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# Uncertainty and business cycles

Anssi Kohonen
University of Helsinki and HECER

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## Abstract

The paper develops a vector autoregressive model with autoregressive conditional heteroskedasticity in mean effects to decompose the effect of a stock market crash on industrial production into two components, the effect of negative returns and the effect of higher volatility. Our special attention is on the effect of volatility as it is our proxy for business cycle effects of uncertainty. We estimate the model with US data from 1919 to the mid 2013 and find uncertainty significantly countercyclical. Impulse response analysis shows that a monthly drop of ten percent in stock market prices is followed by a cumulative decline of three percent in the industrial production. Of this decline, around two thirds are explained by higher uncertainty.

**JEL Classification:** C32, E32

**Keywords:** uncertainty, business cycles, GARCH-in-mean

Anssi Kohonen

Department of Political and Economic Studies
University of Helsinki
P.O. Box 17 (Arkadiankatu 7)
FI-00014 University of Helsinki
FINLAND


e-mail: anssi.kohonen@helsinki.fi

# 1   Introduction

Does uncertainty aggravate business cycles? The recent financial crisis has again brought up this question. For example, the bankruptcy of the Lehman Brothers in Autumn 2008 was followed by a jump in the US stock market volatility which in its turn coincided with declining industrial production (see Figure 1). There are many theoretical reasons why higher uncertainty could *cause* a negative business cycle. For example, higher uncertainty might lead firms to scale down and postpone their investments and hiring (Bernanke (1983), Bloom (2009)), or consumers to postpone purchases of durable goods (Romer (1990)[1]). On the other hand, declining (and hence usually more volatile) stock market prices in a recession could be a *consequence* of investors expecting lower future dividends and capital gains.

Either way, one would assume that stock market returns and volatility *predict* business cycles. This paper brings together two (possible) real economic effects of a stock market crash: the first order effect of negative returns, and the second order effects via higher uncertainty which we measure by stock market volatility[2]. The methodological contribution of this paper is to extend the multivariate general autoregressive conditional heteroskedastic (GARCH) model of Vrontos, Dellaportas, and Politis (2003) to a vector autoregressive (VAR) model with GARCH-in-mean effects. This model provides an ideal framework to study both jointly and separately the importance of the two possible effects of a stock market crash.

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[1] Actually, Romer (1990) simply extends the intuition of the "wait and see" hypothesis for investments of Bernanke (1983) to consumable durable goods.

[2] Although there are many other possible measures of uncertainty, stock market volatility is probably the most common one. Also, it is highly correlated with the other measures (see, for example, Arnold and Vrugt (2008), Bloom (2009)).

The variables of our model are the monthly stock market return and the change in industrial production. In order to to study the business cycle effects of negative stock market returns and higher uncertainty, we need to identify a structural shock that generates stock market surprises. By referring to the high autocorrelation in the monthly capacity utilization in the manufacturing industry, we argue that the production of an industrial company necessarily is quite persistent. This enables us to identify one of the structural shocks of our model as a stock market specific shock which is interpreted as *financial news*. Then, financial news can affect the stock market returns immediately but the industrial production only with a lag. Hence, our financial news variable can generate unexpected increases in the stock market volatility. The model can be estimated with the method of maximum likelihood (ML), and we can statistically test the significance of the first and second order effects of a stock market crash on the industrial production. Also, our model allows us to separately study the importance of these two effects by means of impulse responses.

In the empirical application, we estimate the model with US data covering the period from the beginning of 1919 to the mid 2013. According to the estimation results the stock market volatility (as well as the return) is a statistically significant predictor of the change in industrial production. Furthermore, as the theoretical contemplations would predict, financial volatility is countercyclical, meaning that higher volatility decreases the growth rate of industrial production. The impulse response analysis shows that a (monthly) negative stock market shock of ten percent is followed by a slump in the growth rate of industrial production that lasts for around two years, with the cumulative effect on the industrial production of roughly minus three percent. Approximately half of the duration of the business cycle is

explained by the direct effects of negative stock market returns. The other half is due to the higher volatility, or uncertainty.

As the emphasis of the paper is to study the business cycle effects of uncertainty, it is closely related to the literature on the linkages between financial and macroeconomic volatility. The question of predicting financial volatility with macro variables (and their volatility), is of course an old theme in the financial literature (Schwert (1989) is a classical reference, whereas Beltratti and Morana (2006), Diebold and Yilmaz (2008), and Engle, Ghysels, and Sohn (2013) are more recent ones, only to mention a few). According to Diebold and Yilmaz (2008) the main finding of this research is that, perhaps unsurprisingly, stock market volatility is higher in recessions. This is also the main conclusion of Hamilton and Lin (1996) who, furthermore, notice that it is the higher stock market volatility that *precedes* a fall in the US industrial production by one month. However, in their model stock market volatility and industrial production follow the same latent process which determines the state of the economy. Hence, they do not consider the direct links between the two variables.

The literature that studies the macroeconomic effects of financial volatility is not very voluminous but growing, especially due to the recent financial crisis. From the perspective of this paper, the most relevant part of this literature consists of the papers that explicitly focus on the effects of uncertainty or volatility shocks. The main methodology of this line of research is to write down and calibrate a theoretical macroeconomic model where the uncertainty shock is modeled as a second order shock to the productivity process (see, for example, Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012)). The main finding is that uncertainty shocks can create business cycles that last for about six to twelve months. Our result on the

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magnitude of the second order effect of a stock market crash is consistent with this.

There are only few truly empirical studies on the subject. Alexopoulos and Cohen (2009), Beetsma and Giuliodori (2012), and Denis and Kannan (2013) are some rare exceptions. As the model specifications of these papers come quite close to our model, we will discuss them (and problems in their identification) in detail later on. Also Bachmann, Elstner, and Sims (2013), and Baker and Bloom (2013) use statistical methods to determine the business cycle effects of uncertainty. But the methods and data they use are quite different from ours. As a measure of uncertainty, the former uses dispersion of forecasts for economic conditions of manufacturing companies. The latter considers an event study framework where natural disasters, coups, and revolutions are used as exogenous sources of uncertainty shocks. Overall, these studies find that higher uncertainty has a statistically significant negative effect on economic growth. Our results reconfirm this and, also highlight the relative importance of the second order effects to the first order effects in explaining a recession.

The rest of the paper is organized as follows. In the next section, we introduce the model and discuss its estimation and identification of the structural shocks. In Section 3, we present the estimation results on the US data. Finally, Section 4 concludes.

## 2  The empirical framework

In this section, we first introduce the model for the joint dynamics of industrial production and the stock market return and discuss its estimation. Then, we discuss both the identification of the structural shocks and the

econometric analysis of the identified model. Finally, we briefly compare the model to a number of similar ones in the literature.

## 2.1 The model

Let us denote by $\Delta ind_t$ the monthly percentage change in industrial production and by $r_t$ the monthly stock market return. We collect the variables into the $(2 \times 1)$ vector $\mathbf{y}_t = [\Delta ind_t, r_t]'$ and assume that $\mathbf{y}_t$ follows a bivariate GARCH model with a non-zero conditional mean. Specifically, we assume the following multivariate specification of the (G)ARCH-in-mean model of Engle, Lilien, and Robins (1987):

$$\mathbf{A}(L)\mathbf{y}_t = \boldsymbol{\mu} + \mathbf{C}\mathbf{h}_t + \mathbf{u}_t, \tag{1}$$

where $\mathbf{A}(L) = \mathbf{I}_2 - \mathbf{A}_1 L - \ldots - \mathbf{A}_p L^p$ is a $(2 \times 2)$ matrix polynomial, $\boldsymbol{\mu}$ is a $(2 \times 1)$ vector of the intercepts, $\mathbf{C}$ is a $(2 \times 2)$ coefficient matrix, and $\mathbf{h}_t = [h_{1,t}, h_{2,t}]'$ is a $(2 \times 1)$ vector of the conditional volatilities $h_{1,t}$ and $h_{2,t}$ of the structural shocks $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$, respectively. The structural shocks are discussed shortly. Finally, $\mathbf{u}_t = [u_{ind,t}, u_{r,t}]'$ is the $(2 \times 1)$ reduced from error vector. In the empirical application, the order of $\mathbf{A}(L)$ is determined with the Bayesian information criterion (BIC).

To complete the model, we assume that the reduced form errors are a linear function of the two structural shocks with the following simple specification:

$$\mathbf{u}_t = \mathbf{B}\boldsymbol{\varepsilon}_t, \tag{2}$$

where $\boldsymbol{\varepsilon}_t = [\varepsilon_{1,t}, \varepsilon_{2,t}]$ is the $(2 \times 1)$ vector of the structural shocks, and $\mathbf{B}$ is a $(2 \times 2)$ coefficient matrix. To identify the shocks, we assume that $\mathbf{B}$ is the

following lower triangular matrix:

$$\mathbf{B} = \begin{bmatrix} 1 & 0 \\ b & 1 \end{bmatrix}. \tag{3}$$

This assumption identifies the second structural shock ($\varepsilon_{2,t}$) as a stock market specific shock. The assumption that the diagonal elements are equal to one restricts the number of parameters and, hence, normalizes the model. The structural shocks are assumed to be mutually orthogonal and to follow univariate GARCH(1,1) processes with Gaussian conditional distributions:

$$\varepsilon_{i,t}|I_{t-1} \sim N(0, h_{i,t}^2), \tag{4}$$

$$h_{i,t}^2 = \alpha_i + \beta_i \cdot \varepsilon_{i,t-1}^2 + \gamma_i \cdot h_{i,t-1}^2 \tag{5}$$

for $i = 1, 2$. Here $I_{t-1}$ denotes the information set up to time period $t - 1$ (the period $t - 1$ included), and $\alpha_i, \beta_i$, and $\gamma_i$, $i = 1, 2$, are parameters.

The multivariate GARCH model in equations (2)–(5) was proposed by Vrontos, Dellaportas, and Politis (2003). The model is well defined under rather mild assumptions. To see this, collect first the conditional variances $h_{1,t}^2$ and $h_{r,t}^2$ into the $(2 \times 2)$ diagonal matrix $\mathbf{H}_t^2 = \text{diag}(h_{1,t}^2, h_{2,t}^2)$. Then, given specification (3), the conditional covariance matrix of the reduced form error vector $\mathbf{u}_t$,

$$\Sigma_{\mathbf{u}}|I_{t-1} = \mathbf{B}\mathbf{H}_t^2\mathbf{B}',$$

is always positive definite as long as the conditional variances $h_{1,t}^2$ and $h_{r,t}^2$ are well defined. In order to guarantee this, we follow Vrontos et al. and assume that $\alpha_i > 0, \beta_i \geq 0$, and $\gamma_i \geq 0$ for $i = 1, 2$.

The model can be estimated with the method of ML. Assume a sample of $T$ observations, and denote by $\mathbf{Y}_{t-1}$ the vector of observations up to the time period $t - 1$ ($\mathbf{y}_{t-1}$ included). Then, given the initial values

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$\{\mathbf{y}_0, \dots, \mathbf{y}_{-p}, \mathbf{h}_0, \boldsymbol{\varepsilon}_0\}$, the conditional density function of the model (1)–(5) becomes

$$f(\mathbf{y}_t | \mathbf{Y}_{t-1}) = \det(\mathbf{BH}_t)^{-1} \times$$

$$\exp\left\{-\frac{1}{2}(\mathbf{A}(L)\mathbf{y}_t - \boldsymbol{\mu} - \mathbf{Ch}_t)'(\mathbf{BH}_t^2\mathbf{B}')^{-1}(\mathbf{A}(L)\mathbf{y}_t - \boldsymbol{\mu} - \mathbf{Ch}_t)\right\},$$

where we have omitted the constant terms of the Gaussian distribution. After collecting all the parameters of the model into the vector $\boldsymbol{\delta}$, the log-likelihood function of the model can be written as

$$l(\boldsymbol{\delta}, \mathbf{Y}_T) = -T \times \ln(\det(\mathbf{B})) - \sum_{t=1}^{T} \ln(\det(\mathbf{H}_t)) -$$

$$-\frac{1}{2}\sum_{t=1}^{T}(\mathbf{A}(L)\mathbf{y}_t - \boldsymbol{\mu} - \mathbf{Ch}_t)'(\mathbf{BH}_t^2\mathbf{B}')^{-1}(\mathbf{A}(L)\mathbf{y}_t - \boldsymbol{\mu} - \mathbf{Ch}_t)$$

which can be maximized numerically with standard optimization algorithms. In our empirical analysis, we take the first $p$ observations of $\mathbf{y}$ as the initial values for the dependent variables, set $\mathbf{h}_0$ equal to the sample standard deviations of the residuals $\hat{u}_{ind,t}$ and $\hat{u}_{r,t}$ of a standard $p$th order VAR model estimated from the full sample, and finally assume that $\boldsymbol{\varepsilon}_0 = \mathbf{0}$.

## 2.2 Identification and econometrics analysis

Assumption (3) on matrix $\mathbf{B}$ serves two purposes. On the one hand, as mentioned above, it guarantees that the model is well defined under the stated assumptions (see Vrontos, Dellaportas, and Politis (2003, 314–15)), on the other hand it identifies the second structural shock ($\varepsilon_{2,t}$) as the stock market specific shock, a shock which affects the stock market returns instantaneously, in period $t$, but industrial production only from period $t+1$ onwards.

The second shock $\varepsilon_{2,t}$ can be interpreted as *financial news*. As we are especially interested in the effects of unexpected surges in uncertainty on the

real side of an economy, we will restrict our attention to studying the business cycle effects of this shock. The first structural shock $(\varepsilon_{1,t})$ does not have any specific interpretation here. It is a shock that can affect both the real sector and the stock markets contemporaneously, and hence it could incorporate, for example, productivity shocks.

Why does it make sense to assume that financial news in period $t$ instantly affects only the stock markets but not the industrial production? The monthly capacity utilization in the US manufacturing, mining, and electric and gas sectors (in 1972–2012) is a highly persistent variable (with the coefficient estimate of 0.99 in a first order autoregressive model). Hence, a high level of orders of an industrial company this month predicts a high level of orders also in the next month. This seems natural as probably many industrial products are (investment) goods whose production take more than a month. Assume there is negative financial news, such as the bankruptcy of the Lehman Brothers, in period $t$. During this same period, given the high persistence in the industrial orders, the companies would still be busy in fulfilling their orders from the previous months, and so, the shock would not affect the current production. Of course, it could affect the number of new orders received in period $t$ and, hence, the future production, but this is exactly the effect we are interested in.

In order to avoid any misunderstanding, let us briefly discuss the limitations of our identification scheme. Such dramatic news as the default of the Lehman Brothers and the subsequent stock market crash could of course be a consequence, not necessarily the cause of slowing economic activity; after all, stock market prices should reflect discounted future dividends and capital gains. However, such reversed causality between stock market prices and future economic activity is irrelevant for our purposes of quantifying the

business cycle effects of uncertainty shocks. To this end, we only need to identify a stock market specific shock that can generate stock market volatility surprises. With such a shock available we can separate the direct effect of the drop in the stock market prices from the volatility effect.

To take an example, consider Figure 1, which shows that after the default of the Lehman Brothers, the US stock market prices collapsed and the estimated volatility tripled. Whether the subsequent stock market crash was the cause or the consequence of the recession, the upsurge in the volatility suggests that at least many investors perceived a huge rise in the uncertainty over the actual and future state of the US economy. Our question is whether there is any evidence of this uncertainty prolonging the slump as the theoretical literature referred to in Introduction suggests. This means that higher volatility should be an important variable in explaining variation in the industrial production.

In order to study this question we can first test for the statistical significance of the parameter $c_{1,2}$ (the first row, second column element of the matrix $\mathbf{C}$ in equation (1)). This measures the direct effect of the volatility of the structural shock $\varepsilon_{2,t}$ on industrial production. One would expect that $c_{1,2} \leq 0$, i.e. higher volatility tends to decrease industrial production. Furthermore, assume a negative realization of $\varepsilon_{2,t}$, say, at period $T_0$, and call it $\tilde{\varepsilon}_2$. According to our assumptions, $\tilde{\varepsilon}_2$ affects the stock market return already at period $T_0$ but the growth rate of industrial production only from period $T_0 + 1$ onwards. In our model, the effect of $\tilde{\varepsilon}_2$ on $\Delta ind_{T_0+1}$ comes from two channels; on the one hand via the lagged (negative) stock market return, and on the other hand via the conditional variance of $\varepsilon_{2,t}$ which, according to equation (5), increases at period $T_0 + 1$. The first channel corresponds to the first order effect of a stock market shock, and the second channel to the

second order, or uncertainty, effect.

The dynamic effects of $\tilde{\varepsilon}_2$ and the importance of the two channels on the growth rate of industrial production can be studied with two different impulse response functions. First, as suggested by Elder (2003)[3], we can calculate the total impulse response function by simply introducing $\tilde{\varepsilon}_2$ and numerically compute the responses of $r_t$ and $\Delta ind_t$ to the shock. This gives us the total effect of $\tilde{\varepsilon}_2$. (The details of our actual calculations are explained in the next section.) Then, in order to separate the effect of higher volatility on $\Delta ind_t$ from the total effect of $\tilde{\varepsilon}_2$, we can calculate the responses of the system to another shock which we refer as a "volatility jump". This jump corresponds to an increase only in $h_{2,t}^2$ at period $T_0+1$ which exactly matches the increase in it due to the shock $\tilde{\varepsilon}_2$. The two impulse response functions of $\Delta ind_t$ give us the total effect of the stock market shock and the effect of higher volatility on the growth rate of industrial production. The difference of the two (at each period) tells us the first order effect.

## 2.3   Related literature

Hamilton and Lin (1996) model the joint dynamics of the changes in the US industrial production and the excess stock market return. The framework they consider is a bivariate Markov-switching VAR model with ARCH-effects. Their main finding is that both variables are more volatile in recessions and that increasing volatility in stock markets *precedes* declines in the industrial production by one month. This result supports our identifying assumption.

Alexopoulos and Cohen (2009), Denis and Kannan (2013), and Beetsma and Giuliodori (2012) study the business cycle effect of uncertainty (financial

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[3]Elder (2003) discusses in detail the differences in the impulse response functions of a standard homoskedastic VAR model and the VAR-GARCH-in-means model.

market volatility) with the VAR framework. Unlike us, the first two papers assume that volatility shocks (to financial markets) affect the real sector immediately but that the real sector specific shocks affect volatility only with a lag. On the basis of the discussion above, this seems an incorrect timing of events. At the very least, we should expect shocks to real sector to have an immediate effect on the financial markets.

Like us, Beetsma and Giuliodori (2012) assume that stock market volatility affects the real sector only with a lag, but strangely enough they include the quarterly return of the Dow Jones index *and* its volatility as separate variables in their VAR model and assume that the return can immediately affect the volatility but not vice versa. However, as their volatility variable is necessarily a function of the returns data, dealing these two variables as separate time series is questionable. In our framework, the effect of returns on the volatility is explicitly modeled, and the parameters of the model jointly estimated.

Nonetheless, Alexopoulos and Cohen (2009), Denis and Kannan (2013), and Beetsma and Giuliodori (2012) find that uncertainty (or volatility) shocks can predict recessions which, depending on the size of the shock, last one to two years. In the next section we find quite similar results with our model fitted to US data.

# 3    Uncertainty and business cycles in the US

In order to estimate the model, we consider monthly percentage changes in the US stock market prices (returns $r_t$) and industrial production ($\Delta ind_t$).[4]

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[4]The variables are computed in the following way: $\Delta ind_t = 100 \times (\ln ind_t - \ln ind_{t-1})$, and $r_t = 100 \times (\ln P_t - \ln P_{t-1})$, where $P_t$ is the monthly stock market price index.

The stock market prices are downloaded from Robert Shiller's home page[5] and here we use the nominal prices (the correlation between the nominal and real prices is 0.96). The industrial production data is from the online database (FRED) of the Federal Reserve Bank of St.Louis. As the industrial production data is available only from January 1919 onwards, our data on monthly changes covers the period from February 1919 to July 2013. This means that there are 1134 observations.

## 3.1 Estimation results and testing

Table 1 reports the estimation results for the model (1)–(5) where the lag length $p$ is set to two by the BIC.[6] In the equation of the change in industrial production, all the coefficients of the lagged returns and changes in industrial production are statistically significant at the 5% significance level. On the contrary, in explaining the stock market return, only the first lag of the return seems to have a statistically significant coefficient at the 5% significance level while the coefficient of the first lag of the change in industrial production is statistically significant only at the 10% significance level. All the parameters of the GARCH-processes are statistically significant at the 1% significance level.

As explained in Section 2.2 our main interest is in testing whether the coefficient of $h_{2,t}$, the conditional volatility of the shock market specific structural shock, on the change in industrial production is statistically different from zero. Its estimated value in Table 1 equals -0.08 and, hence, is negative as expected. The value of the likelihood ratio test statistic for the null hypothesis of $c_{1,2} = 0$ against the alternative hypothesis of $c_{1,2} \neq 0$ gets

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[5]http://www.econ.yale.edu/~shiller/data.htm

[6]All the estimations were done with the procedures in the CMLMT library of GAUSS.

value 9.40, which means that the null hypothesis is rejected at any reasonable significance level. Hence, we conclude that uncertainty is a statistically significant explanatory variable for the changes in industrial production. It is also countercyclical in the sense that when it rises, as it usually does in recessions, it decreases the growth rate of industrial production.

Neither of the conditional standard deviations seem to be statistically significant variables in explaining the stock market return. However, somewhat surprisingly, the coefficient of the conditional standard deviation of the first structural shock appears to be a statistically significant predictor of the change in industrial production. However, as the robustness checks in Section 3.3 below shows, this result seems to depend on the fact that our sample period includes the Great Depression of the 1930's. As a final remark on Table 1, notice that the parameter $b$ of the matrix $\mathbf{B}$ in equation (3) is statistically significant only at the 10% significance level. Hence, there is some weak evidence of the second structural shock being a real sector specific shock.

## 3.2 Impulse response analysis

In order to study the economic significance of uncertainty in explaining recessions, we generate a stock market crash by introducing a large negative realization of $\varepsilon_{2,t}$. The magnitude of the shock is minus ten. This generates a drop of ten percentage points in the monthly stock market return which roughly corresponds to the average (-14%) of the monthly returns in September–October 2008, the period when the Lehman Brothers defaulted (Figure 1).

The shock happens in period 0. We assume that in period -1 the variables equal their long run levels (unconditional means) which are computed

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based of our parameter estimates. The long run levels (monthly percentage changes) of stock market return and the change in industrial production are 0.72 percent and 0.37 percent, respectively. When these are transformed into yearly percentage changes, we get 8.64 percent stock market return and 4.44 percent increase in the industrial production. These are reasonable figures, which lends support to our estimation results. Notice also that in our model there is no feedback in equations (4)–(5) from the variables of $\mathbf{y}_t$ back to the GARCH processes of the conditional variances of the structural shocks. This makes the calculation of the impulse responses straightforward.

Figure 2 reports the impulse responses of the stock market return and the change in industrial production to the stock market shock in period 0 with the 95% confidence intervals[7]. The impulse responses are demeaned with the long run levels of $r_t$ and $\Delta ind_t$ in order to highlight the effect of the shock. Hence, for example the period 0 value of -10 for $r_t$ means that, due to the shock, the stock market return is ten percentage points lower than the return

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[7]The computation of the 95% confidence intervals was carried out in five steps: (Step 1) the ML estimates of the parameters of the model were used to simulate a data set of the same size as our actual data. The simulation of the data consisted of three phases: first, the initial values of $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ were drawn from normal distributions with the variances equal to the long run values of $h_{1,t}^2$ and $h_{2,t}^2$, respectively. Second, the estimated univariate GARCH processes (4)–(5) were used to simulate the realizations of the structural shocks. Third, the simulated structural shocks (and the estimated equations (1)–(3)) were used to construct the new data set on $r_t$ and $\Delta ind_t$. In 'Step2', the model was re-estimated for these new (simulated) data. 'Step 3' consisted of using the new parameter estimates from the previous step to compute the impulse responses of $r_t$ and $\Delta ind_t$ to a negative realization of $\varepsilon_{2,t} = -10$ (the same magnitude as in the original case). In 'Step 4', the previous three steps were repeated 10000 times. Finally, in 'Step 5', for each lag separately, we ordered the 10000 impulse responses into ascending order and selected the elements that were the 500th and 9500th in order. We did the fifth step separately for both variables, $r_t$ and $\Delta ind_t$.

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in the long run. Gradually, both variables converge back to their long run levels (level zero in the graphs).

For both variables the drop is significant. As the upper panel of Figure 2 shows, for the stock market return the highest impact of the shock is right away after the shock (period 0), and the stock market accommodates to the shock quite quickly; after four to six months the stock market return has converged back to its long run level. In period 4, there is even a small boom in the stock markets as the volatility has started to decrease from its high levels right after the shock (the volatility time series is not reported) and uncertainty decreases. In the lower panel, as assumed in our model, the effect of the shock on the change in the industrial production in period 0 is nil. The highest impact of the shock on $\Delta ind_t$ comes three months after the shock, and the negative effect lasts much longer than for the stock market return. It is only after around two to two and a half years (!) that $\Delta ind_t$ has basically converged back to its long run level.

Figure 3 decomposes the total effect of the stock market crash into the first and second order effects (for details on the concepts, see the end of Section 2.2). The second order effect measures the share that uncertainty explains of the negative business cycle following the stock market crash. As seen from the figure, the first order effect lasts only around nine to ten months which is consistent with the quick recovery in the stock market return. After this, for around one more year, it is only the effect of higher volatility that still drags down the growth rate of industrial production. At the trough of the business cycle (period 3), uncertainty explains around one third of the minus 0.6 percentage points deviation of $\Delta ind_t$ from its long term level.

Figure 4 shows the cumulative effect of the stock market crash on the change in industrial production and decomposes it into the shares explained

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by the first and second order effects. The cumulative effects were computed by summing the demeaned impulse responses in the previous figure. As Figure 4 shows, the total cumulative effect of the stock market crash on $\Delta ind_t$ is around minus three percentage points. This means that around two years after the shock, the level of industrial production is three percent lower than without the shock (assuming the growth rate of industrial production at its long run level). As seen from the figure, the second order effect, or uncertainty, explains around *two* thirds of the total cumulative effect. Based on Figure 3, this is result is intuitive as it is the second order effect that prolongs the business cycle with another year while the first order effect dies out quickly. Clearly, uncertainty is an important factor in propagating and prolonging business cycles.

## 3.3   Robustness checks

Beetsma and Giuliodori (2012) argue that the responsiveness of the real sector of an economy to stock market volatility shocks changes in time. They find that, after the 1980's, the GDP growth has become less responsive to volatility shocks. This raises the question of how robust our findings are for different time intervals, especially as our sample period includes two severe economic crises, one at the beginning and the other at the end of the sample.

Table 2 shows the estimates of the coefficients $c_{1,1}$ and $c_{1,2}$ for a number of subsamples. Encouragingly, the estimate of the effect of stock market volatility on the industrial production (the coefficient $c_{1,2}$) is always negative with p-values below 0.05, but we also reconfirm the finding of Beetsma and Giuliodori (2012) that the absolute value of $c_{1,2}$ decreases towards the end of the sample period. Also, according to Table 2 the coefficient $c_{1,1}$ appears to become statistically insignificant towards the end of the sample. It

seems that this coefficient gets its largest value in the period including the Great Depression and the Second World War. Overall, our main finding that uncertainty is countercyclical, seems robust.

# 4 Conclusions

The aim of this paper was to study the business cycle effects of uncertainty. According to theory, one expects uncertainty to be countercyclical. To examine this, we proposed measuring uncertainty with stock market volatility and introduced a bivariate VAR-GARCH-in-mean model for the monthly stock market return and the change in industrial production. We identified stock market specific structural shock which can generate volatility surprises whose effects on industrial production we study. The framework enables us to test the statistical significance of uncertainty in explaining variations in the industrial production.

In analysis of US data from the beginning of 1919 to the mid 2013, we found that, in accordance with the theoretical models, uncertainty is countercyclical with statistically significant coefficient. The result was robust for varied time periods. The impulse response analysis shows that a ten percent monthly decrease in the stock market prices is followed by a slump in the growth rate of the industrial production that lasts for about two years and leaves the industrial production three percent lower than without the stock market crash. Roughly half of the duration of the business cycle and two thirds of the total cumulative effect of the stock market shock are explained by higher uncertainty.

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Figure 1: Monthly US stock market returns, estimated stock market volatility, and change in the US industrial production in January 2007–December 2010
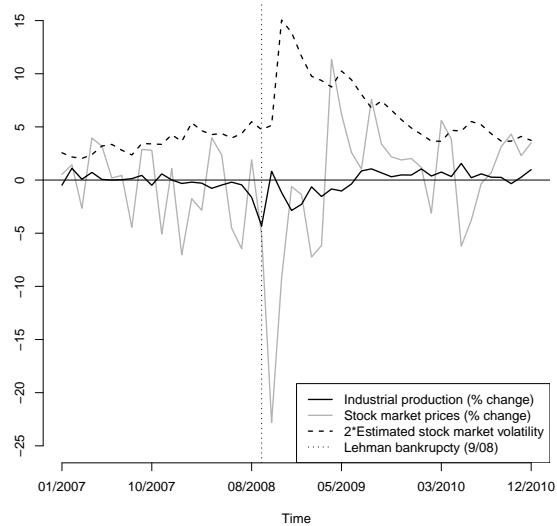


Note: Here volatility of the stock market returns is computed as the conditional standard deviation of the returns implied by the univariate GARCH(1,1) model estimated from our full sample period (January 1919–July 2013). Sources: `http://www.econ.yale.edu/~shiller/data.htm` (stock market data), St.Louis FED's FRED database (industrial production), and own calculations.

Figure 2: Response of $r_t$ and $\Delta ind_t$ to a negative stock market specific shock
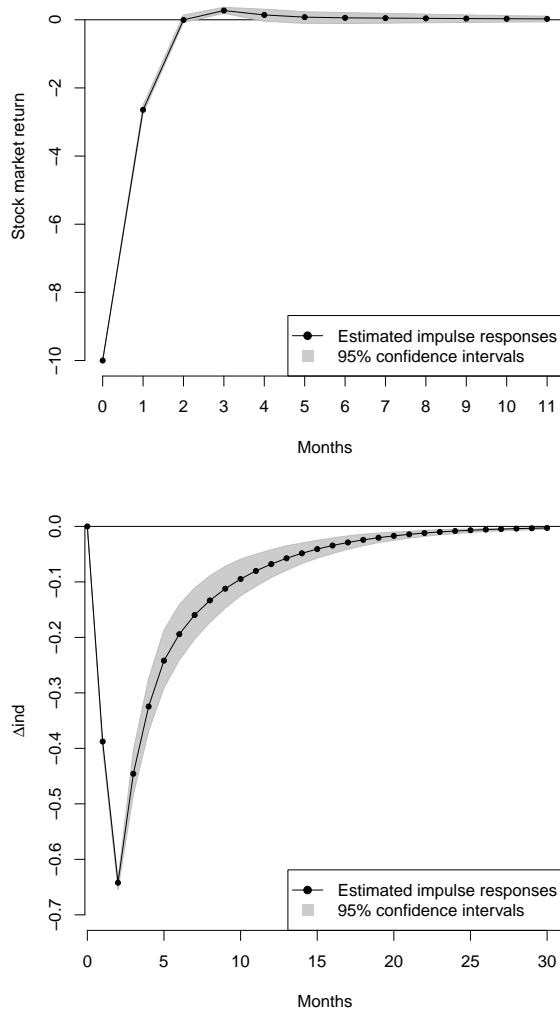


Note: Negative stock market specific shock at period t=0. The panels show demeaned impulse responses (demeaned by the long-run levels of the variables). Hence, the levels $r_t = 0$ and $\Delta ind_t = 0$ correspond to the long run stock market return and the growth rate of industrial production, respectively. The bootstrapped confidence intervals are based on 10000 replications (for details, see footnote 7).

Figure 3: Decomposition of the IRF of $\Delta ind_t$
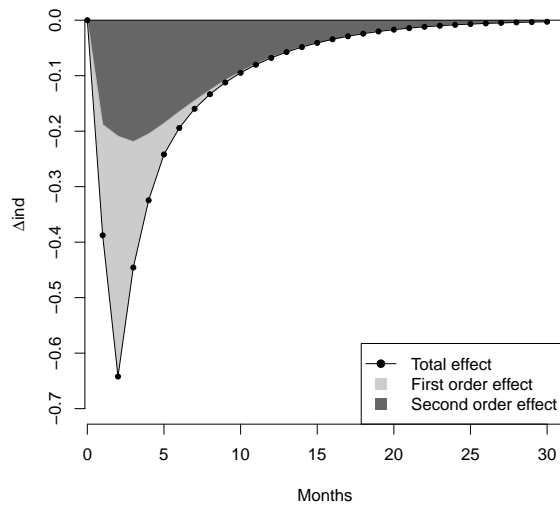


Note: The first order effect refers to the direct effect of $\varepsilon_{2,t}$ on $\Delta ind_t$ via stock market returns, the second order effect refers to the effect of $\varepsilon_{2,t}$ on $\Delta ind_t$ via higher $h_{2,t}$ only, or uncertainty. For details, see the end of Section 2.2.

Figure 4: Cumulative effect of the stock market specific shock on $\Delta ind_t$



Cumulative effect on $\Delta$ind
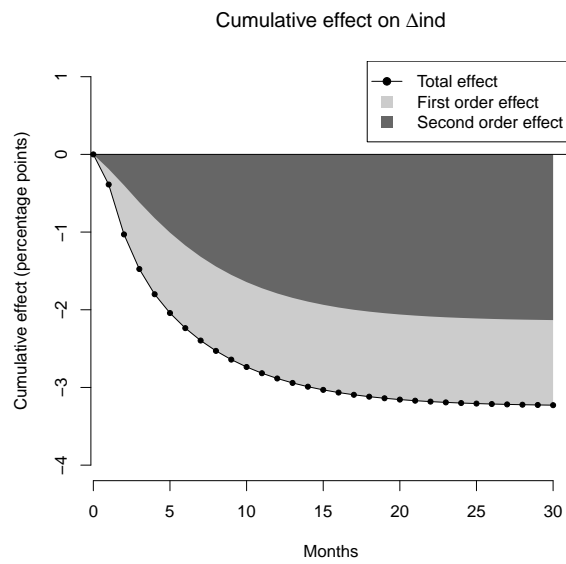
Note: For explanations, see the note to Figure 3.

Table 1: Estimation results (standard errors in parentheses)

| | Dependent variables | |
|---|---|---|
| | $\Delta\mathbf{ind_t}$ | $\mathbf{r_t}$ |
| Intercepts | 0.239 | 0.560 |
| | (0.101) | (0.384) |
| $\Delta ind_{t-1}$ | 0.244 | -0.135 |
| | (0.033) | (0.075) |
| $r_{t-1}$ | 0.020 | 0.269 |
| | (0.007) | (0.033) |
| $\Delta ind_{t-2}$ | 0.151 | 0.037 |
| | (0.033) | (0.077) |
| $r_{t-2}$ | 0.033 | -0.061 |
| | (0.007) | (0.033) |
| $h_{1,t}$ | 0.241 | 0.001 |
| | (0.060) | (0.124) |
| $h_{2,t}$ | -0.080 | 0.022 |
| | (0.027) | (0.113) |
| | $\mathbf{h_{1,t}}$ | $\mathbf{h_{2,t}}$ |
| Intercepts | 0.062 | 0.622 |
| | (0.013) | (0.169) |
| $h_{1,t-1}^2$ | 0.646 | $\cdots$ |
| | (0.032) | $\cdots$ |
| $h_{2,t-1}^2$ | $\cdots$ | 0.832 |
| | $\cdots$ | (0.021) |
| $\varepsilon_{1,t-1}$ | 0.394 | $\cdots$ |
| | (0.048) | $\cdots$ |
| $\varepsilon_{2,t-1}$ | $\cdots$ | 0.140 |
| | $\cdots$ | (0.022) |
| | $\mathbf{u_{ind,t}}$ | $\mathbf{u_{r,t}}$ |
| $\varepsilon_{1,t-1}$ | $\cdots$ | 0.117 |
| | $\cdots$ | (0.077) |

Continued on next page

NOTE: Standard errors in parenthesis are
obtained from the inverse Hessian of
the log-likelihood function.

Table 2: Robustness of volatility coefficients (p-values in parentheses)

| Time period | $c_{1,1}$ | $c_{1,2}$ |
|---|---|---|
| Full sample period | 0.24 | -0.08 |
| | (0.00) | (0.00) |
| Feb/1919–Dec/1954 | 0.43 | -0.16 |
| | (0.00) | (0.00) |
| Jan/1955–Dec/1989 | 0.07 | -0.22 |
| | (0.73) | (0.03) |
| Jan/1955–Jul/2013 | 0.21 | -0.09 |
| | (0.23) | (0.02) |

NOTE: p-values are based on the standard
errors as detailed in the note to Table 1,
$c_{1,1}$ ($c_{1,2}$) is the effect of $h_{1,t}$ ($h_{2,t}$) on $\Delta ind_t$.