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## Uncertainty Shocks in Times of Low and High Uncertainty

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# Uncertainty shocks in times of low and high uncertainty

Christian Grimme\*      Steffen R. Henzel<sup>†</sup>

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## Preliminary Draft

### Abstract

The general economic environment may influence the way uncertainty affects real activity. These non-linearities in the uncertainty-output relationship may help to explain severe crisis events. We base our analysis on an uncertainty measure obtained from firm-level data from a large business survey panel covering a long time-span 1980-2018. We suggest that the level of uncertainty itself is an important driver of the reaction of real activity to a surprise increase in uncertainty. We tackle the question using an interacted VAR model, where coefficients depend on the level of uncertainty, and uncertainty enters as an endogenous variable. Uncertainty shocks have particularly adverse effects when the level of uncertainty is low, while negative effects are dampened when firms are already highly uncertain. This non-linear effect occurs during recession and non-recession phases.

*JEL classifications:* C32, C33, E32.

*Keywords:* Uncertainty, Survey Data, Non-Linear VAR.

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# 1 Introduction

It has been forcefully argued that sudden increases in uncertainty may have detrimental effects on economic activity.<sup>1</sup> When linear models are used to assess the importance of uncertainty shocks, quite restrictive assumptions regarding the propagation of shocks are made. A more recent strand of literature thus emphasizes the importance of nonlinearities and document a heightened potential of uncertainty to trigger business cycle downturns. For instance, Caggiano, Castelnuovo, and Groshenny (2014), Jones and Enders (2016), Caggiano, Castelnuovo, and Figueres (2017), Cacciatore and Ravenna (2021), Caggiano, Castelnuovo, and Nodari (2021), Caggiano, Castelnuovo, and Pellegrino (2021) document an amplifying effect for uncertainty shocks, when the economy is in a recession, while Alessandri and Mumtaz (2019), Alfaro, Bloom, and Lin (2021), Angelini, Bacchiocchi, Caggiano, and Fanelli (2019) emphasize the role of financial distress. We analyze whether the effect of surprise increases in uncertainty depend on the level of this uncertainty. We base our analysis on a measure of firms' business uncertainty derived from monthly firm-level survey data.

Uncertainty shocks may materialize during tranquil times as well as in a highly uncertain environment and this may matter for decision makers facing a surprise increase in uncertainty. When do decision makers respond most to increasing uncertainty, when businesses act under low uncertainty or when uncertainty is high already? Whether uncertainty (or its absence) amplifies or dampens the effect is an empirical matter. For instance, under low uncertainty, decision makers may perceive a sudden increase in business uncertainty as a normalization due to mean reverting behavior, simply ignore fluctuations or they may have expected an increase before, such that the expectation error is small. They would thus make only small adjustments under low uncertainty. Larger adjustments may, however, result under low uncertainty if forward-looking lenders believe that a surprise increase is a signal for more turbulent times ahead. Thus, decision makers would respond in a precautionary way and strongly revise their decisions.

Few papers have analyzed the influence of different uncertainty regimes on the uncertainty-activity relation. Jackson, Kliesen, and Owyang (2020) suggest that the level of uncertainty matters for the propagation of uncertainty shocks. They find additional effects for uncertainty shocks that raise uncertainty above a moving average of past observations. Their approach does, however, not allow for low uncertainty to have

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<sup>1</sup>See, e.g., Bloom (2009), Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011), Bachmann and Bayer (2013), Bachmann, Elstner, and Sims (2013), Born and Pfeifer (2014), Gilchrist, Sim, and Zakrajšek (2014), Bundick and Basu (2017).

an effect.<sup>2</sup> Analyzing the so-called financial frictions channel of uncertainty and using microdata, we show in a companion paper that the level of borrowers' business uncertainty affects the extent to which credit conditions are tightened (Grimme and Henzel, 2021).<sup>3</sup>

We use a non-linear interacted vector autoregressive (iVAR) model to analyze whether the state dependence of the uncertainty-output relationship is quantitatively important from a macroeconomic perspective. In the iVAR model the regime variable, i.e. the level of uncertainty, is determined endogenously together with real output. Moreover, we restrict the model such that the dynamics of uncertainty itself do not directly depend on a particular uncertainty state. Since the model nests the linear alternative, we may test whether non-linearities play a role. We quantitatively assess the differences across uncertainty regimes using impulse responses which account for the non-linearity of the model. We also perform a battery of robustness checks.

Any empirical analysis of the effects of uncertainty depends on a reliable measure of the uncertainty a decision maker faces. We construct a business uncertainty measure from micro data of the German ifo Business Climate Survey (ifo-BCS) following the approach of Bachmann, Born, Elstner, and Grimme (2019). The ifo-BCS contains monthly data for the years 1980 to 2018 and, thus, covers several recessions. We believe using firm-level survey data instead of aggregate or financial data is advantageous, since it polls actual decision-makers at firms in contrast to, for example, financial analysts (Bachmann et al., 2013). Further, we construct uncertainty at the firm level which should comprise firm-specific, industry-specific and aggregate developments. By averaging over many firms, we obtain an aggregate measure of uncertainty of the representative firm. Notably, we do not have to rely on the dispersion across firms, which is, in general, not a direct proxy of uncertainty. Moreover, the ifo-BCS encompasses firms of all sizes and strategic behavior in the responses is also less of an issue, since the data is highly confidential.

We document that non-linearities exist, since the linear alternative is clearly rejected by the data. The largest effect of business uncertainty on output is obtained when uncertainty is low. State dependence also matters quantitatively. Considering the maximum

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<sup>2</sup>Comparing high and low uncertainty episodes Bijsterbosch and Guérin (2013) calculate contemporary correlations among different uncertainty measures and aggregate variables in different uncertainty regimes. While they document higher correlations during high uncertainty episodes, correlations are, however, not informative about uncertainty-dependent effects of an increase in uncertainty.

<sup>3</sup>Gilchrist et al. (2014) show that after an uncertainty shock (and in the presence of financial frictions) lenders react with a tightening of credit conditions, thereby reducing aggregate investment (Christiano, Motto, and Rostagno, 2014; Arellano, Bai, and Kehoe, 2019).

response, going from high to low uncertainty approximately doubles the effect. This result holds for different VAR specifications. Moreover, differences between the low and the medium uncertainty state are small. The main mitigating effect thus obtains when decision makers' uncertainty is high already. Using variance decompositions, we demonstrate that the explanatory power of an uncertainty shock is roughly cut in half when we move from low to high uncertainty.

Since recent literature emphasizes the role of recessions for the propagation of uncertainty shocks, we also demonstrate that dependence on the level of uncertainty is obtained for both, recession and non-recession phases. It thus appears that both nonlinearities co-exist. Our results support the notion that, more than recessions per se, it appears to be the combination of low uncertainty and recessions that matters. Overall, rising uncertainty may accelerate the way into economic crises, since it is particularly damaging when uncertainty is still low.

The analysis is structured as follows. Section 2 introduces the interacted VAR model. In section 3 we derive our measure of firms' business uncertainty. Results for different iVAR specifications are presented in section 4, and a comparison of recession and non-recession phases is given in section 5. Section 6 concludes.

## 2 Interacted VAR model

We use an iVAR model to analyze the impact of uncertainty on aggregate activity. Aggregate quantities are usually found to be persistent, and the VAR model allows us to measure the impact of an unforeseen increase in uncertainty, controlling for feedback effects of real activity on uncertainty. Further, we require that the reaction of real activity to uncertainty is dependent on the level of uncertainty. This can be achieved by augmenting the linear VAR model with interaction effects, which makes the estimated dynamics state dependent. Since the iVAR model nests the linear alternative, it allows to directly test the hypothesis that the uncertainty state is important. While the model presented in this section represents our baseline specification, several modifications are presented below. Given real activity  $y$  and uncertainty  $\sigma$ , the iVAR model is written as follows:

$$\begin{pmatrix} 1 & 0 \\ \alpha_{21}^0 & 1 \end{pmatrix} \begin{pmatrix} y_t \\ \sigma_t \end{pmatrix} = C + Dt + \sum_{l=1}^L \begin{pmatrix} \alpha_{11}^l & \alpha_{12,t}^l \\ \alpha_{21}^l & \alpha_{22}^l \end{pmatrix} \begin{pmatrix} y_{t-l} \\ \sigma_{t-l} \end{pmatrix} + E_t, \quad (1)$$

where

$$\alpha_{12,t}^l = \bar{\alpha}_{12}^l + \tilde{\alpha}_{12,1}^l d_{t-1}^{\text{low}} + \tilde{\alpha}_{12,2}^l d_{t-1}^{\text{high}}, \quad (2)$$

such that  $\bar{\alpha}_{12}^l$  measures the respective impact at medium uncertainty. Given that there is no such term in the uncertainty equation, the response of uncertainty does not directly depend on a particular uncertainty state, which ensures that the dynamics of uncertainty is similar across uncertainty states.<sup>4</sup> Any change in the dynamics of real activity across uncertainty regimes would thus be due to changes in the response of output. We also include a constant  $C$  and a linear trend  $Dt$  to control for long-term growth.  $E_t$  represents the vector of iid shocks.

We follow previous literature and apply a zero restriction in the contemporaneous matrix.<sup>5</sup> That is, real activity may contemporaneously affect uncertainty, while there is no immediate reaction of real activity to changes in uncertainty. In what follows, we thus analyze the effect of shock events that lead to unforeseen increases in our uncertainty measure, affecting real activity only with a lag of one period. Considering that

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<sup>4</sup>There may, however, be repercussions from changes in the dynamics of real activity. Given the relatively large number of coefficients in the model, restricting the interaction effect to the activity equation also prevents parameter proliferation. See also Appendix C for a non-restricted version of the model.

<sup>5</sup>See, among others, Bloom (2009), Bachmann et al. (2013), Gilchrist et al. (2014), Jurado, Ludvigson, and Ng (2015), Henzel and Rengel (2017), Jackson et al. (2020).

we use monthly data, we believe that this is not an overly restrictive assumption.<sup>6</sup>

The different uncertainty states of the economy are identified using dummy variables, where  $d^{\text{low}} = 1$ , when uncertainty is low and zero otherwise, while the high uncertainty state is identified using  $d^{\text{high}} = 1$ . Consequently, the medium uncertainty state provides the reference category. Using dummies instead of the level of uncertainty itself has the advantage that the impact on  $y$  is allowed to depend in a non-proportionate fashion on the level of uncertainty. For instance, we are able to identify a possibly small effect for medium and low uncertainty states, while the strongest reaction might be observed during high uncertainty only, or vice versa. To identify the three different regimes, we thus need to impose thresholds which determine a high, a medium and a low uncertainty regime, respectively.<sup>7</sup>

**Difference to Markov-Switching VAR: level of uncertainty determines the regime shift - direct test of a particular type of non-linearity we propose here. Difference to Threshold VAR, Smooth Transition VAR (unobserved thresholds) or max uncertainty VAR in Jackson et al. (2020): definition of high uncertainty, differences only between high and average, mixes asymmetry (increase/decrease) and large/small shocks and uncertainty high/average: cannot elicit on the effects of (in historical perspective) low uncertainty.**

### 3 Measuring uncertainty

We derive our measure of economic uncertainty using data from the German ifo Business Cycle Survey (ifo-BCS), which is a monthly survey among business entities.<sup>8</sup> The ifo-BCS covers a long time-span and contains a high number of participants. We use firm-level survey data from the manufacturing sector from 1980 M1 until 2018 M8 (IBS-

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<sup>6</sup>Other identification procedures in linear VARs such as in Ludvigson, Ma, and Ng (2021), which deliver a multitude of admissible shock series, are not straightforward and much more computationally demanding in our (restricted) non-linear VAR. Finding admissible constraints from external variables not included in the VAR but presumably correlated with firm-level uncertainty. Since there is no uniformly accepted theory as to the origins and effects of uncertainty shocks, in our case sign restrictions to disentangle the shocks are disputable as well.

<sup>7</sup>Also note that, when estimating the model using uncertainty itself as interaction variable instead of dummy variables, a high and a low uncertainty state would still have to be defined. The distinction between different states would, however, have to be made after model estimation. Given that, in our case, there are no stability problems involved when estimating the model, we believe that the dummy variable approach is advantageous, since it provides more flexibility.

<sup>8</sup>From the survey the ifo Institute derives the ifo Business Climate Index, which is a much-followed leading indicator for economic activity in Germany.

IND, 2015).<sup>9</sup> At the beginning of our sample, the average number of respondents is approximately 5,000; at the end the number declines to 2,000. Firms participate voluntarily in the survey, and only 8% of all firms are one-time participants, while, on average, firms participate 40 times. The ifo-BCS also achieves a high degree of representativeness (see table A.1 in Appendix A). To estimate firm-specific uncertainty, we use the following two qualitative questions:<sup>10</sup>

**Q1 Production** ( $\text{prod}_{i,t}$ ): *Our domestic production activity with respect to product XY has (1) increased (= +1), (2) roughly stayed the same (= 0), (3) decreased (= -1).*

**Q2 Expectation** ( $\text{prod}_{i,t+2|t}^e$ ): *Expectations for the next 3 months: Our domestic production activity with respect to product XY will probably (1) increase (= +1), (2) remain virtually the same (= 0), (3) decrease (= -1).*

Firms respond to the survey during the first half of the month, and our timing assumption is that firms respond in month  $t$ . Therefore,  $\text{prod}_{i,t+2|t}^e$  contains a nowcast, i.e. expectations are formed about the current month and the two subsequent months. Likewise, the information in  $\text{prod}_{i,t}$  assumably relates to production in the past month.

To calculate firm-specific uncertainty, we use firm  $i$ 's expectation to derive a realized forecast error  $fe_{i,t}$  (compare Bachmann et al., 2019). Following Bachmann et al. (2013),  $fe_{i,t}$  can be inferred from Q1 and Q2. We compare the expectation  $\text{prod}_{i,t+2|t}^e$  to the realization during the current and subsequent two months:

$$\overline{\text{prod}}_{i,t+3} = \text{prod}_{i,t+1} + \text{prod}_{i,t+2} + \text{prod}_{i,t+3}, \quad (3)$$

where  $\overline{\text{prod}}_{i,t+3}$  lies in the range  $[-3, 3]$ . Table 1 summarizes the possible outcomes of the forecast error  $fe_{i,t}$ , which can take on values between  $-4$  and  $4$ . The latter is obtained, when a firm expects production to increase, but in all three months production actually declines.

Calculation of each  $fe_{i,t}$  thus requires three subsequent months, i.e. one quarter of observations. We proxy firm-level uncertainty by the standard deviation of the forecast error based on three non-overlapping forecast errors (see, for instance, Comin and

<sup>9</sup>Before 1991 the data contains only West-German firms.

<sup>10</sup>The questions of the ifo-BCS for manufacturing for Germany have been translated into English. Firms are explicitly asked to ignore differences in the length of months or seasonal fluctuations. The ifo-BCS is conducted at the plant level, so the number of participants does not exactly conform to the number of firms. However, more than 97% of the participants are single-product plants (Balleer, Hristov, and Menno, 2017). Therefore, we use the term "firm" for each participant.



Expectation	Realization	Forecast Error
$\text{prod}_{i,t+2 t}^e$	$\overline{\text{prod}}_{i,t+3}$	$fe_{i,t}$
+1	$> 0$	0
+1	$\leq 0$	$\overline{\text{prod}}_{i,t+3} - 1$
= 0	$> 0$	$\overline{\text{prod}}_{i,t+3}$
= 0	= 0	0
= 0	$< 0$	$\overline{\text{prod}}_{i,t+3}$
-1	$< 0$	0
-1	$\geq 0$	$\overline{\text{prod}}_{i,t+3} + 1$

**Table 1: Firm-specific forecast errors.** Production expectations  $\text{prod}_{i,t+2|t}^e$  may take three different values: increase : +1, unchanged : 0, decrease : -1.

Mulani, 2006; Davis, Haltiwanger, Jarmin, and Miranda, 2006; Bachmann et al., 2019).

$$\sigma_{i,t} = \sqrt{\frac{1}{3} \sum_{k=0}^2 (fe_{i,t-3k} - \overline{fe}_{i,t})^2}, \quad (4)$$

where  $\overline{fe}_{i,t} = \frac{1}{3} \sum_{l=0}^2 fe_{i,t-3l}$  is the rolling mean of three non-overlapping forecast errors observed during the last three quarters. We thus avoid that forecast errors are persistent by construction. Moreover, perceived uncertainty of the decision maker is measured when expectations are formed, which implies that  $fe_{i,t}$  and, thus,  $\sigma_{i,t}$  are observed only ex-post. Since we require time variation, we discard firms which have participated less than **XXX** times. Even though uncertainty is derived from categorical data, it is quasi-continuous;  $\sigma_{i,t}$  takes on values between 0 and 3.06 and has an overall standard deviation of 0.43.

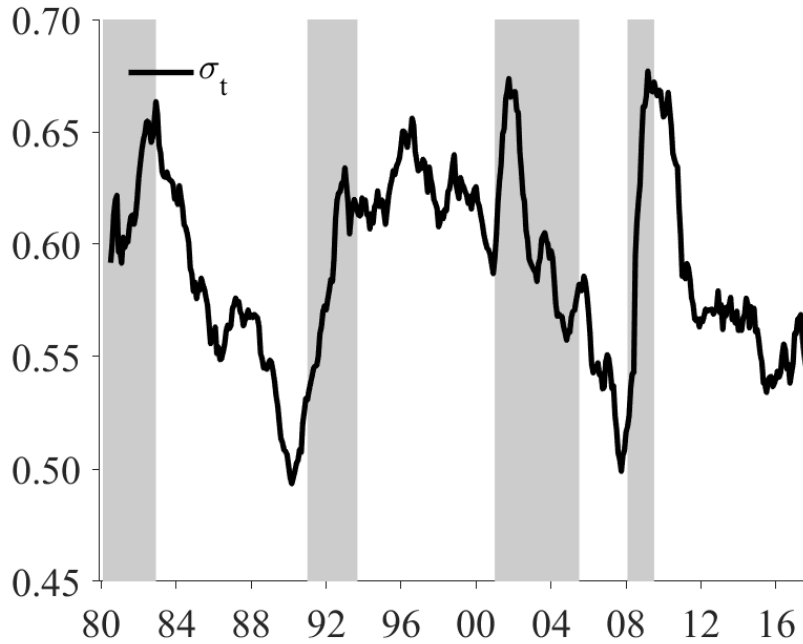
We use the average individual uncertainty about the business outlook of a representative firm as our measure of aggregate uncertainty (see, among others, Giordani and Söderlind, 2003):

$$\sigma_t = \frac{1}{N} \sum_{i=1}^N \sigma_{i,t} \quad (5)$$

Average firm-level uncertainty is shown in Figure 1 along with recession periods shaded in gray.<sup>11</sup> It appears that  $\sigma$  is countercyclical.

Unlike cross-sectional measures of forecast dispersion, which assume a close rela-

<sup>11</sup>Since we work with monthly survey data, the time series are seasonally adjusted prior to estimation.



**Figure 1: Average uncertainty.** This figure shows average uncertainty of the representative firm measured by  $\sigma_t$ . Shaded areas indicate recession periods as published by the German Council of Economic Experts (2017).

tionship between disagreement among firms and individual uncertainty,  $\sigma$  relies on the dispersion of forecast errors within a firm.<sup>12</sup> It measures the size of the expected forecast error, and thus of perceived uncertainty, of an individual decision maker.

**Our measure is different from aggregate macro uncertainty and financial uncertainty (low correlation even to BES). Results are however relatively robust...** Note that our firm-level measure differs from uncertainty about aggregate production as in, for instance, Jurado et al. (2015) or Henzel and Rengel (2017). Imagine two heterogeneous firms (or industries), whose production is negatively correlated, since one firm profits from a particular event (e.g. a technology shock), whereas the other firm suffers. Firm (or industry) heterogeneity may provide an insurance against shocks at the aggregate level. While both firms likely experience increased firm-level uncertainty, aggregate production – and its predictability – may be hardly affected.<sup>13</sup> However, it is

<sup>12</sup>For instance, the dispersion would increase, when there are more optimistic and more pessimistic firms in the sample, all of which are equally certain about their future production. Consequently, when we compute the cross-sectional dispersion of firm-level forecasts, the correlation of this measure to  $\sigma$  is only 0.29.

<sup>13</sup>Comin and Mulani (2006) provide a similar argument for aggregate versus firm-specific volatility of sales.

conceivable that decision makers pay close attention to firm-specific (or industry specific) developments, which are not appropriately captured by uncertainty related with aggregate outcomes. **In this vein, existing research tends to document a reduced role for exogenous movements in macroeconomic uncertainty for business cycle movements.**

Moreover,  $\sigma_{i,t}$  is robust to large first-moment shocks to production, since a bias in the forecast due to persistent over- or under-prediction will not affect the standard deviation (see also Comin and Mulani, 2006). Particularly,  $\sigma_{i,t}$  is large when the underlying forecast errors are large *and* unpredictable. Conceptually,  $\sigma_{i,t}$  is comparable to the outcome of a stochastic volatility model, which provides an estimate of the time varying (expected) forecast error variance.<sup>14</sup>

## 4 Results from iVAR model

Our baseline results are based on (the log of) monthly industrial production (IP) as a measure of real activity, since the manufacturing industry is the cycle maker in industrialized economies. The fact that we are able to use monthly observations may indeed be advantageous. Since uncertainty may shift rather quickly, some of the short-run effects may be washed out when quarterly data is used. The observation period is defined by the availability of  $\sigma_t$  and starts in 1980 M7 and ends in 2018 M2. In addition to the monthly model, we estimate a quarterly model using GDP to measure aggregate activity. While the lower frequency of the observations is a disadvantage, GDP captures all sectors of the economy. Results for GDP are based on observations 1980Q3 through 2017Q4.

To avoid arbitrariness, we conduct a grid search and use the BIC to simultaneously select the appropriate lag length of the iVAR model and the possibly asymmetric thresholds required for the definition of  $d^{\text{low}}$  and  $d^{\text{high}}$ . For the monthly model a lag-length of  $L = 5$  is selected, and a high uncertainty state is identified for the 10% highest realizations, while the 28% lowest realizations are in the low uncertainty regime, which leaves 62% of all observations to the medium uncertainty state. The iVAR model assumes the same impact of positive and negative shocks, which appears appropriate since increases and decreases are roughly evenly distributed in each uncertainty state. Conditional on

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<sup>14</sup>Instead of using the standard deviation, individual uncertainty may also be measured using the absolute forecast error of three subsequent forecasts. Moreover, we may use the root mean squared forecast error of each firm as a measure of uncertainty, which does not control for persistent bias in the forecast. We use these measures to perform robustness checks.

being in a high uncertainty state, we observe 47% increases, and the average increase (decrease) is 0.0043 (-0.0059) units. In the low uncertainty state, there are 56% increases with an average increase (decrease) of 0.0048 (-0.0048) units.<sup>15</sup> The quarterly model yields  $L = 3$ , where the 18% highest observations belong to the high uncertainty state, and the lowest 32% define the low uncertainty state.<sup>16</sup> In both cases, an LM test rejects a simple linear VAR in favor of the iVAR model at the 1% level. It appears that non-linear behavior proposed here helps to explain the dynamics of real activity.

To see what this implies in quantitative terms, we analyze the impact of uncertainty using impulse responses from the iVAR model. However, standard impulse response functions from the non-linear VARs have no meaningful interpretation, since the response depends on future shocks hitting the system after the shock of interest. Further, the response is history depended. We thus calculate generalized impulse response functions as in Koop, Pesaran, and Potter (1996), who propose to take the expectation over future shocks and, thus, generate impulse responses which only depend on the shock of interest and the history of the data.<sup>17</sup> We repeat this procedure for each time period in our sample.

The responses of IP to a one standard deviation surprise increase in aggregate uncertainty are shown in the upper panel of Figure 2. It documents that increased uncertainty depresses real activity in any state of the economy. However, there appears to be considerable time variation in the magnitude and persistence of the effect. When looking at the largest negative response, a sudden increase of uncertainty of the same magnitude (i.e. one standard deviation) foreshadows a decline of IP between -0.62% and -1.02% per month. For real GDP the range is between no decline at all and -1.23% per quarter.

In the lower panel of Figure 2, we show the response of uncertainty to an unforeseen increase. It appears that uncertainty exhibits considerable persistence. In accordance with the restrictions on the uncertainty equation in equation 1, the dynamic adjustment of uncertainty is very similar across uncertainty regimes. This result also implies that lagged real activity exerts only a minor influence on the adjustment path of uncertainty.

In the lower panel of Figure 3, we present average responses of IP during the low

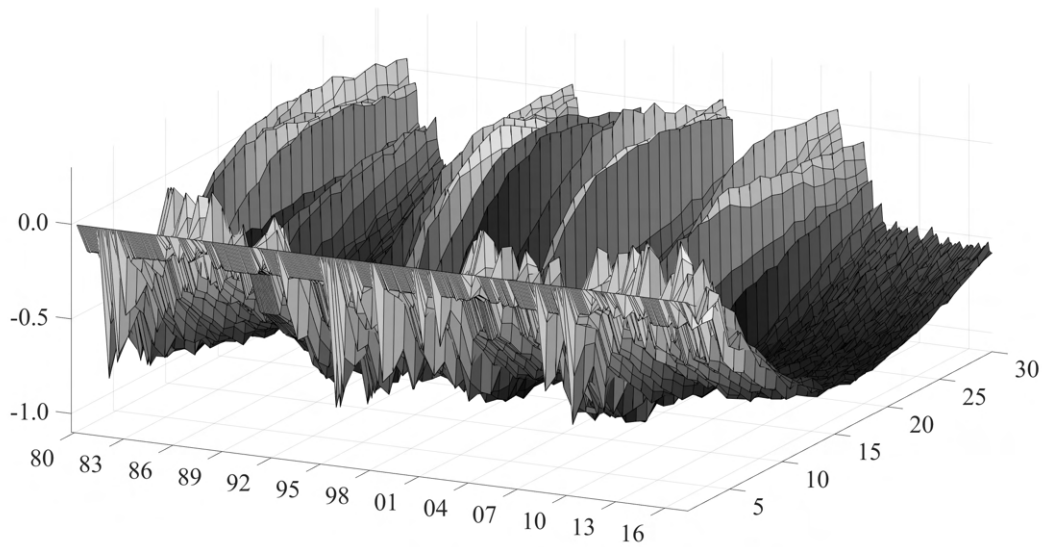
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<sup>15</sup>The medium uncertainty regime comprises 47% increases with an average increase (decrease) of 0.0048 (-0.0047) units.

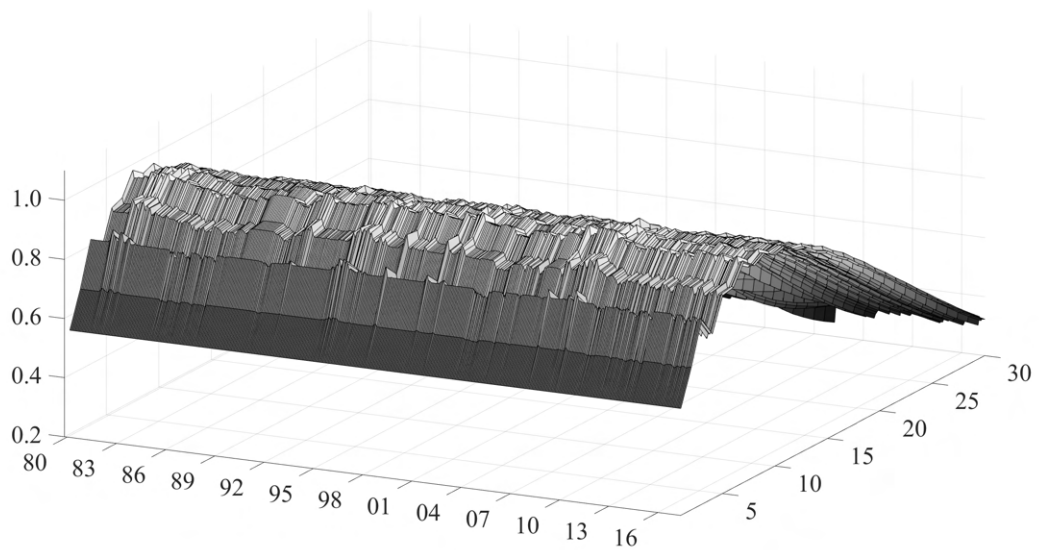
<sup>16</sup>Conditional on being in a high uncertainty state, we observe 37% increases, and the average increase (decrease) is 0.0079 (-0.015) units. In the low uncertainty state, there are 56% increases with an average increase (decrease) of 0.011 (-0.010) units.

<sup>17</sup>The conditional expectation can be evaluated by simulating different possible future economies given a sequence of shocks and the history of the data, and taking the average. We use 500 Monte Carlo draws to compute impulse response functions.

### Responses IP



### Responses $\sigma$



**Figure 2: Generalized impulse response functions over time.** The upper panel shows the generalized impulse responses of IP to a one standard deviation surprise increase in uncertainty for each month in our sample. The lower panel shows the corresponding responses of uncertainty  $\sigma$  over time.

uncertainty state (red) and the high uncertainty state (black). We also plot bootstrapped

confidence intervals (67%, 90%, 95%).<sup>18</sup> It appears that increased uncertainty significantly depresses real activity measured by IP. Further, we document a negative effect for both, the high and the low uncertainty state. Moreover, there seem to be non-negligible differences in the responses of IP. During the first few months, we observe a more instantaneous decline when uncertainty is high. This decline is, however, reversed rather quickly after about six months. In the low uncertainty state, the drop in real activity seems to be more persistent and slightly larger. The upper right panel of Figure 3 documents the dynamic adjustment of uncertainty over time. Since both responses are similar, it appears that the different responses of real activity over time are driven by differences in the transmission of uncertainty, i.e. by a state dependent reaction of decision makers to a comparable increase in uncertainty.<sup>19</sup>

For both, the monthly and the quarterly model, the difference in the responses for the two uncertainty states are shown in Figure 4 along with bootstrapped confidence intervals. For IP, we observe that the positive distance during the first few months is indeed significant **Significance maybe due to zero restriction...** It thus appears that the reaction in the first few months after the shock is more instantaneous when uncertainty is high. However, the distance eventually becomes significantly negative. When we consider GDP, the reaction is significantly more pronounced when uncertainty is low for all periods after the shock. The maximum estimated distance amounts to 0.74 ppts per month for IP and 0.57 ppts per quarter for GDP.<sup>20</sup>

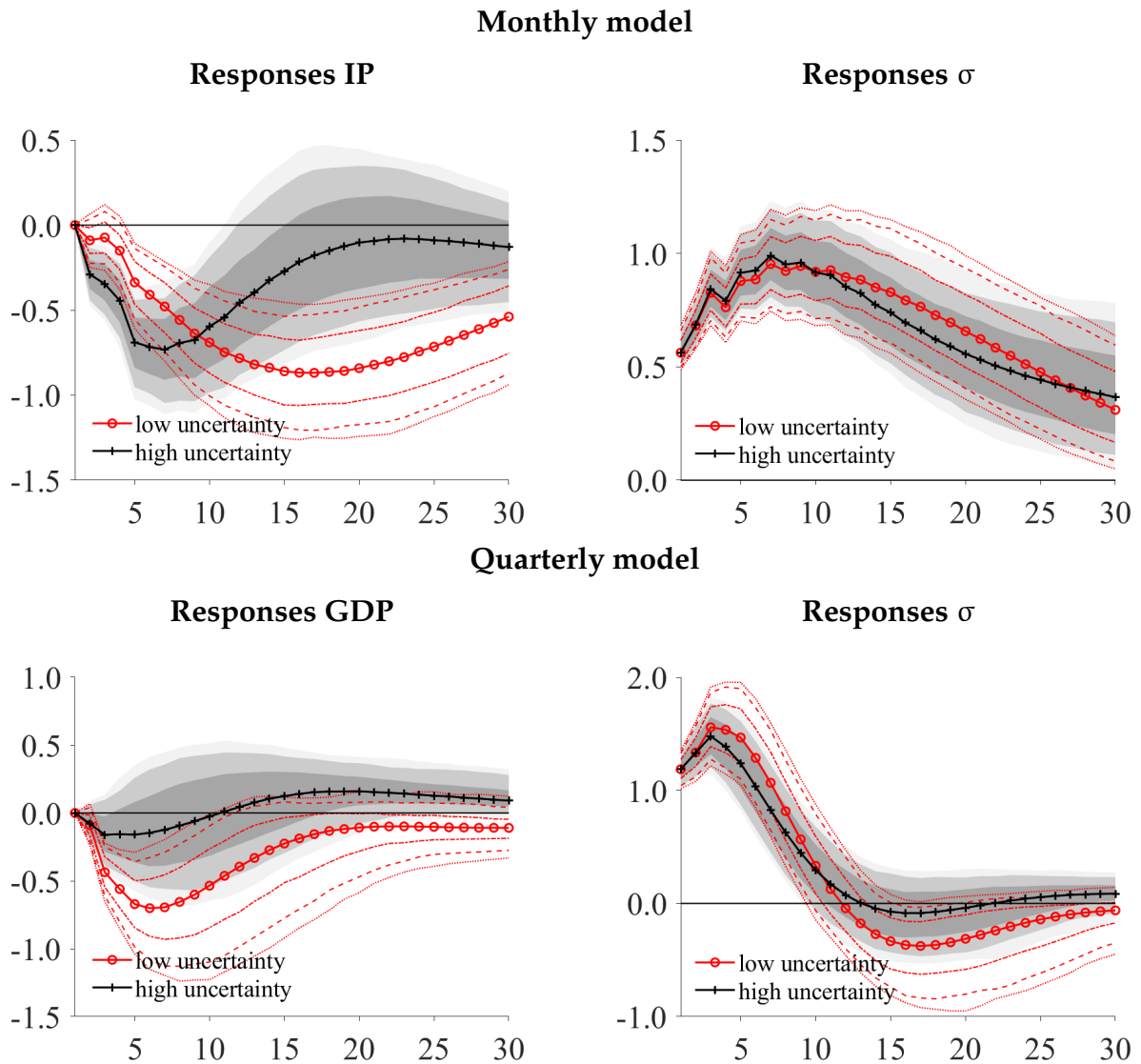
Our specification also warrants a comparison of responses under medium uncertainty. The upper part of Figure 5 documents the distance between responses during either medium and high, and medium and low uncertainty. Like the distance between high and low uncertainty, the distance between high and medium uncertainty becomes negative after about one year. Moreover, it is similar in magnitude and statistically sig-

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<sup>18</sup>Bootstrapped confidence bands are based on 1000 simulated datasets using the estimated coefficients and drawing from estimated shocks from the iVAR with replacement. For each simulated dataset we then calculate generalized impulse response functions based on 500 simulated time paths for each period. Uncertainty regimes are identified as above, using the 10% highest and 28% lowest observations (monthly). Results for quarterly GDP are obtained accordingly.

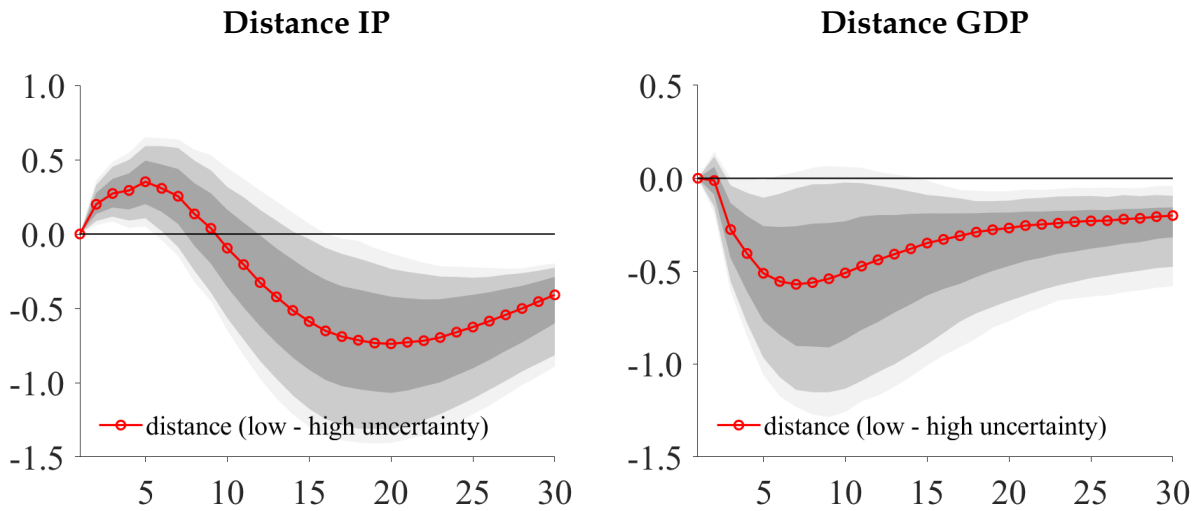
<sup>19</sup>A further robustness check is provided in Appendix B, where we document the effect of a surprise increase in uncertainty using a reversed ordering of variables. This change leaves our results qualitatively unchanged.

<sup>20</sup>As a robustness check, we estimate an unrestricted version of the baseline iVAR model where interaction effects are allowed in both equations. Results are shown in Appendix C. There is slightly more variation in the responses of  $\sigma$  across uncertainty states, and we observe a slightly larger increase for low uncertainty. It appears, however, that this change does not alter our conclusions. Notably, the response of  $\sigma$  is similar across different uncertainty states in this unrestricted version of the model, as well. Such a finding supports our earlier result that the differences in the dynamics of real activity are indeed driven by differences in the reaction to uncertainty, rather than differences in the dynamics of uncertainty itself.



**Figure 3: Impulse response functions for different states.** The upper left panel shows all impulse response functions of IP to a one standard deviation shock to uncertainty, while the lower left panel shows the responses of GDP. Different uncertainty states are indicated by color and line style, where low uncertainty is identified by the red line with circle markers, medium uncertainty is represented by the blue solid line, and high uncertainty is shown by the black line with cross markers. The upper right panel shows the average response of IP for low uncertainty states (red) and high uncertainty states (black), and the lower right panel shows responses of GDP. Shaded areas and dotted lines indicate 95%, 90%, and 68% bootstrapped confidence intervals, respectively.

nificant. The distance between low and medium uncertainty appears less pronounced and only marginally significant. Overall, responses in the medium uncertainty state seem to resemble those during the low uncertainty state, when we consider the monthly model. Uncertainty thus tends to depress IP in the majority (90%) of all observed states



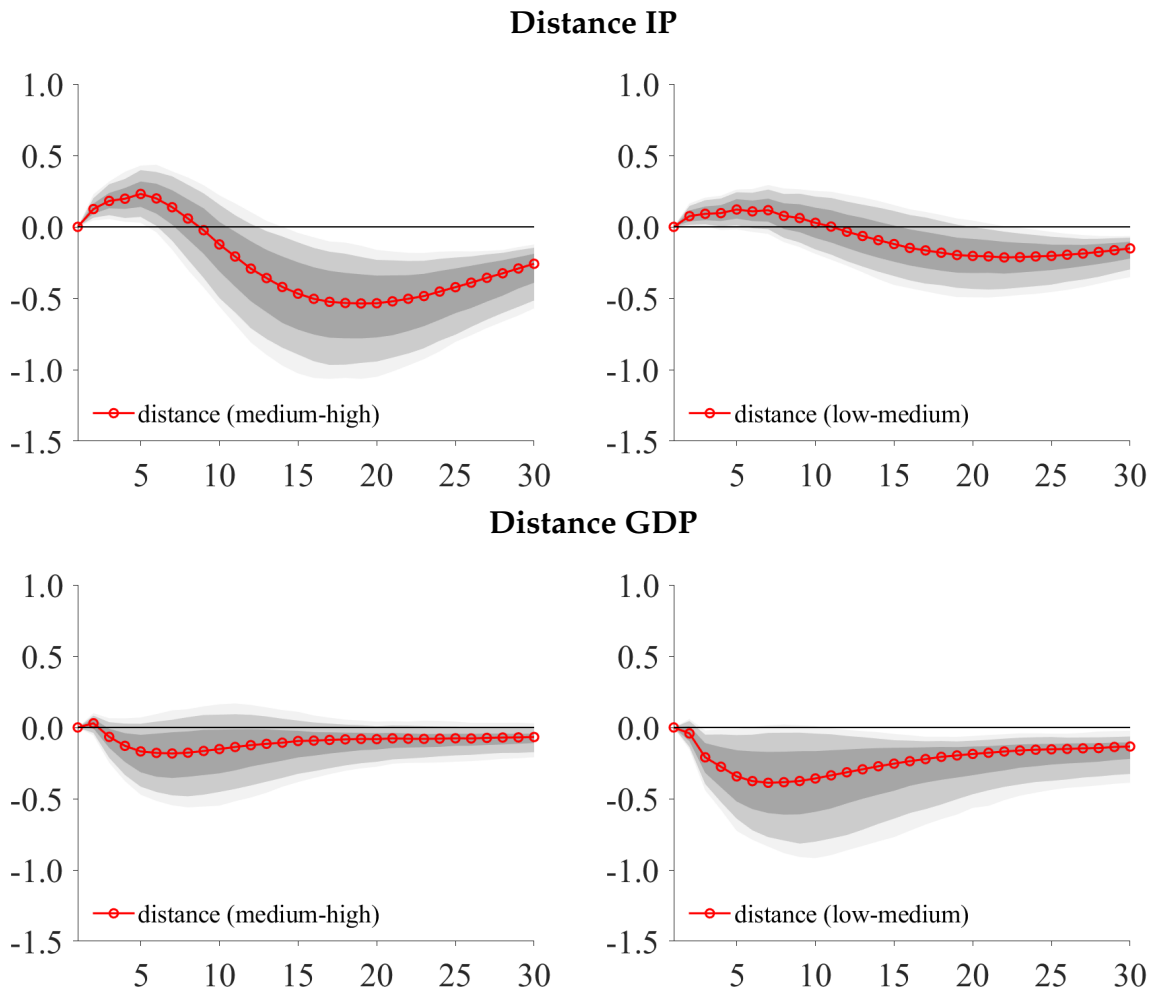
**Figure 4: Distance of impulse response functions.** This figure shows the average distance between responses of IP and GDP in the low and high uncertainty state. Shaded areas indicate 95%, 90%, and 68% bootstrapped confidence intervals, respectively.

in our sample.

Results for quarterly GDP are shown in the lower part of Figure 5. All distances are negative, which suggests that the largest effect is still obtained for low uncertainty. However, in this case, the distance between medium and high uncertainty remains insignificant, whereas the distance between low and medium uncertainty is significant and similar to the distance between low and high uncertainty. For the quarterly model, we might conclude that a substantial effect of uncertainty is found for the low uncertainty regimes (32% of all observations) only.

Our measure of uncertainty  $\sigma_t$  should, in principle, be unaffected by first-moment shocks, since it reflects the predictability of the forecast error. Yet, we might be concerned that fluctuations of uncertainty are confused with pessimistic (or optimistic) expectations. To control for first-moment shocks in expectations, we estimate a larger three-variable iVAR model which includes aggregate business expectations. Maintaining the recursive structure of the model, we order expectations between real activity and uncertainty, that is, expectations may affect uncertainty contemporaneously but not vice-versa. Results for this model are provided in Figure 6. In addition, we also document in Figure 6 results for larger alternative iVAR specifications including – in addition – a stock price index, and consumer prices as well as a short-term interest rate. While the stock price index controls for financial market expectations, consumer prices may control for supply shocks, and interest rates control for monetary policy. In all models uncertainty is ordered last, such that the other variables may affect uncertainty



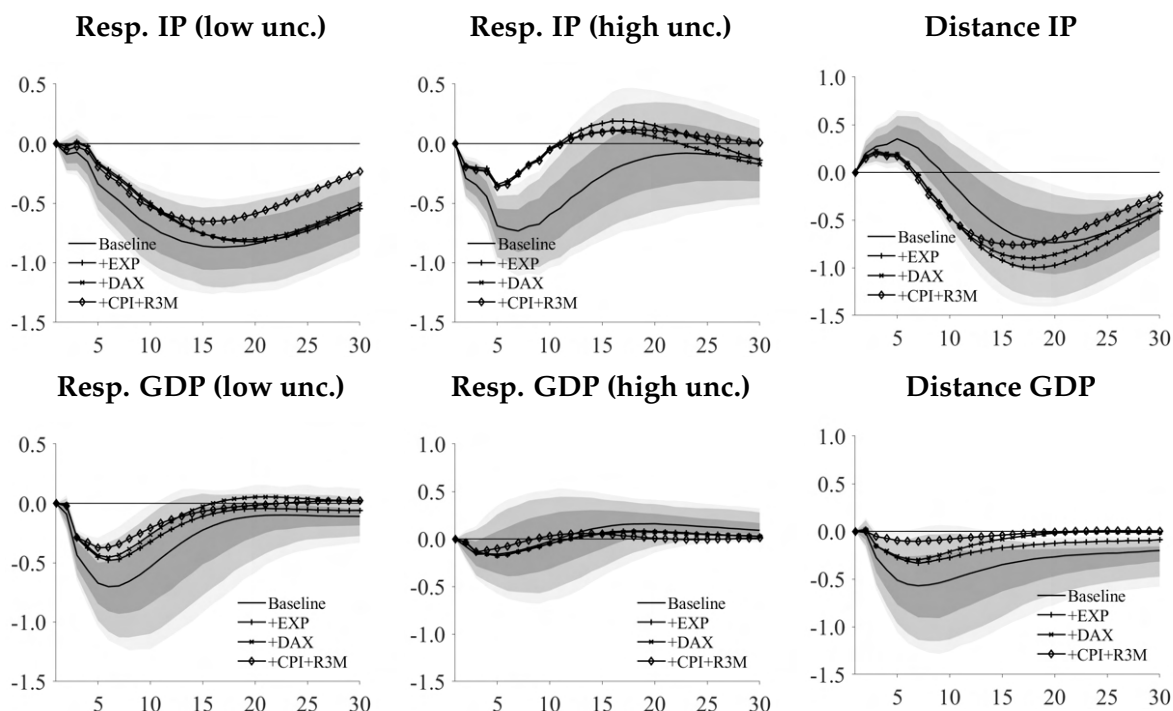


**Figure 5: Distance of impulse response functions.** This figure shows the average distance between responses of IP and GDP in the medium and high uncertainty state, and between the low and medium uncertainty state, respectively. Shaded areas indicate 95%, 90%, and 68% bootstrapped confidence intervals.

contemporaneously, while uncertainty has only a lagged impact on the other variables. The larger models put more restrictions on the uncertainty shock in the iVAR model since we control for the immediate impact of all other variables on real activity. Using this identifying assumption, we thus bias our results against finding large short-term effects of uncertainty. In all cases, an LM test rejects a simple linear VAR in favor of the iVAR model at conventional levels.

For the monthly model our results appear largely robust to these changes. If anything, we observe for the high uncertainty state that the instantaneous response of IP is mitigated and even more short-lived. As a result, the (positive) distance for the first few months tends to shrink. While the response of quarterly GDP remains negative

in the low uncertainty state, it seems to be mitigated when we control for business expectations. Adding further variables leaves this response largely unaffected. Moreover, the response in the high uncertainty stays roughly the same, when additional variables enter the iVAR model. While it appears that the distance between both states is less pronounced when we control for other shocks, results are robust with respect to the sign of the distance.<sup>21</sup>



**Figure 6: Results for larger iVAR models.** This figure shows generalized impulse response functions of IP and GDP following a one standard deviation surprise increase in uncertainty for the low uncertainty regime (left panel), the high uncertainty regime (middle panel) and the average distance between responses in the low and high uncertainty state (right panel). Variables used are: Uncertainty  $\sigma$ , the log of industrial production IP or real gross domestic product GDP, IFO business expectations EXP, the log of the share price index DAX, the log of the consumer price index CPI, and the 3-month money market interest rate R3M. Uncertainty is ordered last, such that the other variables may affect uncertainty contemporaneously, while uncertainty has only a lagged impact on the other variables. As in the baseline model, interaction effects of uncertainty  $\sigma$  are assumed for all equations in the iVAR except uncertainty itself. The restricted linear version of each iVAR model considered here is rejected by a LR-test at 1% significance.

We document the economic significance of the previous finding using a forecast error variance decomposition. We calculate the share of the variance of real activity, that is IP

<sup>21</sup>Taken together, this result could be interpreted in the sense that it is difficult to robustly identify a shock to uncertainty in a quarterly model, since the lower frequency makes it harder to disentangle the different shocks impinging on GDP.

and GDP, explained by a shock to uncertainty according to the different iVAR models from above.<sup>22</sup> In Figure 7 we depict – for each horizon – the average variance share of the shock to uncertainty for low, medium and high uncertainty states. It appears that the surprise increase in uncertainty may explain up to 58% of the variation in IP in the long run, when we are in a low uncertainty state. When we control for more variables, this figure is cut in half but still remains at 29%. In a high uncertainty state, the long-run explanatory power of uncertainty is between 34% and 13% for the largest iVAR model. We conclude that a firm’s business uncertainty has a non-negligible role for the dynamics of IP. While the long-run explanatory power for GDP is smaller than for IP, shifts in uncertainty still explain between 8 and 23% of the variation in the low uncertainty state, and between 3 and 13% in the high uncertainty state, depending on the size of the model.

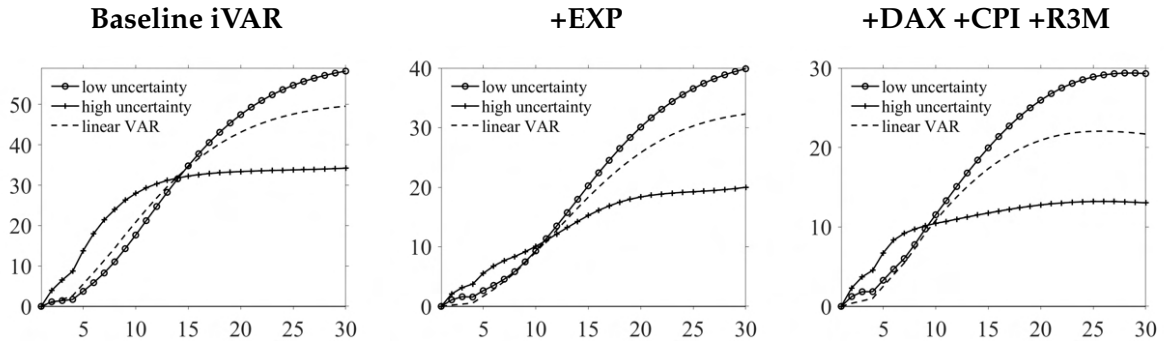
Figure 7 also contains the contribution of uncertainty in a standard linear VAR model, a restricted version of our model. Considering only the largest model, we may explain 29% of the variation in the low uncertainty regime instead of 22% in the linear specification.<sup>23</sup> Likewise, shifts in uncertainty are able to explain up to 11% of GDP in the iVAR model, whereas the linear VAR yields only 6%. It appears that the gain of the non-linear specification compared to a standard linear VAR model is also non-negligible in economic terms.

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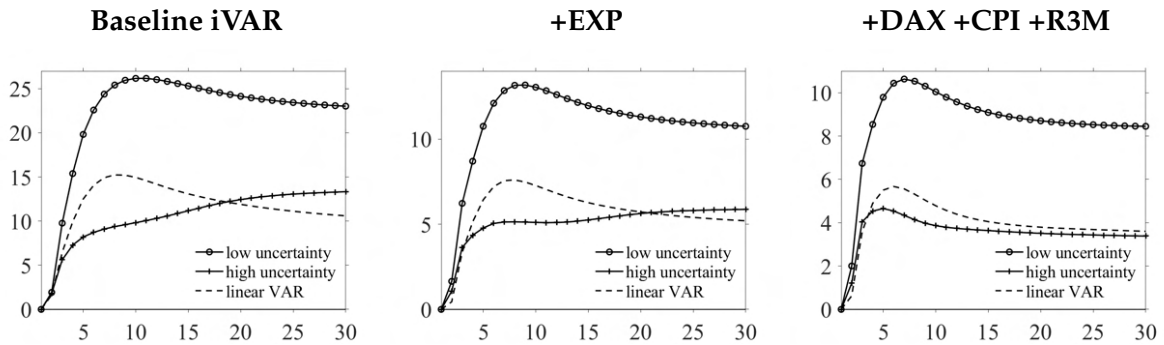
<sup>22</sup>The forecast error variance decomposition is based on the generalized impulse responses from orthogonal shocks indexed  $k = 1 \dots K$ . Omitting an index for each state of the economy, the mean squared error of variable  $j$  is given by  $MSE_j = \sum_{i=0}^{h-1} \sum_{k=1}^K \theta_{jk,i}^2$ , where  $\theta_{jk,i}$  denotes the generalized impulse response of variable  $j$  to shock  $k$  at horizon  $i$ . The forecast error variance of variable  $j$  accounted for by innovation  $k$  at horizon  $h$  is given by  $fev_{jk} = \sum_{i=0}^{h-1} \theta_{jk,i}^2$ .

<sup>23</sup>This gain comes at the expense that shifts in uncertainty are less powerful when the economy is in a high uncertainty state.

## Variance decomposition IP



## Variance decomposition GDP



**Figure 7: Forecast error variance decomposition.** This figure shows in the upper panel the share of the variance of IP explained by the shock to uncertainty, and the lower panel shows results for GDP. Each panel contains average results for low and high uncertainty states, as well as a linear VAR model. The left figure shows results for the baseline iVAR, the middle figure documents results when business expectations are controlled for, and the right figure shows results for a large iVAR when CPI, R3M and DAX are added. Variables used are: Uncertainty  $\sigma$ , log of industrial production IP, IFO business expectations EXP, log of share price index DAX, log of consumer price index CPI, 3-month money market interest rate R3M. Uncertainty is ordered last, such that the other variables may affect uncertainty contemporaneously, while uncertainty has only a lagged impact on the other variables. As in the baseline model, interaction effects of uncertainty  $\sigma$  are assumed for all equations in the iVAR except uncertainty itself.

## 5 Uncertainty regimes and recessions

Another state-dependence documented in previous research relates to a recession being present (Caggiano et al., 2014; Jones and Enders, 2016; Caggiano, Castelnuovo, and Nodari, 2017, see, for instance,). It might thus be the case that high and low uncertainty states fall together with recession and non-recession phases and uncertainty states pick up the effect of being in a recession (or vice versa). In Table 2 we document that there is not a complete overlap of both variables, since each of the uncertainty states seems

to occur for recession phases as well as non-recession phases. However, as is to be expected, both variables are related to some extent. With a value of 19.7% the likelihood to observe high uncertainty in the monthly model is higher during recessions compared to non-recessions (6%), while low uncertainty tends to be more likely in non-recession phases (33.9% vs. 13.6%). A similar albeit less pronounced result is obtained when we consider quarterly data.

		Recessions			
		Monthly		Quarterly	
		recession	non-recession	recession	non-recession
Uncertainty	low	0.136	0.339	0.190	0.368
	medium	0.667	0.601	0.571	0.472
	high	0.197	0.060	0.238	0.160
	$\Sigma$	1.000	1.000	1.000	1.000

**Table 2: Contingency table: uncertainty and recessions.** This table shows the likelihood of each uncertainty state conditional on being in a recession or non-recession phase. Recession periods are defined according to the German Council of Economic Experts (2017).

We thus expand our analysis and check whether responses of real activity depend on recessions being present during either a high or a low uncertainty state.<sup>24</sup> Results shown in Figure 8 suggest that responses of IP depend on the uncertainty state, no matter whether we are in a recession phase or not.

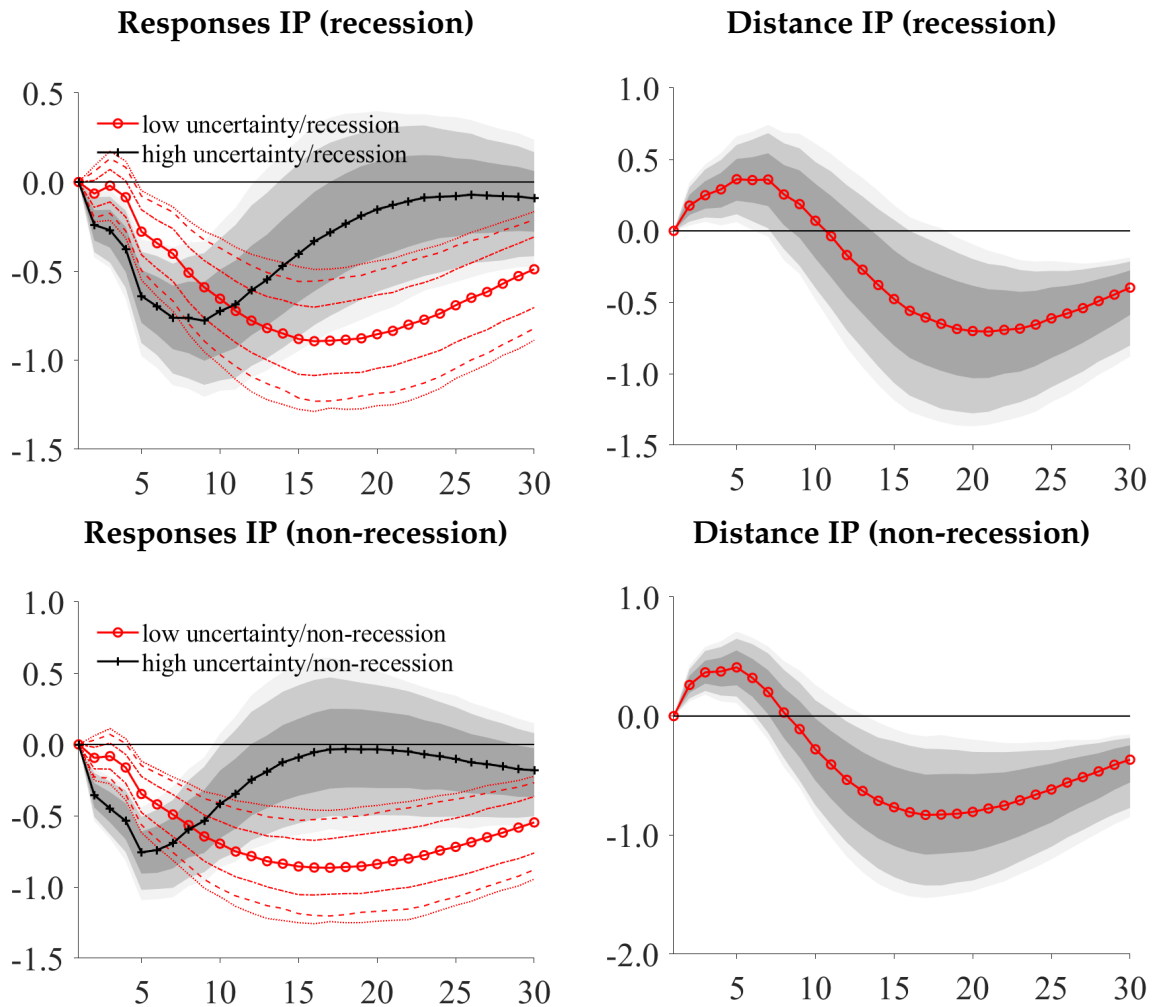
Figure 9 contains the state-dependent responses of GDP to a surprise increase in uncertainty for recession and non-recession phases.<sup>25</sup> In the upper part of the figure, when we are in a recession, there appears to be no significant difference of GDP responses between high and low uncertainty states. For both, the high and the low uncertainty state, GDP is depressed when uncertainty rises during a recession. However, we note that for the quarterly model there are only few observations in our sample, which fall into these categories.<sup>26</sup> By contrast, the lower part documents that the distance between responses remains significant when we consider non-recession phases only.<sup>27</sup> The distance even

<sup>24</sup>For completeness, we show in Appendix E, that responses of real activity do not differ whether there is a recession phase or a non-recession phases.

<sup>25</sup>Appendix E provides additional results for GDP. It appears that responses of real activity do not differ between recession phase and non-recession phase.

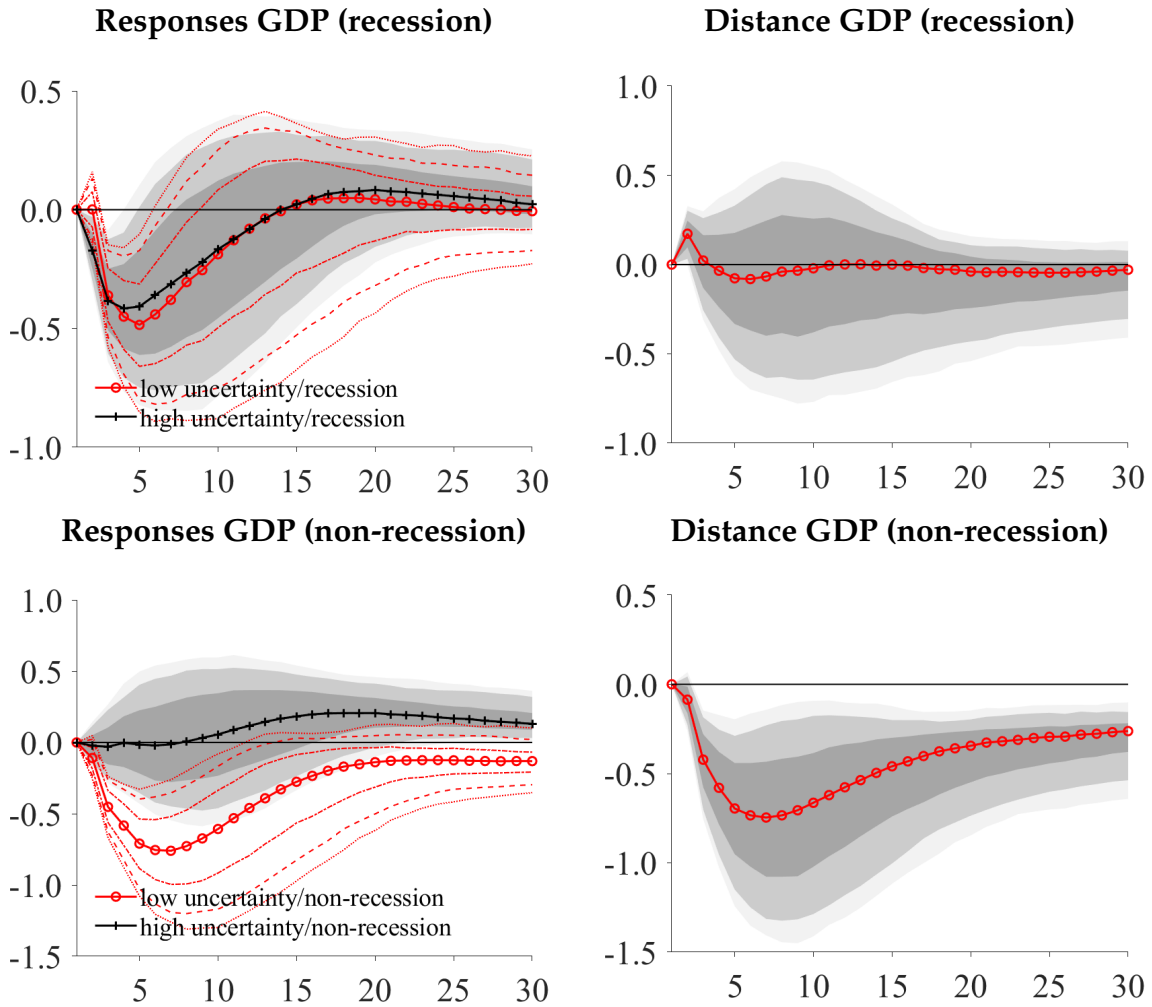
<sup>26</sup>There are 10 (of 148) observations, which belong to the high uncertainty/recession category and 8 observations belong to the low uncertainty/recession category.

<sup>27</sup>In this case, there are 39 (of 148) observations in the high uncertainty/non-recession category, and 17 observations belong to the low uncertainty/non-recession category.



**Figure 8: Recession and non-recession periods (monthly model).** This figure shows the effects of a one std surprise increase in uncertainty for a high and a low uncertainty state, conditional on being in recessions and non-recession periods, respectively. The upper left panel contains generalized impulse responses of IP during recessions, and the upper right panel contains the distance between these responses. The lower left panel shows responses of IP during non-recession periods, and the lower right panel shows the distance between these responses.

appears somewhat more pronounced when compared to the full sample result (see Figure 4). Further, the response in the low uncertainty state is roughly comparable across recession and non-recession phases. Overall, the distance between responses in our iVAR model is not fully explained by recessions being present or not.



**Figure 9: Recession and non-recession periods (quarterly model).** This figure shows the effects of a one std surprise increase in uncertainty for a high and a low uncertainty state, conditional on being in recessions and non-recession periods, respectively. The upper left panel contains generalized impulse responses of GDP during recessions, and the upper right panel contains the distance between these responses. The lower left panel shows responses of GDP during non-recession periods, and the lower right panel shows the distance between these responses.

## 6 Conclusion

We estimate a state-dependent interacted Vector Autoregressive model to identify the possibly non-linear effect of uncertainty on real activity. We base our results on (aggregate) firm-specific uncertainty derived from a large panel of monthly firm-level survey data from 1980 until 2018, thereby avoiding problems usually related to proxies which rely on cross-sectional dispersion, i.e. disagreement among decision makers. We suggest that decision makers at firms might react different under different economic

environments. In particular, they might be concerned about the level of uncertainty attached to firm-specific economic outcomes. We use a non-linear VAR model to account for state-dependence of the effects of uncertainty, where the uncertainty state (high, medium, and low) is derived from the endogenous uncertainty variable in the model. Our monthly specification implies that 28% (10%) of the observations belong to the low (high) uncertainty state. Using impulse responses as in Koop et al. (1996), we find a substantial negative effect of uncertainty on industrial production, which is also largely in line with previous studies. Responses are more short-lived when uncertainty is high already, while longer-lasting and larger effects are found for the low uncertainty state. Since uncertainty itself behaves quite similar across all uncertainty states, the distance of responses seems to be driven by differences in the transmission of uncertainty on real activity. We may thus conclude that the non-linearity is indeed the result of a state-dependent reaction of decision makers to an otherwise comparable increase in uncertainty.

Overall, it appears that the response of real activity is mitigated when firms are already highly uncertain. Controlling for additional variables like for instance optimistic or pessimistic expectations does not eliminate the state dependence. We also document that dependence on uncertainty states appears to be different from the well-documented effect during recession periods (Caggiano et al., 2014; Jones and Enders, 2016; Caggiano et al., 2017). Indeed, rising uncertainty when firms' uncertainty is still low may foreshadow a recession.

We obtain similar results when we consider quarterly GDP, one exception being that the instantaneous decline in real activity is not amplified by high uncertainty. By contrast, for high uncertainty states, there is no significant response of quarterly GDP to a surprise increase in uncertainty at all. The negative response of GDP under low uncertainty is, however, mitigated when we control for additional economic variables.

Previous literature emphasizes that uncertainty exerts its effect via financial frictions, when firms require external finance e.g. for investment projects (Gilchrist et al., 2014; Christiano et al., 2014; Arellano, Bai, and Kehoe, 2016). Our results are broadly consistent with a financial frictions channel, where forward-looking lenders tighten credit conditions more when uncertainty is low, for instance when an increase in uncertainty is perceived as a signal of turbulent times ahead. Although we use a reduced form time series model, our results hint at the fact that (most) decision makers react most to increased uncertainty when the latter is still low.

When using a linear model, which averages over these periods, there is a danger to misjudge the impact of increased uncertainty. It is in certain periods that uncertainty



has a decisive effect on real activity, while in the remaining states the effect is mitigated. Overall, uncertainty of decision makers should be closely monitored by policy makers and forecasters during times of low uncertainty, when usually there is reduced interest in uncertainty measures.

# Appendix

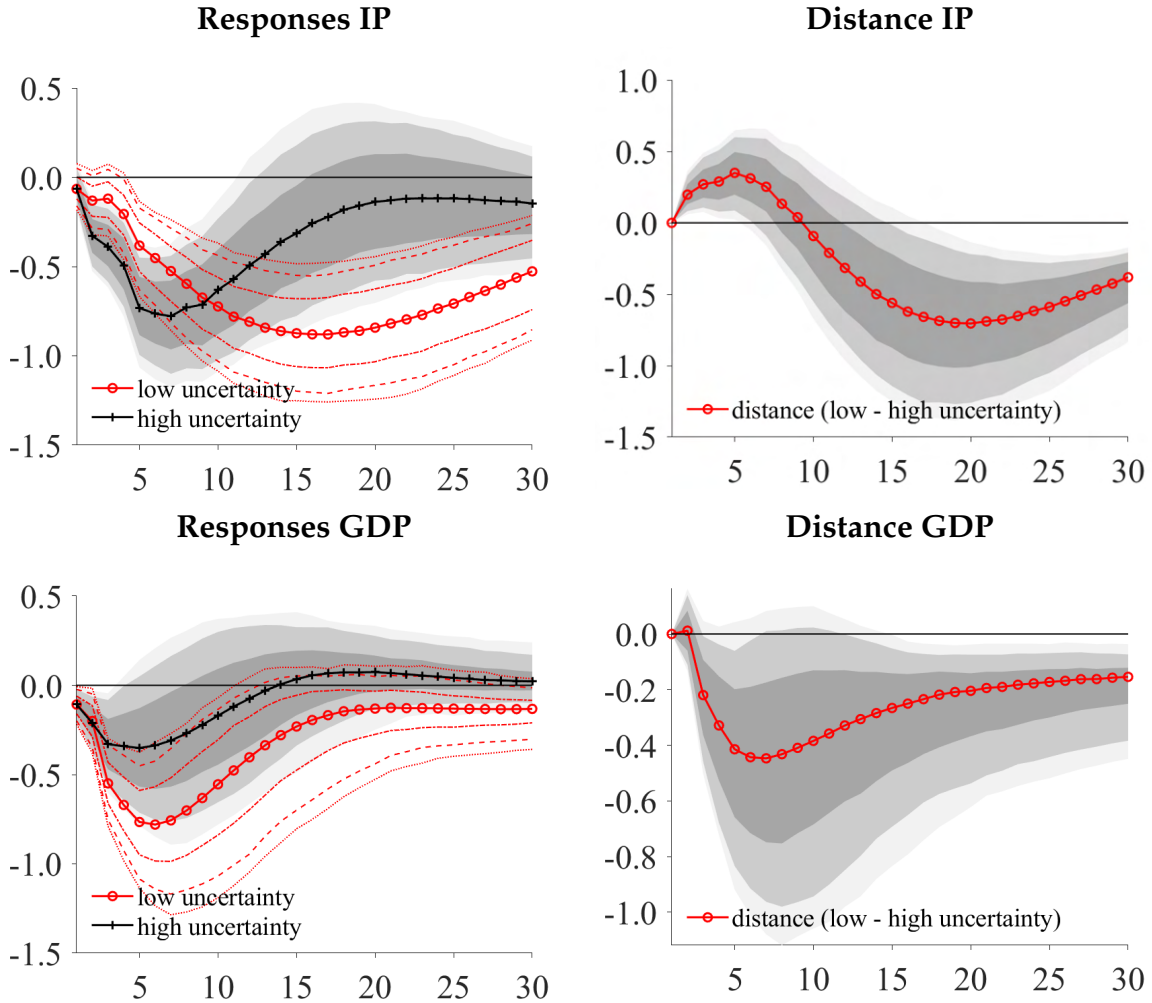
## A The ifo-BCS

Group of Firms	Number of employees				Total
	0 – 19	20 – 99	100 – 999	≥ 1000	
Food and tobacco	19.0	37.0	35.8	8.2	5.8
Textile products	6.1	33.0	54.1	6.8	8.0
Leather	12.1	39.3	42.2	6.5	1.6
Cork and wood products	31.0	45.2	19.9	3.9	4.1
Furniture and jewelery	9.6	32.5	53.1	4.8	5.2
Paper and publishing	14.7	42.4	38.8	4.1	16.3
Elect. and opt. equipment	7.3	28.4	49.2	15.1	11.8
Chemical products	10.5	26.1	42.3	21.1	3.0
Rubber and plastic	12.7	41.0	38.4	7.9	6.9
Other non-metallic products	12.9	35.2	45.4	6.4	6.0
Metal products	9.0	31.5	43.6	15.8	13.2
Machinery and equipment	4.6	26.1	53.7	15.7	15.8
Transport equipment	2.7	11.5	41.7	44.2	2.3
Manufacturing	10.8	33.4	44.6	11.1	

**Table A.1: Frequency of Observations** The table provides in the first four columns the shares of observations for each firm size and group of firms. **The fifth column provides the share of each group of firm in total manufacturing (ifo or in destatis?).**

## B Reverse ordering

In our baseline iVAR model, uncertainty is ordered last to control for possible contemporaneous effects of real activity, while uncertainty affects activity only with a lag. However, we may also assume that uncertainty has a contemporaneous effect on real activity, which admits a larger relevance of uncertainty for the fluctuations in real activity, but implies that uncertainty reacts only with a lag to changes in production. It appears that our results are robust to the ordering assumption.

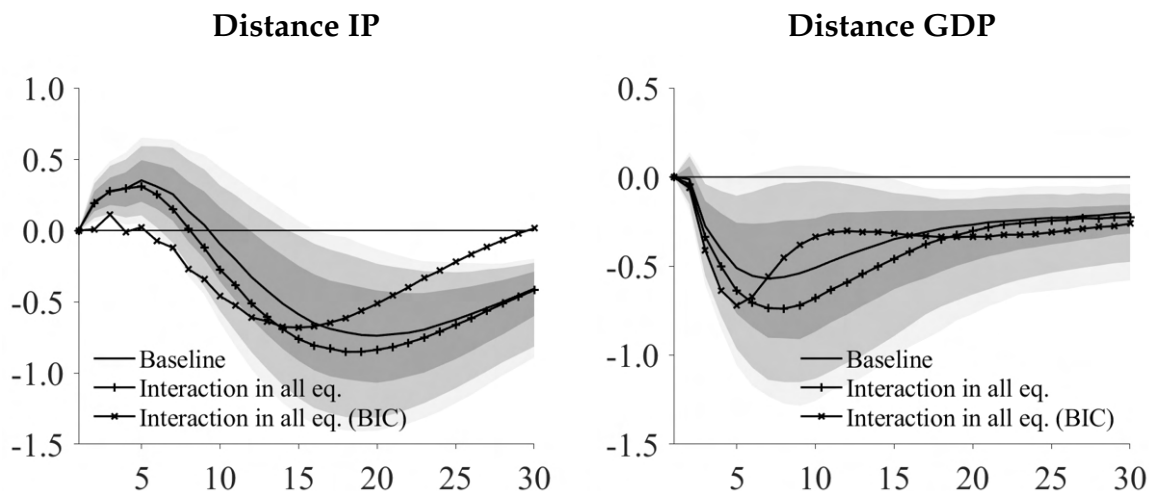


**Figure B.1: Generalized impulse response functions reverse ordering.** The upper left panel shows the average responses of IP to a one standard deviation surprise increase in uncertainty in the low and high uncertainty state. The upper right panel shows the distance in these responses. The lower panel shows the same estimations for GDP. Shaded areas indicate 95%, 90%, and 68% bootstrapped confidence intervals, respectively.

### C Interaction in uncertainty equation

We demonstrate the effect of adding interaction effects in the equation of uncertainty by letting  $\alpha_{22,t}^l = \bar{\alpha}_{22}^l + \tilde{\alpha}_{22,1}^l d_{t-1}^{\text{low}} + \tilde{\alpha}_{22,2}^l d_{t-1}^{\text{high}}$ . Note that BIC selects  $L = 5$  lags for the monthly model, whereas a high uncertainty state is identified for the 15% highest realizations, and the 6% lowest realizations are now in the low uncertainty regime. Using  $L = 3$  lags for the quarterly model, high uncertainty is selected for the 18% highest observations, and low uncertainty contains the 5% lowest observations. It appears that BIC is sensitive to this change in the model specification, since selects less observations

into the low uncertainty state when compared to the baseline model. The results obtained for this specification are provided in Figure C.1.



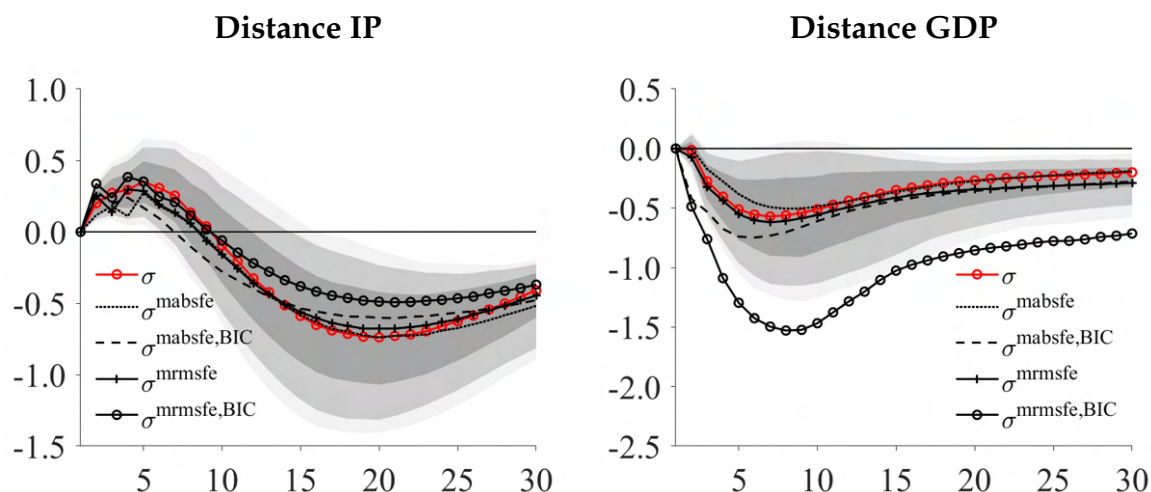
**Figure C.1: Distance with interaction effect in all equations.** The left panel of this figure shows results for the monthly model. We depict the estimated distance of responses of IP between high and low uncertainty state following a one standard deviation surprise increase of uncertainty. Along with the result from the baseline specification, we provide an estimate of the distance for an unrestricted version of the baseline model, where we allow for an interaction with uncertainty in the equation for uncertainty, as well. Lines indicated by BIC show results when thresholds and lag length for low and high uncertainty are newly selected using the BIC instead of using the baseline specification (monthly iVAR:  $L = 5$  lags, 28% quantile low uncertainty, 90% quantile high uncertainty; quarterly iVAR:  $L = 3$  lags, 32% quantile low uncertainty, 82% quantile high uncertainty). For the monthly model BIC chooses  $L = 5$  lags, 6% quantile low uncertainty, 85% quantile high uncertainty. For the quarterly model BIC chooses  $L = 3$  lags, 5% quantile low uncertainty, 82% quantile high uncertainty. Shaded areas indicate 95%, 90%, and 68% bootstrapped confidence intervals, respectively.

## D Distance for alternative uncertainty measures

We estimate our baseline iVAR model using alternative uncertainty measures. First, we consider the mean absolute forecast errors (MAFE) instead of the standard deviation of the forecast errors to calculate uncertainty at the firm level, and the aggregate measure is again obtained by averaging over individual firms and obtains the label  $\sigma^{\text{mafe}}$ . By taking absolute values, it will be less affected by large forecast errors. Second, we calculate the root mean squared forecast error (RMSFE) to measure uncertainty for each firm. Average uncertainty derived from individual RMSFE values is labeled  $\sigma^{\text{mrmsfe}}$ . While the standard deviation removes the mean forecast error from the calculation and is thus not affected by persistent bias in the forecast,  $\sigma^{\text{mafe}}$  and  $\sigma^{\text{mrmsfe}}$  both increase in case

of persistent over- or underprediction.

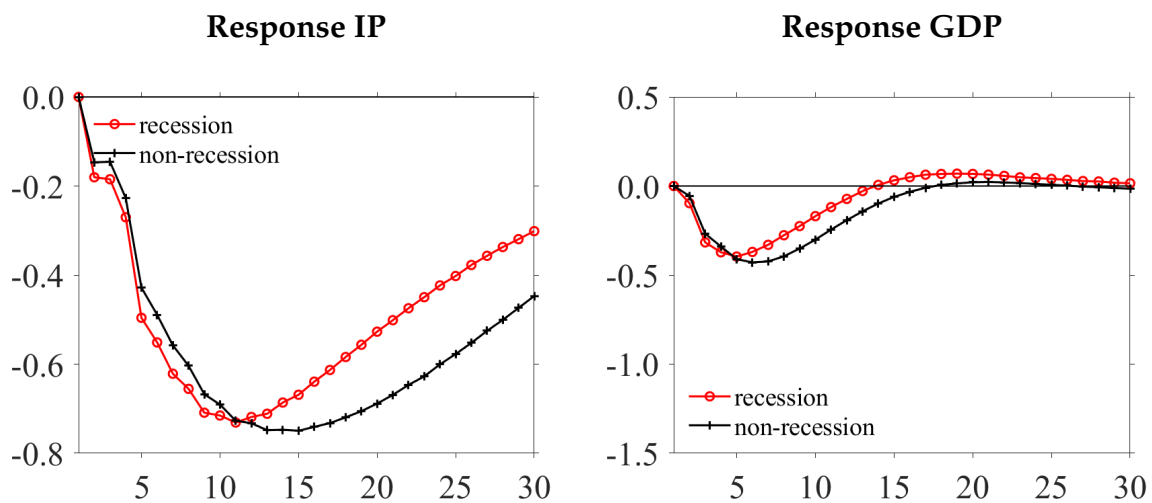
We estimate the model using the original baseline specification but with an alternative uncertainty measure (monthly iVAR: L = 5 lags, 28% quantile low uncertainty, 90% quantile high uncertainty; quarterly iVAR: L = 3 lags, 32% quantile low uncertainty, 82% quantile high uncertainty), thereby maintaining the definition of low and high uncertainty states. However, we also estimate the models using the respective specification chosen by BIC, which implies that the definition of the regimes may change. Results are presented in Figure D.1. Overall, the choice of the measure does not alter our results. It appears, however, that the BIC in one case (quarterly model,  $\sigma^{\text{mrmsfe}}$ ) indicates that only 5% of the observations should belong to the low uncertainty regime. However, reducing the number of observations in the low uncertainty regime seems to further increase the distance between uncertainty states.



**Figure D.1: Distance of impulse response functions for alternative measures.** This figure shows the average distance between responses of IP and GDP in the low and high uncertainty state for different uncertainty measures ( $\sigma$ ,  $\sigma^{\text{mabsfe}}$ ,  $\sigma^{\text{mrmsfe}}$ ). Lines with superscript BIC show results when thresholds and lag length for low and high uncertainty are newly selected using the BIC instead of using the baseline specification (monthly iVAR: L = 5 lags, 28% quantile low uncertainty, 90% quantile high uncertainty; quarterly iVAR: L = 3 lags, 32% quantile low uncertainty, 82% quantile high uncertainty). For the monthly model and  $\sigma^{\text{mabsfe}}$  BIC chooses L = 3 lags, 8% quantile low uncertainty, 89% quantile high uncertainty. For the monthly model and  $\sigma^{\text{mrmsfe}}$  BIC chooses L = 4 lags, 28% quantile low uncertainty, 90% quantile high uncertainty. For the quarterly model and  $\sigma^{\text{mabsfe}}$  BIC chooses L = 3 lags, 24% quantile low uncertainty, 93% quantile high uncertainty. For the quarterly model and  $\sigma^{\text{mrmsfe}}$  BIC chooses L = 4 lags, 5% quantile low uncertainty, 91% quantile high uncertainty. Shaded areas indicate 95%, 90%, and 68% bootstrapped confidence intervals for  $\sigma$ , respectively.

## E Recession vs non-recession

We document in Figure E.1 whether being in a recession phase or not impacts the response of real activity in our model. We present the average impulse responses from our model for, both, recession and non-recession phases according to the definition of the German Council of Economic Experts (German Council of Economic Experts, 2017). It appears that no difference in the responses is obtained in this case. We take this as a hint that our study reveals a different type of non-linear behavior. Note, however, that such a result does not imply that non-linear effects of uncertainty during a recession are absent, since our iVAR model is not informative about this type of non-linear behavior.



**Figure E.1: Recession and non-recession periods.** This figure shows the model responses to a one std surprise increase in uncertainty when the sample is split according to recession periods and non-recession periods. The left panel contains generalized impulse responses of IP, the right panel shows the respective responses of GDP.

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