulse responses from two-variable SVARs with U.S. manufacturing industrial production and, respectively, an innovation to business confidence and business uncertainty. The variables are ordered such that innovations to the survey measure influence economic activity on impact but not vice versa.[18] Both variables enter the system in levels and we include 12 lags. [19]

As noted in the Introduction, the impulse response of manufacturing production to an innovation to 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. As the upper panel of the figure shows, the response of production to uncertainty is roughly the same as its response to a negative confidence innovation.

Figure 3 provides corroborating evidence with a different measure of sectoral economic activity. In addition to the forward-looking confidence question, the BOS in Q 2 asks about current business conditions relative to the recent past. We estimate bivariate SVARs with General Conditions-$Confidence_t^{BOS}$ and General Conditions-$Uncertainty_t^{BOS}$ and an activity index based on Q 2, again with activity ordered second. The responses are strikingly similar to that using overall manufacturing production as the activity measure. This is particularly important, as we do 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.[20] The fact that the results are nearly identical across two related, but different activity measures lends credence to our findings.[21]

Two additional observations from Figure 1 in the Introduction and Figure 3 here are worth

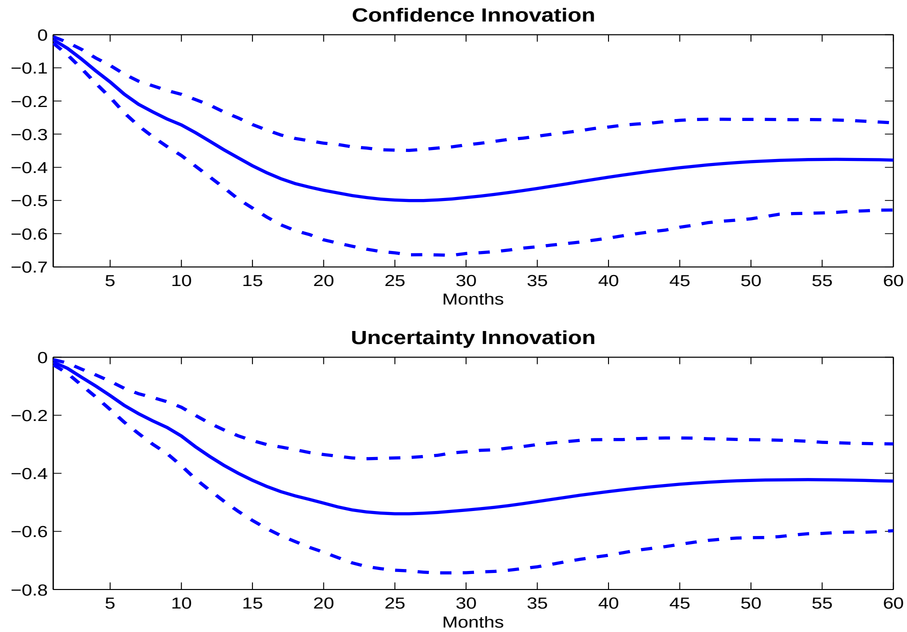
[18] One might be worried that uncertainty should not affect economic activity on impact because of various information or decision lags. For instance, one might assume that companies know uncertainty only through the published surveys themselves, when they see a lot of disagreement there. It is reasonable to assume that decision makers at the firms care very much about the survey results and let their decision making be influenced by them, as there is no direct financial incentive to participate in these surveys. Figure 15 in Appendix B.3 presents the analog to the lower panel of Figure 1 with economic activity ordered first. From this graph it is clear that timing does not drive our results.

[19] 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. For the cases in which we use a long run restriction to identify the uncertainty shock, the activity variable enters the VAR in first differences and we show cumulated impulse responses.

[20] Such employment data are only available from 1990 on.

[21] In Table 9 in Appendix B.2 we compare various BOS activity measures with the monthly Third FED district BLS manufacturing employment data from 1990 on. 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

Figure 3: Confidence and Uncertainty Innovations on BOS General Conditions Activity



Notes: Both IRFs are based on Q 1. The SVARs are estimated with 12 lags and confidence/uncertainty ordered first. Both responses are those of General Conditions-$Activity_t^{BOS}$ (based on Q 2). The upper panel is based on a two-variable SVAR with General Conditions-$Confidence_t^{BOS}$ (negative innovation). The lower panel is based on a two-variable SVAR with General Conditions-$Uncertainty_t^{BOS}$ (positive innovation). All confidence bands are at the 95% significance level using Kilian's (1998) bias-corrected bootstrap.

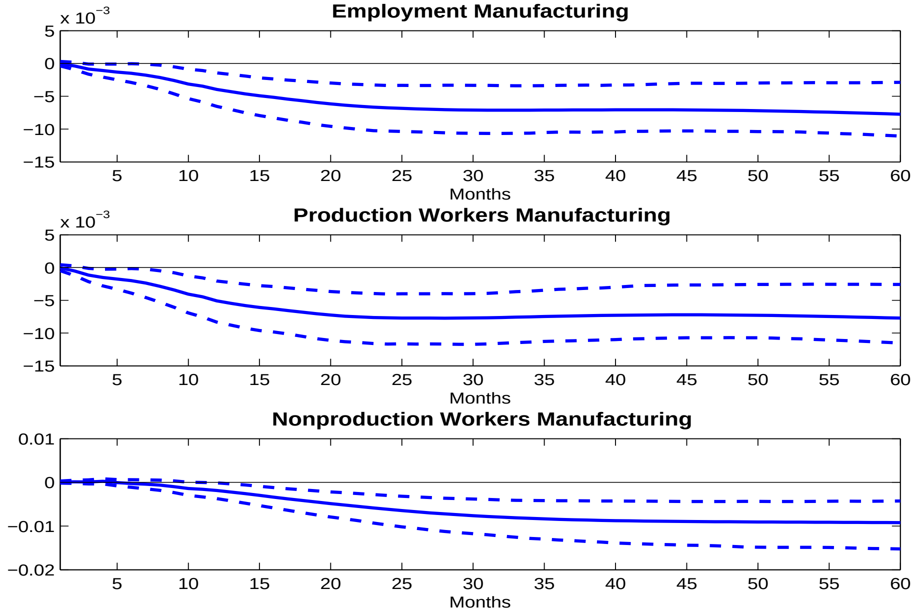
noting. First, the fact that the General Conditions-$Confidence_t^{BOS}$-variable predicts both manufacturing industrial production and the General Conditions-$Activity_t^{BOS}$-variable well at medium and long horizons shows that the BOS survey answers reflect accurate expectations of firms about their future.[22] This in turn lends credence to our expectation-based uncertainty measures. Secondly, the prolonged negative response of economic activity to an innovation in business uncertainty is consistent with the empirical impulse response of economic activity to a credit shock in Gilchrist, Yankov and Zakrajsek (2009),[23] and the theoretical impulse response of economic activity to a persistent uncertainty shock in a model with financial frictions in Arellano et al. (2010).

real economic activity in the manufacturing sector of the Third FED district reasonably accurately.

[22]Barsky and Sims (2009) find a similar result for consumer confidence and aggregate economic activity. Figure 14 in Appendix B.2 shows the dynamic cross-correlations between BOS $Confidence_t$-variables and BOS $Activity_t$-variables and they indeed peak at medium to long horizons with confidence leading.

[23]Figure 26 in Appendix E shows the analog to Figure 1, using readily available corporate bond spread data as a measure of uncertainty. The impulse response of industrial production to a corporate bond spread innovation looks very similar to the one when our survey-based business uncertainty measure is used. In contrast, the impulse response to stock market volatility is rather different.

Figure 4: Uncertainty Innovations on Manufacturing Employment



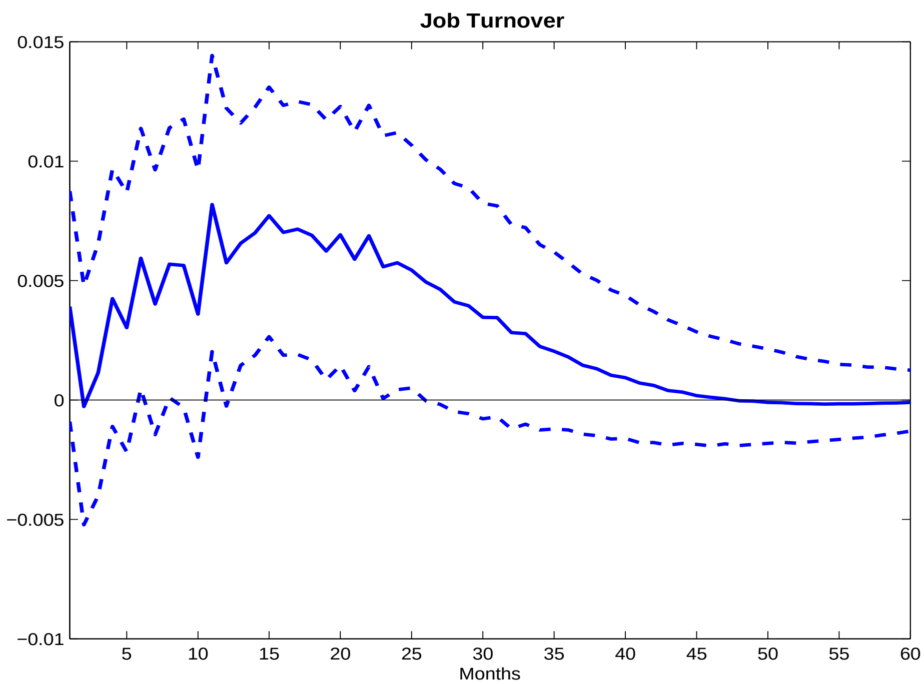
Notes: see notes to Figure 3. Uncertainty is ordered first. The employment measures are seasonally adjusted and logged and are taken from the BLS-CES data base.

In Figure 4 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. Wait-and-see theories of the transmission from uncertainty shocks to business cycles emphasize hiring and firing frictions. If the "wait-and-see"-channel were important, we would observe a large reduction in employment followed by a quick recovery in response to an uncertainty shock, similarly to the output response in Figure 2 in Section 2. However, the response of manufacturing employment is rather consistent with our other results: it moves little on impact, followed by a period of sustained reductions, with no obvious tendency for reversion, even at very long horizons. There is no discernible difference for production and non-production workers, who might be subject to different adjustment costs.[24]

[24]In Appendix B.3 we provide robustness checks to our first result that in two-variable SVARs uncertainty innovations trigger prolonged declines in economic activity. Figures 16 and 17 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 labor productivity. Figures 18 to 20, in turn, vary the uncertainty measure: an indicator variable for high uncertainty in the spirit of Bloom (2009), an uncertainty measure, based on information-theoretic uncertainty (see Rich and Tracy (2006)), and uncertainty measures derived from other expectation questions in the BOS. We also experimented with the aggregate investment rate as the activity measure, given that "wait-and-see"-theories equally stress capital adjustment frictions. The impulse response looks essentially the same as with output and employment. However, since we do not have sectoral investment data at at least a quarterly frequency, we do not want to over-interpret this result.

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 are inconsistent with this prediction. Figure 5 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.[25]

Figure 5: Uncertainty Innovation on BOS Job Turnover Index



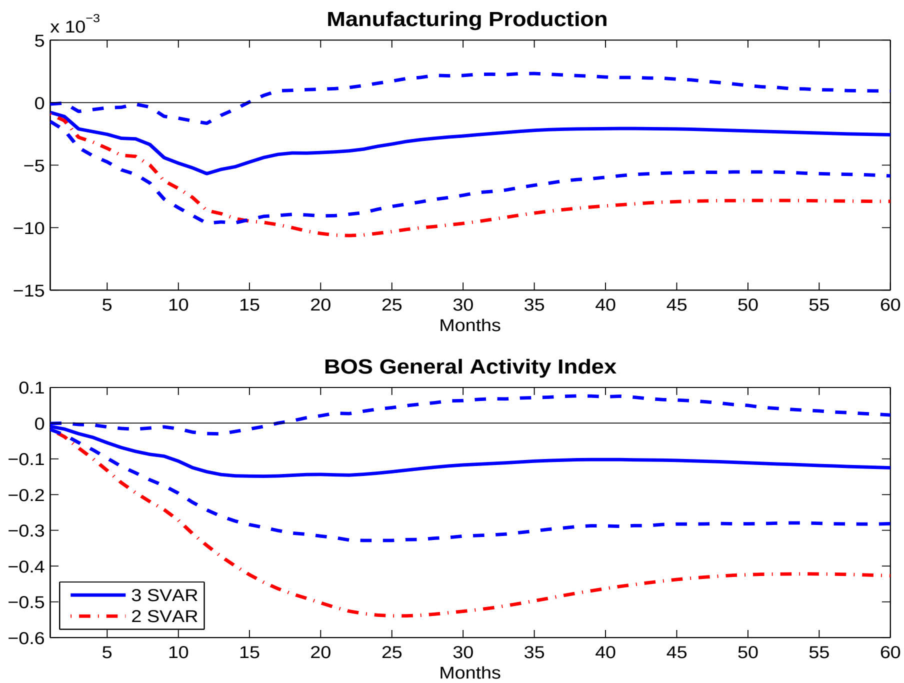
Notes: see notes to Figure 3. The turnover variable is based on Question 3.

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 "wait-and-see"-mechanism. On the positive side we have that innovations to uncertainty appear to contain significant predictive information for the future path of sectoral economic activity. To explore these conclusions 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 in three exercises. First, we include business confidence in the SVAR. As noted previously, confidence is informative about eco-

[25]Admittedly, this evidence is somewhat weak, given that the lower confidence band is rather consistent with "wait-and-see". Nevertheless, overall we view Figure 5 as unfavorable evidence for this mechanism. Also, the dynamic unconditional correlations between the BOS job turnover measure and the BOS uncertainty measures are, albeit mildly, positive for the uncertainty measures leading between zero and twelve months.

nomic activity in the long-run. Orthogonalizing uncertainty with respect to confidence should control for the long-run predictive component of uncertainty, thereby making it more likely for the high-frequency impacts of time-varying uncertainty to shine through. Second, we adopt an identification approach in the spirit of Blanchard and Quah (1989): in a two-variable VAR with an uncertainty and an activity measure, we identify the uncertainty shock as a shock that does not impact activity in the long-run. Here the long-run impact of uncertainty, guided by the "wait-and-see"-hypothesis, is shut down by construction. Third, we include the aggregate unemployment rate in the Blanchard and Quah (1989)-type SVAR in order to be able to 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. The result in all three exercises is clear: once the long-run impact of uncertainty is "controlled" for, there is (almost) no economically or statistically significant impact of uncertainty on activity left.

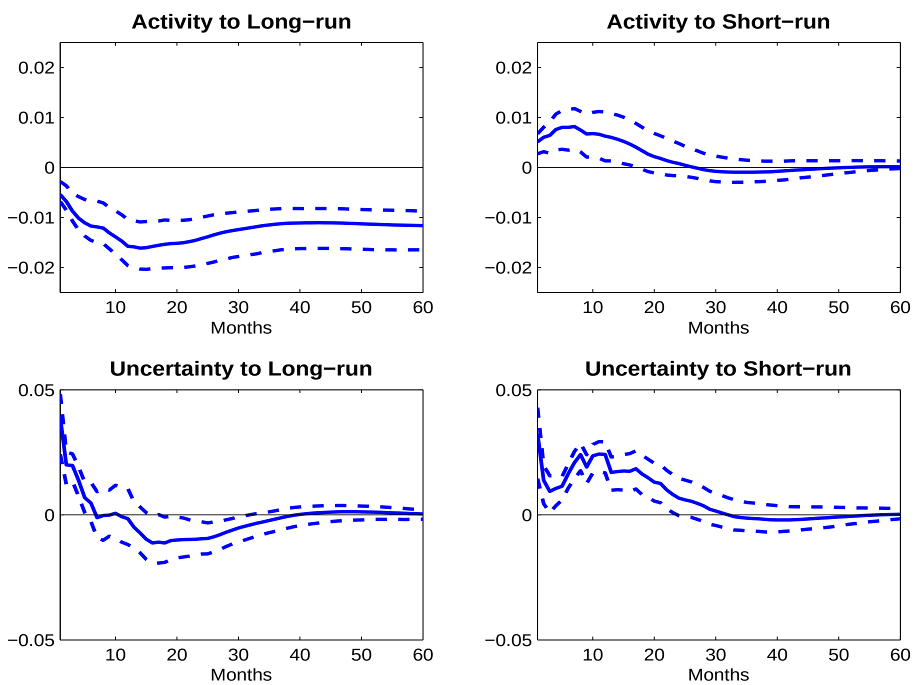
Figure 6: Uncertainty Innovations Orthogonalized to Confidence Innovations



Notes: see notes to Figures 1 and 3. General Conditions-$Confidence_t^{BOS}$ is ordered first, then General Conditions-$Uncertainty_t^{BOS}$, then the activity variable, manufacturing production (upper panel) and the General Conditions-$Activity_t^{BOS}$ index (lower panel).

Figure 6 depicts impulse responses of two different measures of activity – manufacturing production and the General Conditions-$Activity_t^{BOS}$ index – to an uncertainty innovation orthogonalized with respect to General Conditions-$Confidence_t^{BOS}$. As expected, orthogonalizing with respect to a confidence series lowers the quantitative magnitude of the responses of activity to uncertainty – compare the solid lines and the dashed-dotted lines in Figure 6 – and makes it almost statistically insignificant, but it appears to do little to change the qualitative nature of the responses. The response of sectoral activity, however measured, to uncertainty is small and insignificant on impact, followed by further reductions, and then some evidence of reversion at longer horizons. Nevertheless, orthogonalizing with respect to the confidence series does not point to an important "wait-and-see"-effect.

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

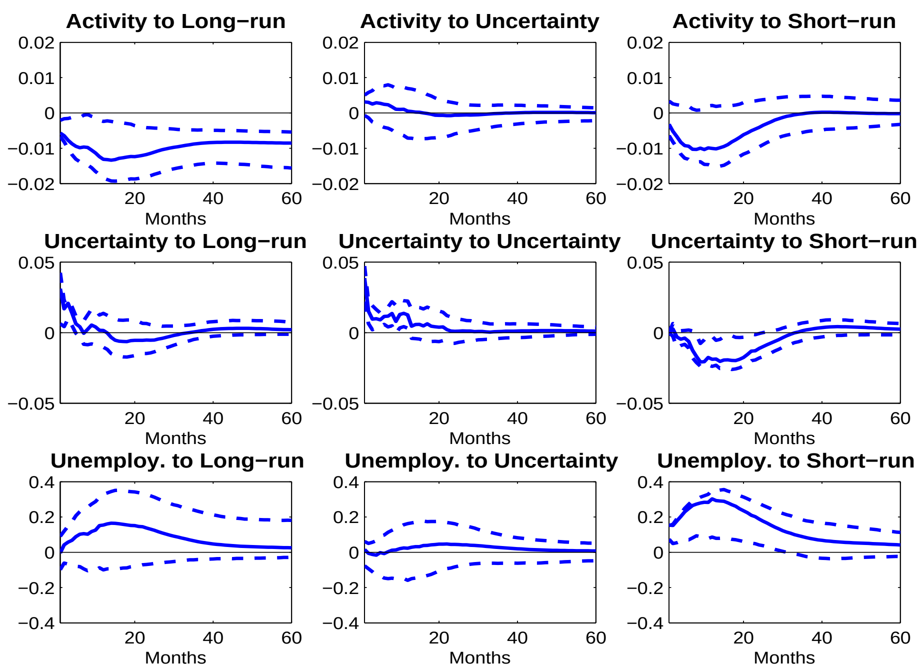


Notes: see notes to Figures 1 and 3. We use manufacturing production as the activity measure, and the General Conditions-$Uncertainty_t^{BOS}$ index as the uncertainty measure. The uncertainty innovation is identified as the shock that does not impact manufacturing production in the long-run.

Figure 7 shows the impulse responses from a two-variable SVAR with manufacturing production as the activity variable (just as in Figure 1) and the General Conditions-$Uncertainty_t^{BOS}$ index. We identify the uncertainty shock as the one with zero long-run impact on economic activity. Notice that the corresponding long-run shock in our case, unlike in Blanchard and Quah (1989) who used aggregate production, need not literally be a productivity shock, as we are dealing with sectoral activity variables. Rather, it is any shock that permanently affects sectoral output. We find that once uncertainty is bereft of its long-run effect, the impact of higher uncertainty on economic activity becomes positive, but economically small. On the other hand, we find a statistically significant positive impact of a negative long-run innovation on the uncertainty measures. This is precisely what our epiphenomenon hypothesis with respect to uncertainty implies.

For a two-variable VAR specification we are concerned that the short-run shock we identify as an uncertainty shock might be confounding true innovations to uncertainty and a more conventional aggregate demand shock. Like Blanchard and Quah (1989), we therefore include the aggregate unemployment rate in the two-variable VAR with sectoral uncertainty and business activity measures and identify two short-run shocks using the usual long-run restriction for each. We then identify the conventional short-run shock by ordering unemployment last. Consistent with the "wait-and-see"-hypothesis, this means that uncertainty can change the unemployment rate on impact.

Figure 8: A Three-Variable Blanchard-Quah-Type SVAR



Notes: see notes to Figures 1 and 3. We use manufacturing production as 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 innovation that does not affect the uncertainty index on impact.

Figure 8 shows the impulse responses in such a three-variable SVAR, and Table 5 the corresponding forecast error variance decomposition for horizons ranging from one month to five years. Both results from the two-variable specification – no significant impact of uncertainty on economic activity and an increase of uncertainty to negative long-run innovations – "survive".[26] The forecast error variance for activity is mainly driven by the long-run and the conventional short-run shock, while 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.[27] The long-run shock accounts for a significant fraction of the fluctuations in the uncertainty index in the first six months.

Table 5: 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 8.

4.2 IFO Business Climate Index

We next present results from the German IFO Business Climate Index. The main advantage here is that we have access to the micro data, which allows us to compute a measure of uncertainty based on the ex post forecast error standard deviation – $Uncertainty_t^{fe^{IFO}}$ – and compare the results with the ex ante disagreement uncertainty measure – $Uncertainty_t^{IFO}$. The results using either uncertainty measure are quite similar to those from the BOS. This provides corroboration of the results from U.S. data. It also serves as support for our use of a disagreement measure as an uncertainty proxy when micro data are unavailable.

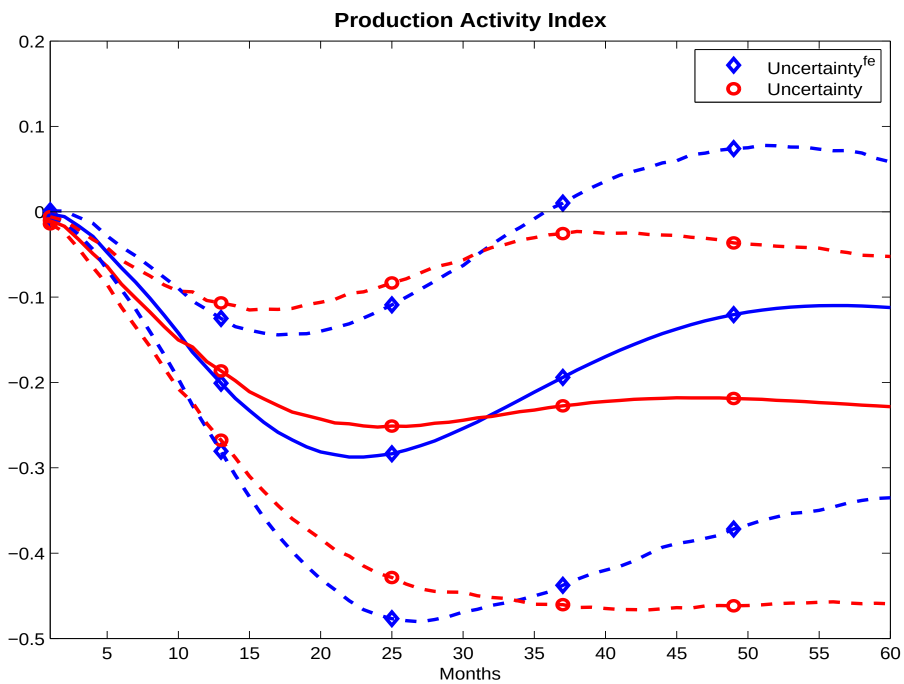
Figure 9 shows the activity responses for the baseline two-variable SVARs to the two types of uncertainty innovations we are considering. The activity variable is based on Q 5, the IFO current production question. The SVARs here include a dummy variable from 1991 on to account for structural breaks associated with the German reunification, though our results are quite insensitive to alternative ways of dealing with that event. There are two important results: First, we see that the responses of activity to the two different measures of uncertainty

[26] If we reverse the Choleski order between the uncertainty and the conventional aggregate demand shock, i.e. we allow the latter to have an immediate impact on the uncertainty index, we often also find uncertainty increasing to negative aggregate demand innovations, but this effect turns out to be hardly statistically significant. The other impulse responses are quite robust to changing the Choleski order.

[27] It is somewhat larger for the IFO-BCS (Table 6, next section) and the SBETS (Table 11, Appendix D).

are quite similar to each other, in fact statistically indistinguishable. 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.

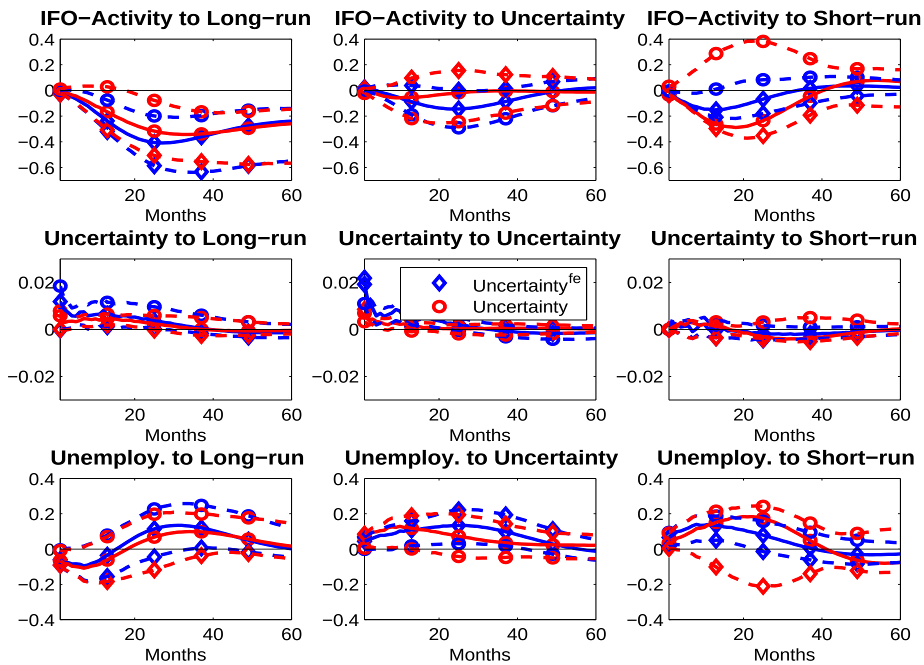
Figure 9: Uncertainty Innovations on Production-$Activity_t^{IFO}$



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 SVARs with 12 lags. All confidence bands are at the 95% significance level using Kilian's (1998) bias-corrected bootstrap.

We conclude by largely 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 10 and Table 6. We find that uncertainty measured either way has 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 neither uncertainty measure is similar to "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-BCI results suggests that the negative findings in Bachmann and Bayer (2009) as well as Popescu and Smets (2009) with regards to the role of uncertainty innovations as a major driving force of short-run fluctuations are not driven by their use of German data.

Figure 10: A Three-Variable Blanchard-Quah-Type SVAR - IFO



Notes: see notes to Figure 9. The unemployment rate is the (seasonally adjusted) monthly unemployment rate from the Bundesanstalt für Arbeit. 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 6: FORECAST ERROR VARIANCE DECOMPOSITION - IFO-BCS

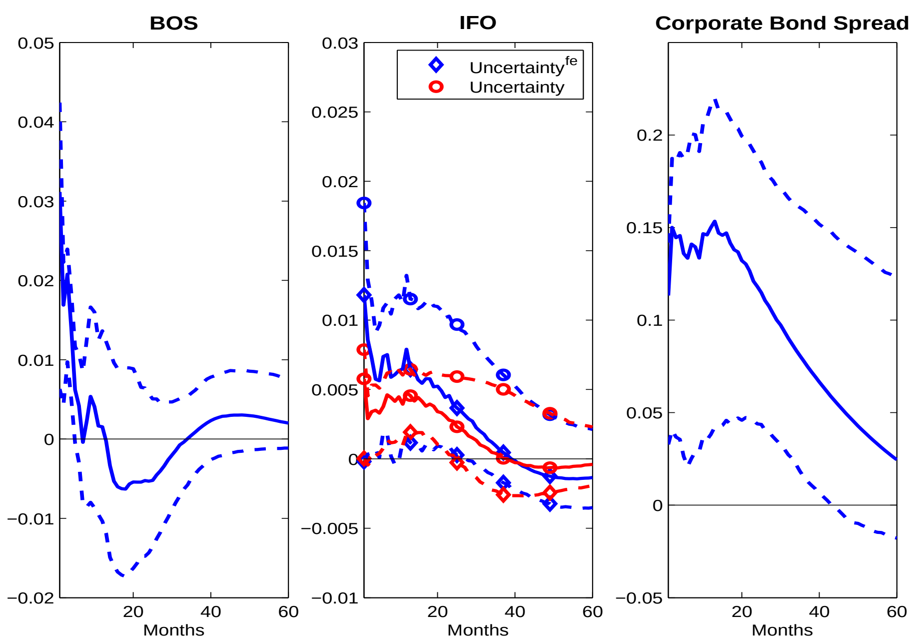
	Shock	1M	3M	6M	1Y	2Y	5Y
$Uncertainty_t^{fe}$							
Activity	Long-run	22%	22%	32%	51%	74%	87%
	Uncertainty	5%	1%	2%	6%	10%	7%
	Short-run	73%	77%	66%	43%	16%	6%
Uncertainty	Long-run	28%	31%	36%	40%	45%	44%
	Uncertainty	72%	67%	63%	59%	53%	51%
	Short-run	0%	2%	2%	2%	2%	5%
Unemployment Rate	Long-run	37%	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 10.

4.3 Discussion

In simple two-variable VARs with sectoral business uncertainty and economic activity variables we find protracted negative impulse responses of activity to uncertainty innovations. Job turnover reacts positively to the same shocks. This is inconsistent with the high-frequency "wait-and-see"-dynamics recently advocated in the literature. Imposing somewhat more structure on the SVAR identification makes the effects of sectoral business uncertainty on sectoral economic activity essentially vanish. These 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, similar to productivity innovations. In this case our SVARs show that structural models using these innovations need a mechanism that transmits rather transitory uncertainty shocks into very persistent output declines. Alternatively, uncertainty can be viewed as mainly an epiphenomenon that accompanies bad economic times.

Figure 11: Long-Run Innovation on Uncertainty



Notes: see notes to Figures 8 and 9. The first and second panel are simply a replication of the 'Uncertainty to Long-Run' impulse responses from these figures. The third 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. '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.

We lean towards the second interpretation. Figure 11 shows the response of the BOS and IFO uncertainty indices, respectively, to the identified long-run shock. We also run an analogous SVAR with the 30 year corporate bond spread as the uncertainty measure. It is clear that negative long-run innovations have significant impact on uncertainty. In other words: bad economic times breed uncertainty. Also, the forecast error variance decomposition in Tables 5 and 6 shows that the long-run innovations contribute significantly to fluctuations in the uncertainty index.[28]

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 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. Since there are costs to establishing new business relationships, the customers of each business stick with them and simply demand more. There is no uncertainty. In a recession, in contrast, 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 preferred 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.[29]

Table 7 shows that almost all NBER recessions were periods of high uncertainty whether it is measured as business uncertainty from survey data, the corporate bond spread as in Gilchrist, Yankov and Zakrajsek (2009), or stock market volatility as in Bloom (2009). We define high uncertainty events as months when either uncertainty measure was one standard deviation above its time series average. But there is also a considerable fraction of months, close to 10 per-

[28] For the SVAR with the corporate bond spread the contribution of the long-run innovation to the 1M, 3M, 6M, 1Y, 2Y, 5Y-ahead forecast error variance is 51%, 55%, 53%, 54%, 61%, 63%, respectively.

[29] It is beyond the scope of this paper to fully flash out a model of intrinsic uncertainty as a result of bad first moment shocks, we leave this for future research.

cent, where uncertainty was high but the economy not in a recession. This is at least suggestive evidence that uncertainty is a concomitant factor of bad economic times rather than a causal factor for them.

Table 7: 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 11. 'Stock Market Volatility' refers to the stock market volatility measure used in Bloom (2009), which until 1986 is realized monthly stock return volatility, and thereafter an implied volatility index. 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 (this is similar to Bloom's (2009) uncertainty index construction). 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.

5 Final Remarks

Using two different measures of business uncertainty from high-frequency, sectoral business surveys in an agnostic structural vector autoregressions framework we find that positive innovations to sectoral business uncertainty have protracted negative implications for sectoral economic activity much in the same way as negative sectoral business confidence shocks have. Shutting down these long-run implications leaves little significant impact on economic activity. We argue that these results are inconsistent with the "wait-and-see"-channel recently advocated in the literature. Rather, we find that negative long-run shocks lead to high uncertainty events. While we leave open the possibility that uncertainty fluctuations are important autonomous economic shocks with long-run implications, we interpret our findings as reflecting the fact that uncertainty is a concomitant phenomenon of negative first moments events in the economy. Bad times breed uncertainty.

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A Appendix - A Simple Model

To illustrate the relationship between such concepts 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 8. 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 8: 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) $Prob(state=1|signal=-1) = 0$

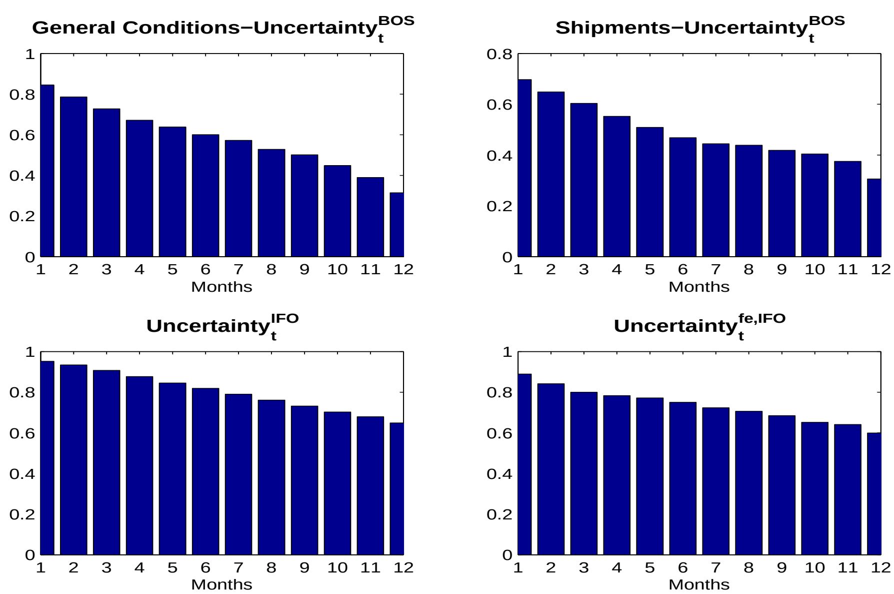
   (b) $Prob(state=0|signal=-1) = \frac{0.5*(1-q)*p}{q*0.5*(1-p)+0.5*(1-q)*p}$

   (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.

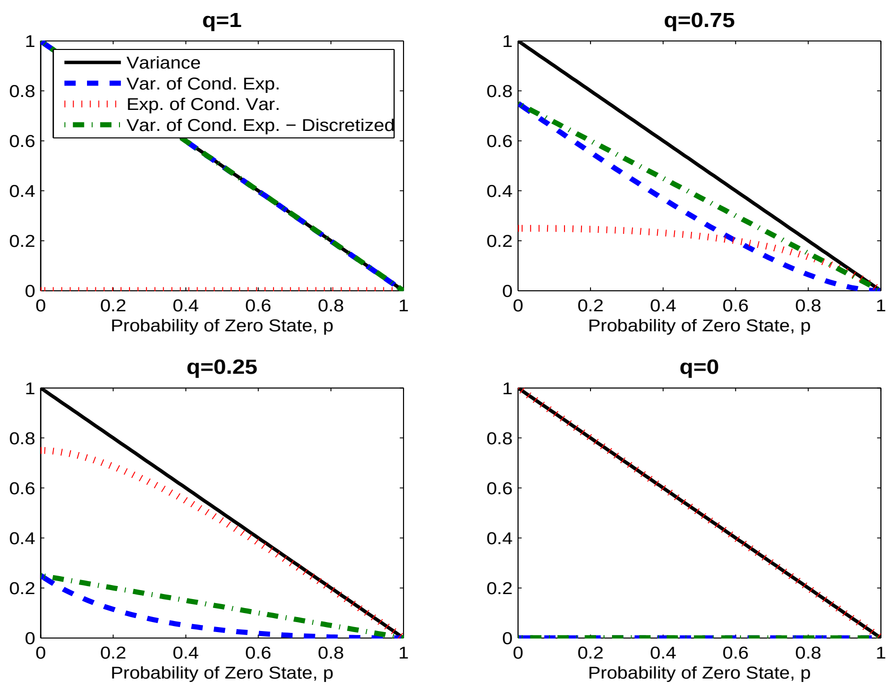
Figure 12: Autocorrelograms of Various Uncertainty Measures



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 conditional expectation, which ranges from 1 (if $p = 0$) to 0 (if $p = 1$). 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:

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

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 a lot 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?"*

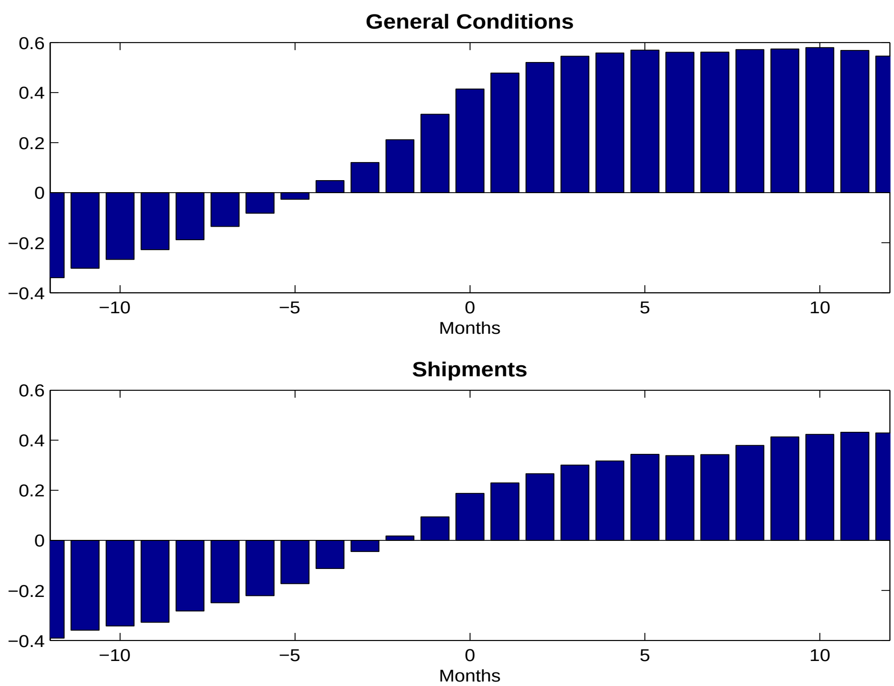
B.2 Additional Information on BOS Variables

Table 9: COMPARISON OF 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 compares BOS-$Activity_t$ Variables, based, in column order, on Q 2, Q 9 and Q 3, with 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.

Figure 14: BOS - Dynamic Cross-Correlations Between $Confidence_t$ and $\Delta\ Activity_t$

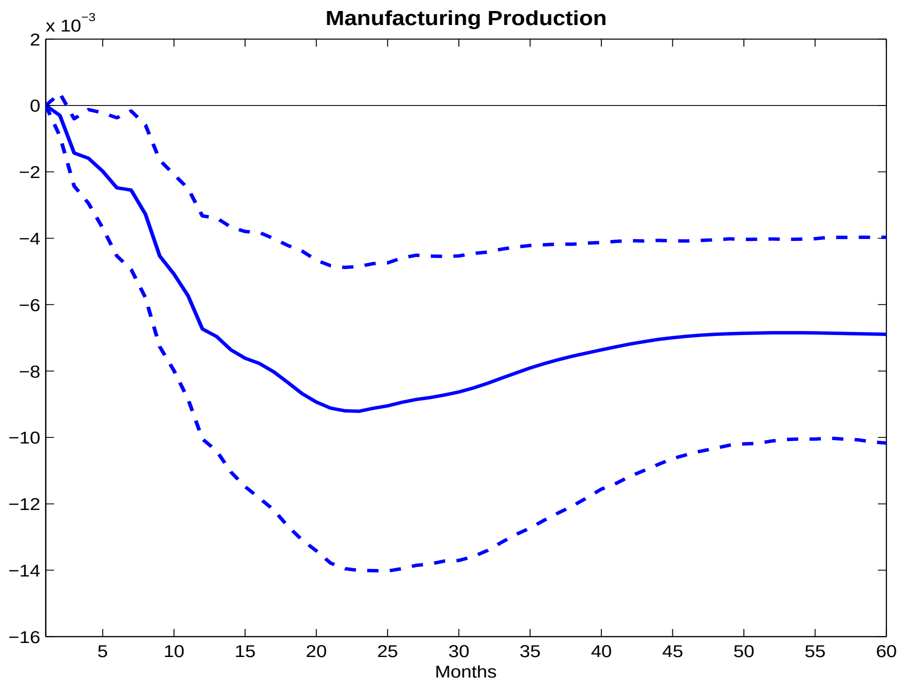


Notes: The upper panel is based on Q 1 and Q 2. The lower panel is based on Q 6 and Q 9. The order is such that $Confidence_t$ leads $\Delta\ Activity_t$ towards the right.

B.3 Additional BOS Results

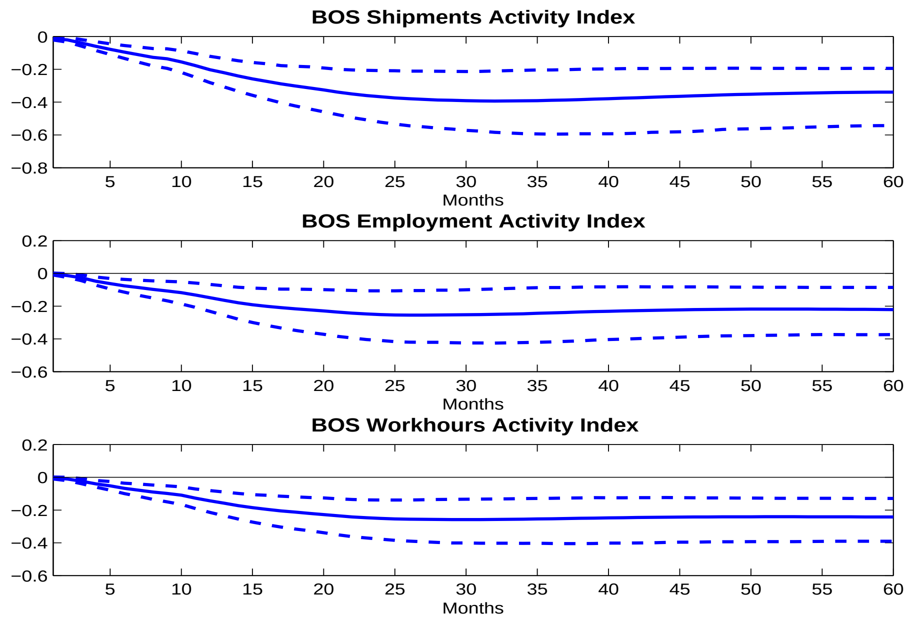
This appendix provides various robustness checks to the results in Section 4.1. Figure 15 shows that the ordering between uncertainty and activity variables is irrelevant for the result that uncertainty innovations in two-variable SVARs trigger prolonged declines in sectoral economic activity. Figures 16 and 17 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 18 to 20, 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 15: Uncertainty Innovation on Manufacturing Production - Reverse Ordering



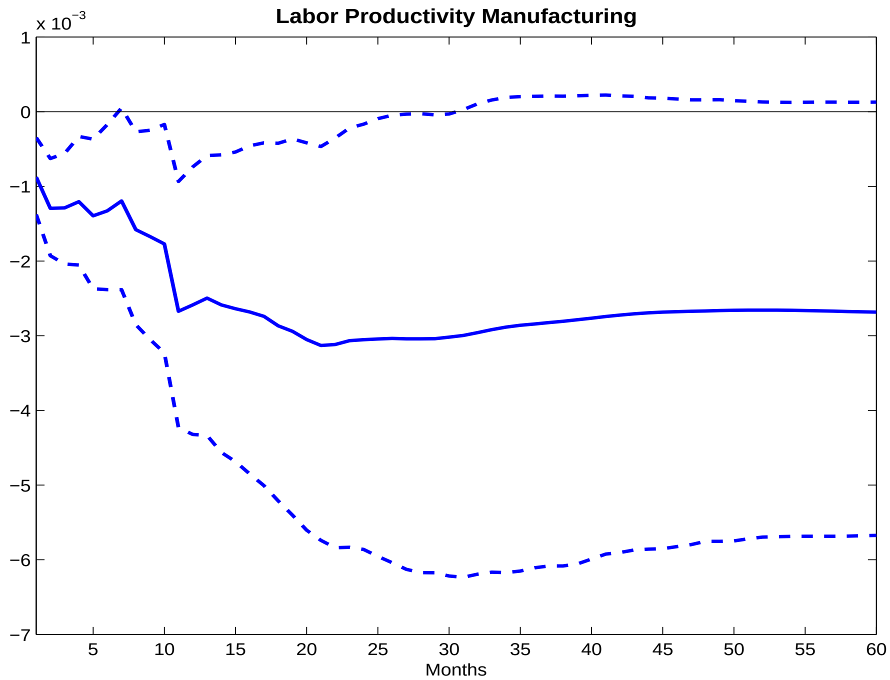
Notes: The IRF is based on a two-variable SVAR with General Conditions-$Uncertainty_t^{BOS}$ (based on Q 1 of the BOS) ordered second and 12 lags. Manufacturing production is the natural logarithm of the (seasonally adjusted) monthly manufacturing production index from the OECD main economic indicators.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

Figure 16: Uncertainty Innovations on Various BOS Activity Indices



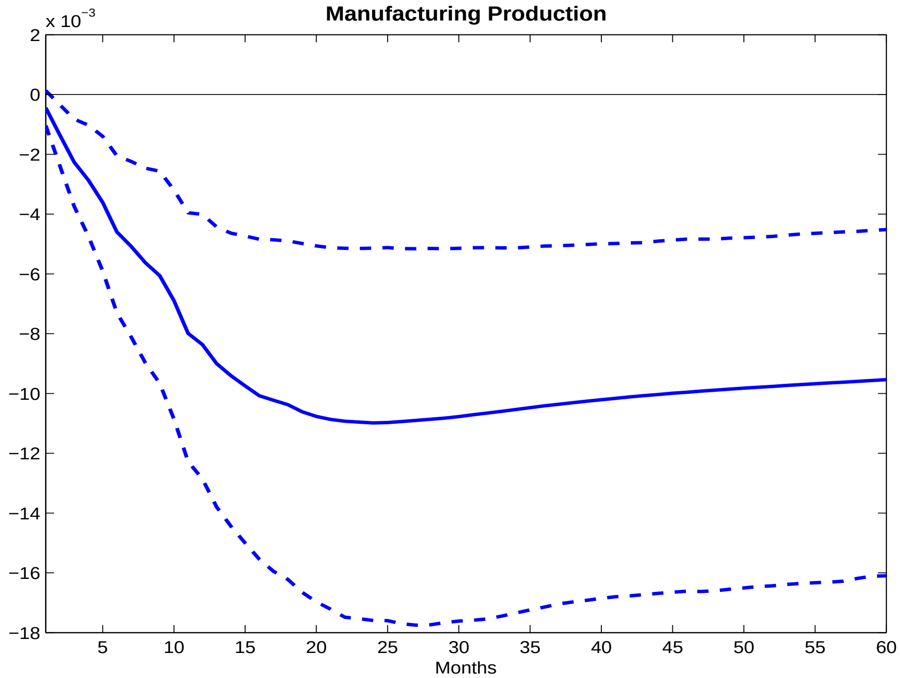
Notes: see notes to Figure 15. Uncertainty is ordered first. The activity indices for the three panels are based on Q 9, Q 3 and Q 10, respectively.

Figure 17: Uncertainty Innovation on Manufacturing Labor Productivity



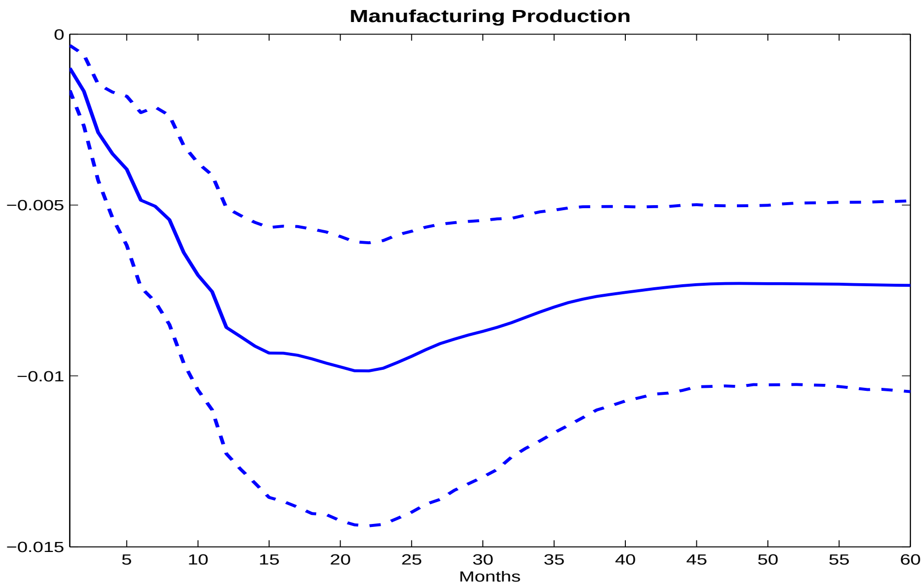
Notes: see notes to Figure 15. Uncertainty is ordered first. Labor productivity is the log-difference between the (seasonally adjusted) monthly manufacturing production index from the OECD main economic indicators and the (seasonally adjusted) monthly manufacturing total hours series, which is itself based on the manufacturing employment and weekly hours per worker series from the BLS-CES data base.

Figure 18: Uncertainty Innovation (Indicator Variable) on Manufacturing Production



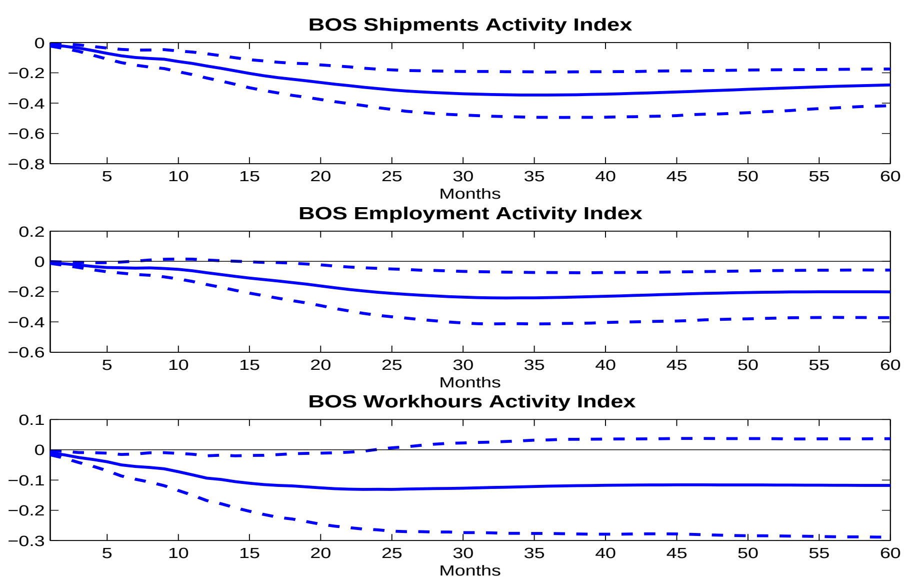
Notes: see notes to Figure 15. The uncertainty variable here is an indicator variable that takes on a value of one, if General Conditions-$Uncertainty_t^{BOS}$, the measure of uncertainty which is based on Q 1, is one standard deviation above its mean, and zero otherwise. There are 60 high-uncertainty observations, or about 12% of the sample. Models with non-convexities typically predict that it is large increases in uncertainty that matter, not the frequent increases and decreases observed in most months. That is why we follow Bloom (2009) and construct such an uncertainty indicator. Using indicator variables in a VAR analysis is similar to the "event study" identifications, for example, in Ramey and Shapiro (1998).

Figure 19: Uncertainty Innovation on Manufacturing Production - Entropy



Notes: see notes to Figure 15. 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 20: Uncertainty Innovations from Other BOS Activity Indices



Notes: see notes to Figure 15. 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)

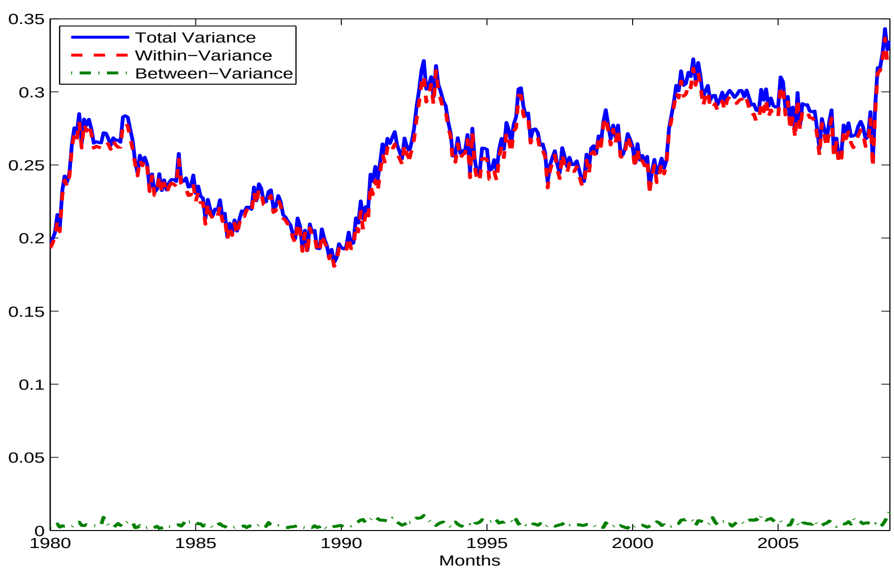
C.1 Original German IFO-BCS Questions

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."*

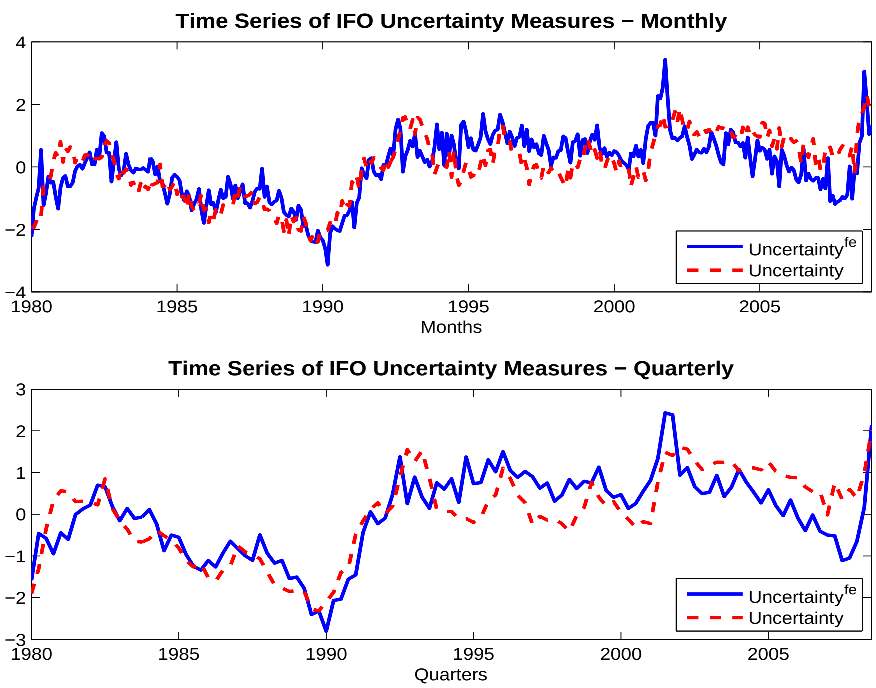
C.2 The IFO-BCS Uncertainty Measures

Figure 21: 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 analogs of $(Confidence_t^{IFO})$.

Figure 22: 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.

Table 10: CYCLICAL PROPERTIES OF $Uncertainty_t$ AND $Uncertainty_t^{fe}$ FOR IFO-BCS INDUSTRIES

	$Uncertainty_t^{IFO}$		$Uncertainty_t^{fe^{IFO}}$	
Industry	Own $Activity_t$	$Activity_t$	Own $Activity_t$	$Activity_t$
Transp. Equipment	-0.38	-0.39	-0.17	-0.10
Machinery and Equipment	-0.43	-0.48	-0.24	-0.29
Metal Products	-0.51	-0.56	-0.34	-0.42
Other non-metal. Products	-0.53	-0.41	-0.29	-0.36
Rubber and Plastic	-0.54	-0.50	-0.34	-0.30
Chemical Products	-0.19	-0.37	-0.29	-0.42
Elect. & Opt. Equipment	-0.50	-0.48	-0.43	-0.39
Paper and Publishing	-0.64	-0.55	-0.56	-0.49
Furniture and Jewelery	-0.45	-0.31	-0.32	-0.17
Cork and Wood Products	-0.53	-0.46	-0.40	-0.35
Leather	-0.26	-0.14	-0.14	-0.25
Textile Products	-0.70	-0.50	-0.51	-0.37
Food and Tobacco	-0.18	-0.29	-0.17	-0.26

Notes: See notes to Table 3 and Figure 21. 'Own $Activity_t$' refers to the industry-specific analog of the activity variable, based on Q 5. '$Activity_t$' refers to the overall activity measure, based on Q 5

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 appendix 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.[30] Almost 25% of respondents are in the retail sector, 20% in construction and 15% in manufacturing, followed by services, which ranges well above 10%. All other one-digit sectors 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[31] 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.[32]

We use three questions from the SBETS. The confidence and uncertainty indices are based on a question about general business conditions just like in the BOS:[33]

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 version is that it is slightly more nuanced in that 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. "*

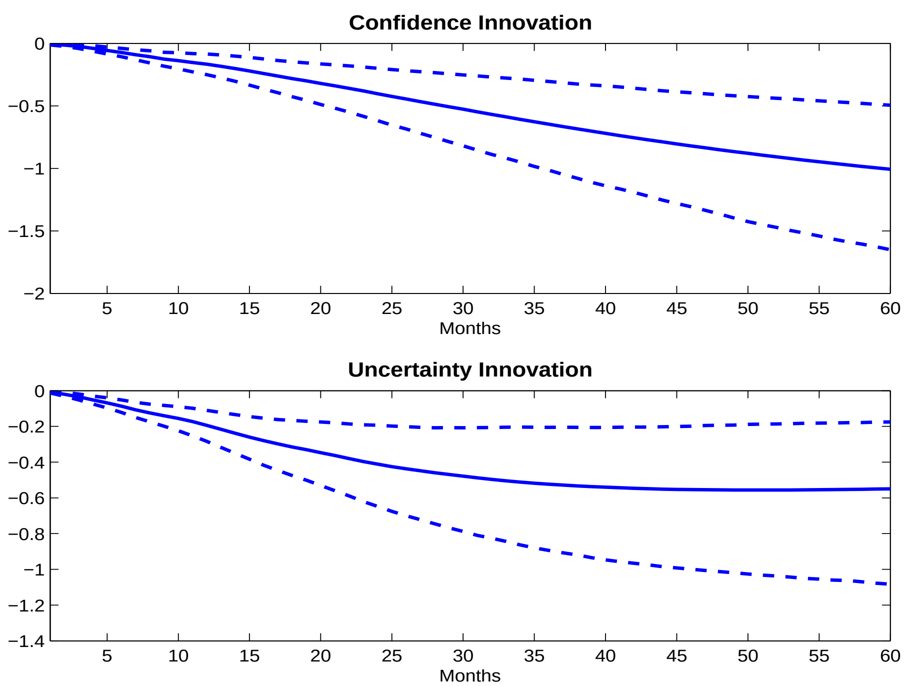
[30] The participation in the quarterly survey is higher, 1200 on average before January 2007 and 1750 thereafter.
[31] This includes full- and part-time employees.
[32] For this and more details, see Dunkelberg and Wade (2009).
[33] The box and the bold font are also used in the original.

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 23 displays the analog of Figure 3 in Section 4.1. Both negative business confidence innovations and 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.

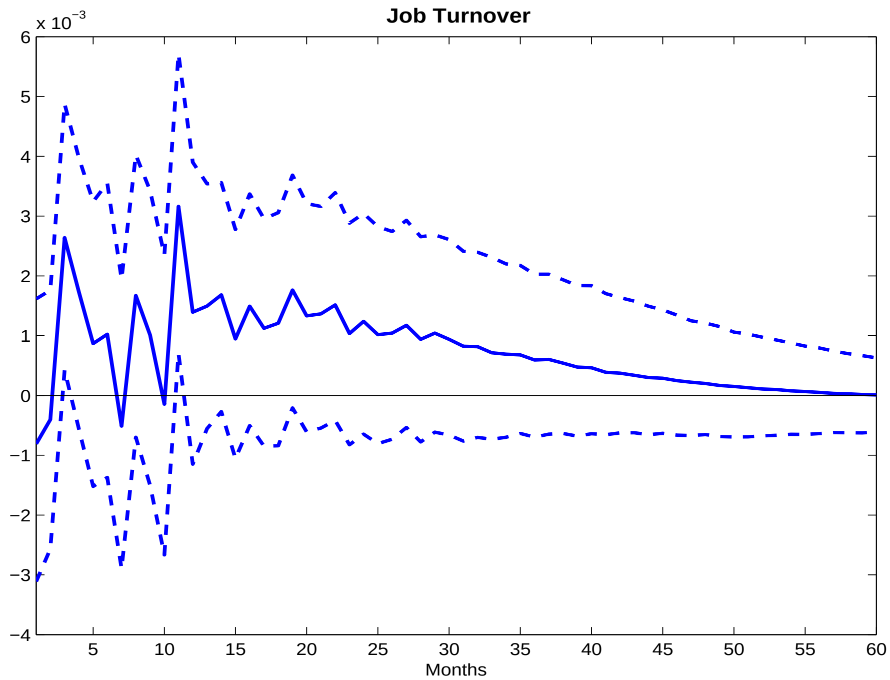
Figure 23: Uncertainty Innovations on SBETS Sales Activity Index



Notes: Confidence and uncertainty are based on Q 13. The activity variable is based on Q 14. The upper panel is based on a two-variable SVAR with confidence ordered first, then activity. It displays the response of the SBETS Sales Activity Index to a negative confidence innovation. The lower panel is based on a two-variable SVAR with uncertainty ordered first, then activity. It displays the response of the SBETS Sales Activity Index to a positive uncertainty innovation.

Figure 24 is similar to Figure 5 from the BOS. 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 is inconsistent with "wait-and-see"-theories of uncertainty shocks.

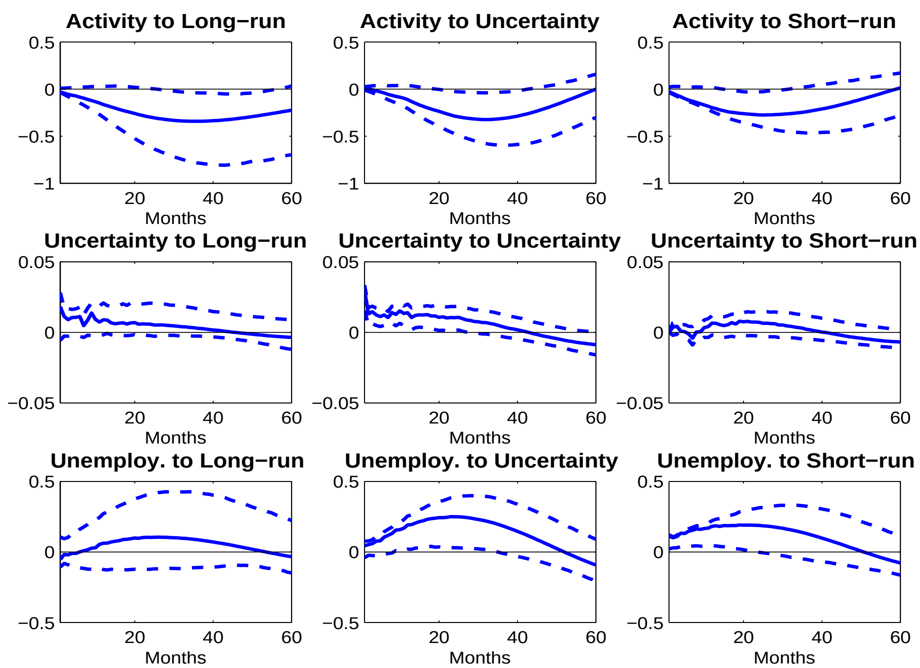
Figure 24: Uncertainty Innovation on SBETS Job Turnover Index



Notes: see notes to Figure 23. 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 25 and Table 11 display the analogs of Figure 8 and Table 5 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 25: A Three-Variable Blanchard-Quah-Type SVAR - SBETS



Notes: see notes to Figure 23. 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.

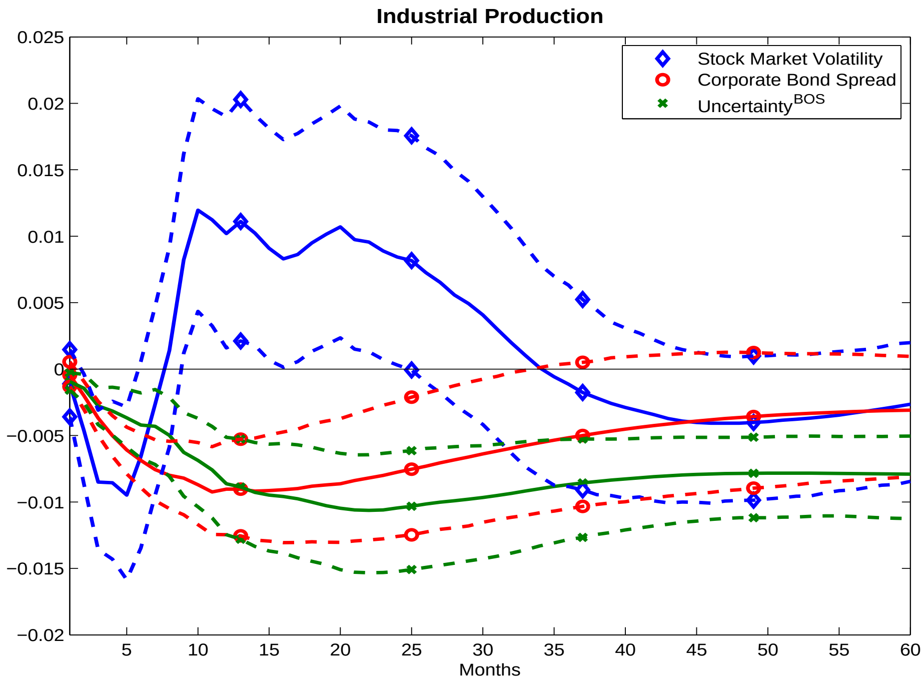
Table 11: Forecast Error Variance Decomposition - SBETS

	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 25

E Appendix - Corporate Bond Spreads and Stock Market Volatility

Figure 26: Uncertainty Innovations on (Manufacturing) Production



Notes: The 'Stock Market Volatility' IRF is a replication of Figure 2 in Bloom (2009), with the exception that we use 95% confidence bands. It shows the response of U.S. industrial production with respect to a stock market volatility shock. The variables in the estimation order are log(S&P500 stock market index), a stock-market volatility indicator, Federal Funds Rate, log(average hourly earnings), log(consumer price index), hours, log(employment), and log(industrial production). All variables are Hodrick-Prescott (HP) detrended (λ = 129,600). The main stock-market volatility indicator is constructed to take a value 1 for a month with particularly high volatility, see Bloom (2009) for details. The 'Corporate Bond Spread' IRF is the analog of the impulse response in the lower panel of Figure 1 for an uncertainty measure based on corporate bond spreads as in Gilchrist, Yankov and Zakrajsek (2009). '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 corresponding activity measure is total industrial production. $Uncertainty_t^{BOS}$ is based on General Conditions-$Uncertainty_t^{BOS}$, i.e. Q 1. The corresponding activity measure is manufacturing industrial production.