Are Expectations About Economic Activity Self-Fulfilling? An Empirical Test*

Christian Grisse[†]
Federal Reserve Bank of New York

This draft: December 2008

Abstract

This paper analyzes the relationship between economic activity and business sentiment, and in particular tests for a causal role of firms' expectations in explaining output fluctuations. Indicators of business and consumer confidence have proved very useful in forecasting subsequent changes in output. However the high correlation between business sentiment indices and economic activity can be the result either of self-fulfilling expectations or of agents correctly anticipating economic activity. To distinguish between these possibilities we estimate a structural model where expectations and economic activity are both endogenous. The model is identified using the heteroskedasticity in the data, following Rigobon (2003), without the *ad-hoc* restrictions typically imposed in the literature. Using monthly data from Germany, we find evidence that firms' expectations about current business conditions, as measured by the Ifo business situation index, can indeed have a causal effect on industrial production.

JEL classification: C32, D84, E32

Keywords: Economic fluctuations, Self-fulfilling expectations, Animal spirits, Identification through heteroskedasticity

*I thank Petra Geraats for many helpful discussions, and Peterhouse college, Cambridge and the Cambridge European Trust for financial support received during the writing of this paper. The views expressed are those of the author and do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System.

[†]International Research Function, Federal Reserve Bank of New York, 33 Liberty Street, New York, NY 10045, USA. E-mail: christian.grisse@ny.frb.org

1 Introduction

A very old idea in macroeconomics is that expectations about economic activity may be self-fulfilling: positive expectations about the state of the economy cause firms to increase investment and consumers to increase spending, thus producing an economic boom which validates the initial expectations. This was first argued by Pigou (1926) and Keynes (1936), who suggested that economic fluctuations might be partially driven by 'animal spirits'. More recently, researchers have analyzed the theoretical requirements for waves of optimism and pessimism to cause economic fluctuations.[1] However, the empirical evidence on the relevance of self-fulfilling expectations in causing business cycles is still inconclusive.[2]

This paper analyzes the relationship between expectations and business cycles using data from Germany. In particular, we ask whether shocks to expectations about contemporaneous economic conditions, measured by a well-known index of business confidence - the Ifo business situation index - can have an influence on economic activity, as measured by industrial production. We identify shocks to investor sentiment and analyze their effect on economic activity in a structural model that is identified by exploiting the heteroskedasticity in the data, following Rigobon (2003). We find that after controlling for fundamental variables that are commonly thought to determine economic activity, shocks to business sentiment - representing changes in firms' assessment of their business conditions in the current period - have a significant effect on subsequent industrial production. This can be interpreted as evidence supporting the hypothesis that business cycles may indeed be influenced by self-fulfilling expectations about contemporaneous economic activity.

Indicators of consumer and business confidence exhibit a high degree of correlation with economic activity and are therefore widely used for forecasting.[3] Figure 1 plots the Ifo business situation index against the year-on-year growth rate of industrial production in Germany. The strong correlation between the two series is apparent. However this high degree of correlation does not in itself imply that changes in sentiment - 'animal spirits', to use Keynes' terminology - affect economic activity. Indeed, a high correlation between sentiment and subsequent output is not surprising if economic agents on average correctly anticipate the future.[4] To distinguish these two possibilities we carefully model the way in which firms form their expectations about business conditions, and estimate both channels directly using a structural vector autoregression (VAR). We then interpret the residuals of the expectations equation of the structural VAR as measures of structural shocks to expectations, and investigate the extent to which expectations are self-fulfilling through (i) analyzing the sign and significance of the estimated structural

[1] Some recent contributions to the theory of expectations-driven business cycles ("Pigou Cycles") include Potter (1999), Beaudry and Portier (2004, 2007), Den Haan and Kaltenbrunner (2007), Jaimovich and Rebelo (2006) and Lorenzoni (2008).

[2] Some recent empirical contributions include Chauvet and Guo (2003), Choy, Leong and Tay (2006) and Barsky and Sims (2006).

[3] There is a large literature that tests whether macroeconomic forecasting can be improved by using indicators of consumer and business confidence. See e.g. Batchelor and Dua (1998) and Claveria, Pons and Ramos (2007). For forecast performance of the Ifo index see e.g. Schöler (1994) and the literature survey in Abberger and Wohlrabe (2006).

[4] This is called the "information view" by Barsky and Sims (2006), as opposed to the "animal spirits view".

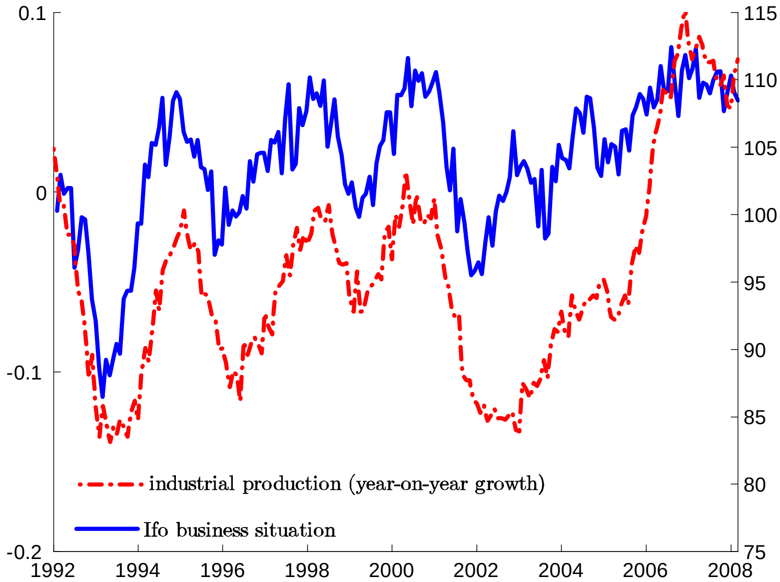

Figure 1: Business confidence and economic activity in Germany

coefficients capturing the effect of contemporaneous and lagged shocks to business confidence on economic activity, after controlling for fundamentals; and (ii) analyzing the contribution of shocks to business confidence to the forecast error variance of industrial production.

This paper improves on and extends previous empirical studies in several ways. We estimate a *structural* model which is better suited to identify shocks to expectations from the residuals than the reduced-form models used in many studies. To allow for contemporaneous effects between business sentiment and economic activity we employ a relatively novel identification methodology, following Rigobon (2003), which avoids the *ad-hoc* restrictions that have typically been imposed to achieve identification of structural models in previous studies. Unlike previous studies, we are therefore able to analyze whether shocks to firms' expectations affect economic activity in the short run (within the same month). Finally, to the best of our knowledge, this paper is the first to test for self-fulfilling expectations using data on Germany, including the business confidence index compiled by the Ifo research institute.

The remainder of this paper is structured as follows. The next section reviews the empirical literature on self-fulfilling expectations and economic activity, pointing out its limitations and highlighting the contribution of this paper to the literature. Section 3 derives the empirical model and illustrates the relationship between indicators of business confidence and economic activity. Section 4 introduces the data and the empirical methodology used in this paper, 'identification through heteroskedasticity', and presents the empirical results. Section 5 discusses avenues for future research, and finally section 6 concludes.

2 Related literature

This section relates the contribution of this study to the previous empirical literature on self-fulfilling expectations. The key idea behind the notion that economic activity may be influenced by waves of optimism and pessimism is that the economy can exhibit *strategic complementarities*: this is the case when the optimal action of an individual agent positively depends on the optimal actions of other agents, and hence on aggregate economic activity. For example, optimal investment by firms may be a positive function of future economic activity: if future aggregate income is expected to be higher, then demand is expected to be stronger and hence it is worthwhile to invest today. Similarly, if consumers expect an economic boom, which would imply stronger income growth, then they may choose to consume more today. In both cases, optimistic or pessimistic expectations about the future induce actions which validate the initial expectations. The economy can then have equilibria in which agents condition their expectations on 'sunspots' - variables that have no actual relevance for forecasting economic activity.[5]

There are in general two ways to test for whether economic fluctuations may be caused by self-fulfilling expectations, or 'animal spirits'. First, starting with a theoretical model which identifies the underlying mechanism through which expectations affect economic activity, one can derive conditions in the parameters which have to be satisfied for multiple equilibria to exist. Then, one can calibrate the model and test whether these parameter restrictions are satisfied in the data.[6]

Alternatively, researchers have attempted to identify shocks to expectations from the data, and then tested whether these shocks influence economic activity. Oh and Waldman (1990, 2005) identify changes in sentiment through revisions of leading indicators. If the economy exhibits strategic complementarities then positive news about the future, such as leading indicator announcements, should positively affect economic activity - even if these announcements later turned out to be based on false data. It follows that revisions of leading indicators can be used to identify episodes when the positive correlation between announcements and subsequent growth is generated not because announcements correctly reflect subsequent economic activity, but instead because the announcements influenced economic behavior. Therefore Oh and Waldman's (1990) finding that good news about the economy have a positive effect on economic activity, even if they are later revised downward, can be interpreted as evidence for the presence of self-fulfilling expectations.

The approach of this paper is closest related to Matsusaka and Sbordone (1995), Chauvet and Guo (2003) and Choy, Leong and Tsay (2006), who employ vector autoregressions (VARs) to identify shocks to expectations. In these studies the relationship between economic activity

[5]For formal theoretical models that describe these mechanisms see e.g. Shleifer (1986), Cooper and John (1988) and Gale (1996). Closely related are Chamley and Gale (1995), Gale (1995), and the literature on business cycles driven by news, see e.g. Beaudry and Portier (2004,2007), Jaimovich and Rebelo (2006) and Lorenzoni (2008). For some interesting recent evidence that expectations are indeed influenced by seemingly irrelevant events see Dohmen *et.al.* (2006).

[6]For examples of this approach see e.g. Dagsvik and Jovanovic (1991), Imrohoroglu (1993), Farmer and Guo (1994), Salyer and Sheffrin (1998) and Beaudry and Portier (2006).

and expectations is captured empirically by the following structural VAR:

$$\begin{bmatrix} 1 & a_1 \\ a_2 & 1 \end{bmatrix} \begin{bmatrix} Y_t \\ S_t \end{bmatrix} = \begin{bmatrix} b_{11}(L) & b_{12}(L) \\ b_{21}(L) & b_{22}(L) \end{bmatrix} \begin{bmatrix} Y_{t-1} \\ S_{t-1} \end{bmatrix} + \mathbf{C}(L)\,\mathbf{x}_t + \begin{bmatrix} \varepsilon_{Y,t} \\ \varepsilon_{S,t} \end{bmatrix} \tag{1}$$

where Y_t is a measure of economic activity (typically GDP or industrial production), S_t is a measure of consumer or business sentiment, $\mathbf{x}_t$ is a vector of control variables, a_1 and a_2 are unknown parameters, $b_{ij}(L)$, $i, j = 1, 2$ are polynomials in the lag operator L and $\mathbf{C}(L)$ is a matrix in the lag operator. Some studies add additional endogenous variables to the VAR, such as consumption or investment, but this is not crucial for the comparison here.[7]

The reasoning behind the econometric model in (1) is as follows. From the first equation in (1) one can estimate how expectations affect economic activity: a_1 and the coefficients in the polynomial $b_{12}(L)$ capture the effect of current and past sentiment on output, respectively. The key idea is that if $b_{12}(L)$ or a_1 are significantly different from zero, even after controlling for economic fundamentals in $\mathbf{x}_t$, then this supports the hypothesis that sentiment has a causal effect on economic fluctuations. It is important to control for all relevant fundamental variables in $\mathbf{x}_t$ in order to minimize the risk that fluctuations in sentiment and output could both be caused by an omitted variable. The second equation in (1) describes how agents form their expectations. If $\mathbf{x}_t$ includes all relevant information available to the agents then the error term $\varepsilon_{S,t}$ can be interpreted as 'animal spirits' - a shock to expectations which is not based on fundamental information. Such non-fundamental shocks would influence economic fluctuations through a_1 and $b_{12}(L)$.

Matsusaka and Sbordone (1995) and Chauvet and Guo (2005) estimate the reduced form version of (1),

$$\begin{bmatrix} Y_t \\ S_t \end{bmatrix} = \begin{bmatrix} b^*_{11}(L) & b^*_{12}(L) \\ b^*_{21}(L) & b^*_{22}(L) \end{bmatrix} \begin{bmatrix} Y_{t-1} \\ S_{t-1} \end{bmatrix} + \mathbf{C}^*(L)\,\mathbf{x}_t + \begin{bmatrix} u_{Y,t} \\ u_{S,t} \end{bmatrix} \tag{2}$$

where we have defined

$$\begin{aligned} \begin{bmatrix} b^*_{11}(L) & b^*_{12}(L) \\ b^*_{21}(L) & b^*_{22}(L) \end{bmatrix} &\equiv \begin{bmatrix} 1 & a_1 \\ a_2 & 1 \end{bmatrix}^{-1} \begin{bmatrix} b_{11}(L) & b_{12}(L) \\ b_{21}(L) & b_{22}(L) \end{bmatrix} \\ \mathbf{C}^*(L) &\equiv \begin{bmatrix} 1 & a_1 \\ a_2 & 1 \end{bmatrix}^{-1} \mathbf{C}(L) \\ \begin{bmatrix} u_{Y,t} \\ u_{S,t} \end{bmatrix} &\equiv \begin{bmatrix} 1 & a_1 \\ a_2 & 1 \end{bmatrix}^{-1} \begin{bmatrix} \varepsilon_{Y,t} \\ \varepsilon_{S,t} \end{bmatrix} \end{aligned}$$

Matsusaka and Sbordone (1995) estimate (2) using data on consumer confidence (the Index of Consumer Confidence, compiled by the University of Michigan). They find that consumer confidence Granger-causes future output: even after controlling for a range of fundamentals, the hypothesis that the coefficients in the polynomial $b^*_{12}(L)$ are jointly equal to zero can be

[7] Furthermore, constants are omitted for simplicity.

rejected. Furthermore, they find that shocks to expectations explain between 13 and 26 percent of the forecast error variance of output. Chauvet and Guo (2005) also estimate a reduced-form model, but allow for the possibility that agents might react differently to economic news depending on the stage of the business cycle by letting constants (which we have omitted above for ease of notation) and the covariance-matrix of the reduced-form errors follow a Markov-switching process. Again using the Michigan survey as a measure of consumer confidence, and the Index of Net Business Formation as a measure of business sentiment, they find that shocks to expectations played an important role during several US recession episodes, even after controlling for fundamentals.

Barsky and Sims (2006) also estimate a reduced-form model analogous to (2), and analyze the impulse-response functions for evidence of self-fulfilling expectations. They argue that if business cycles are indeed driven by non-fundamental shocks to expectations then the effects of such shocks to consumption, investment and economic activity should be temporary, since the economy should eventually return to the equilibrium determined by the underlying fundamentals. Using data from the Michigan survey for consumer confidence, they find that the identified expectations shocks have mostly permanent effects, consistent with the view that agents correctly anticipate and forecast future economic activity.

Working directly with the reduced-form model in (2) has the drawback that the estimated coefficients $b_{12}^{*}(L)$ correspond to the effect of past shocks $u_{S,t}$ on current output; however, if a_1 or a_2 in equation (1) are non-zero, $u_{S,t}$ is actually a composite of the underlying structural shocks to both output and sentiment. Choy, Leong and Tsay (2006) instead estimate a structural model similar to equation (1), and analyze the influence of structural shocks to sentiment $\varepsilon_{S,t}$ through examining impulse responses and forecast error decompositions. As endogenous variables they use several macroeconomic variables, including output growth, inflation, interest rates and stock returns, as well as expectations about each of these variables as measured by the Survey of Professional Forecasters. Using quarterly data, they find that shocks to expectations were not a significant source of economic fluctuations for their sample. However, to identify their structural model Choy, Leong and Tsay (2006) use common zero restrictions on contemporaneous comovements. In particular, while they allow for some contemporaneous comovement across macroeconomic variables, they assume that there is no contemporaneous effect from expectations to macroeconomic variables, and *vice versa*.

They justify this assumption by noting that on the one hand, since forecasts are published towards the end of each quarter after consumption and investment decisions have been taken, they cannot affect macroeconomic variables in that same quarter; and on the other hand, because macroeconomic variables also become known only at the end of each quarter, they cannot affect forecasts made in that quarter. However in this paper we argue that generally such zero restrictions can be potentially problematic. We view indicators of business confidence as a proxy for the expectations of economic agents across the economy. This is especially intuitive for the Ifo survey used in this paper, which comprises the responses of 7000 firms in different industrial sectors. Economic agents are likely to have access to information about the economy which is not observed and cannot be controlled for by the econometrician. If such information is unbiased for a typical economic agent, expectations can be viewed as *reflecting* current macroeconomic variables, even if the actual realizations of the variables have not been announced. Even if indicators are published towards the end of the period, the surveys will have been conducted and expectations will have been formed at the beginning of the period, so that changes in expectations can affect economic behavior and hence macroeconomic variables in the same period, with little or no lag. Taken together, these arguments imply that expectations about current business conditions, as well as those business conditions itself, cannot be treated as predetermined in econometric analysis. The resulting endogeneity problems may be less acute when surveys of professional forecasters are used, as in Choy, Leong and Tsay (2006), since the expectations captured in these forecasts may not correspond closely to the expectations formed by agents across the economy. In general however, depending on the macroeconomic variables and the measures of expectations used, these endogeneity problems imply that standard zero restrictions cannot be used for the identification of structural models.

To summarize, the previous literature has typically either used reduced-form models to test for the role of 'animal spirits' in explaining economic fluctuations, which has the disadvantage that the identified shocks are difficult to interpret, and that possible contemporaneous comovement cannot be analyzed; or has estimated structural models but employed restrictive assumptions to achieve identification, restricting potentially interesting contemporaneous relationships to zero and possibly leading to biased coefficients. To address these shortcomings, this paper models firms' expectations formation process carefully and uses a relatively novel identification method - 'identification through heteroskedasticity' - to identify a structural VAR with data on business sentiment and economic activity, without imposing *ad-hoc* restrictions. The econometric methodology and identification technique is explained in section 4.2.

3 A simple model of firms' expectations and business cycles

This section builds a simple model of the relationship between business confidence and economic fluctuations, which will form the basis for the empirical analysis in section 4. The purpose of this section is not to present a detailed analysis of the theoretical aspects of expectations-driven business cycles, for which there is already a large literature; instead, the aim is to illustrate the implications of modeling firms' expectations as an endogenous variable, and to investigate the error structure of the empirical model.

There are N firms in the economy. Output Y_{it} of a typical firm i in period t depends positively on a factor of production L_{it}, which we shall refer to as labor for concreteness. Firms can change L_{it} in any period by hiring additional workers or by letting the existing workforce work overtime, and changes in L_{it} have an immediate effect on output. We assume that equilibrium output of a typical firm i in period t is given by

$$Y_{it} = \gamma^* + \gamma_L^* L_{it} + \varepsilon_{it} \tag{3}$$

where $\gamma^*, \gamma_L^* > 0$ are positive parameters and ε_{it} is an error term.[8]

We assume that each firm's optimal labor input depends positively on its expected 'business situation', which is denoted by θ_{it}. This somewhat 'fuzzy' variable is thought of as reflecting demand conditions, financing costs, and other parameters which affect profits and optimal strategies. When the labor input choice is made, θ_{it} is still (at least partly) unknown to firms, so that they have to form expectations about θ_{it} as specified below. We assume that the firm's labor input choice is given by

$$L_{it} = gE_{it}\left(\theta_{it}\right) + \mathbf{g}_x'\mathbf{x}_t \tag{4}$$

where $\mathbf{x}_t$ denotes a column vector of economy-wide fundamental variables and $\mathbf{g}_x$ is a column vector of coefficients that has the same length as $\mathbf{x}_t$. The subscript *it* of the expectations operator indicates that each firm i in period t forms expectations conditional on all information it observes in that period, as specified below.

We assume that firm i's business situation is positively related to aggregate economic activity in period t,

$$\theta_{it} = a_i + a_Y Y_t + \mathbf{a}_x'\mathbf{x}_t \tag{5}$$

where $a_Y > 0$ is a positive parameter, $Y_t \equiv \sum_{i=1}^{N} Y_{it}$ is aggregate output and $\mathbf{a}_x$ is a column vector of coefficients that has the same length as $\mathbf{x}_t$. The firm-specific term a_i captures determinants of firm i's business situation that are unrelated to economy-wide developments.

Taken together (4) and (5) imply that each firm's optimal labor input is increasing in the level of expected *aggregate* economic activity in period t: the economy exhibits *strategic complementarities*, which lead to multiple equilibria. If all firms increase production because they expect their business condition to be favorable, the overall increase in economic activity increases firms' individual 'business conditions' - for example, by increasing demand for their products - thus validating the initial expectations. Conversely, negative expectations can lead to an equilibrium with lower production.

After substituting (4) and (5) into equation (3) and summing across all firms in the economy, we find that aggregate output in period t is given by

$$Y_t = \gamma + \gamma_L \sum_{i=1}^{N} E_{it}\left(\theta_{it}\right) + \boldsymbol{\gamma}_x'\mathbf{x}_t + \varepsilon_t \tag{6}$$

where $\gamma \equiv N\gamma^*$, $\gamma_L \equiv \gamma_L^* g$, $\boldsymbol{\gamma}_x \equiv \gamma_L^* N \mathbf{g}_x$ and the aggregate error term is defined as $\varepsilon_t \equiv \sum_{i=1}^{N} \varepsilon_{it}$. Equation (6) shows that output depends on firms' expectations about business conditions θ_{it}; consequently, forecast mistakes can have a causal effect on economic activity through affecting firms' hiring decisions L_{it}.

When forming expectations about current business conditions θ_{it}, firms may make use of a variety of information, such as orders received, contact to customers and other firms and so

[8] For simplicity we assume that parameters are identical across all firms in the economy.

forth. We assume that the resulting expectations are unbiased, so that we can write

$$\begin{aligned} E_{it}\left(\theta_{it}\right) &= \theta_{it} + \eta_{it} \\ &= \left(a_i + a_Y Y_t + \mathbf{a}_x' \mathbf{x}_t\right) + \eta_{it} \end{aligned} \tag{7}$$

where η_{it} is an error term which has a mean of zero and is independently distributed across firms. Here, we have implicitly assumed that the number of firms N is large, so that any individual firm has a negligible impact on aggregate output.

Of the N firms, the first $i = 1, 2, ..., M$ firms, with $M \leq N$ participate in the business climate survey, where they are asked about their assessment of their current business situation. We assume that each firm truthfully reveals its expectations. Then an index of business sentiment S_t is computed as the average of responses received from the M participating firms,

$$\begin{aligned} S_t &= \frac{1}{M} \sum_{i=1}^{M} E_{it}\left(\theta_{it}\right) \\ &= a_0 + a_Y Y_t + \mathbf{a}_x' \mathbf{x}_t + \varepsilon_{S,t} \end{aligned} \tag{8}$$

with $a_0 \equiv \frac{1}{M} \sum_{i=1}^{M} a_i$ and $\varepsilon_{S,t} \equiv \frac{1}{M} \sum_{i=1}^{M} \eta_{it}$.

The problem with estimating equation (6) directly is that firms' expectations are not directly observed. However, the business sentiment S_t can be used to proxy for firms' expectations. Summing equation (7) over all N firms in the economy and combining with (8), we have

$$\sum_{i=1}^{N} E_{it}\left(\theta_{it}\right) = M S_t + \sum_{i=M+1}^{N} a_i + (N - M)\, a_Y Y_t + (N - M)\, \mathbf{a}_x' \mathbf{x}_t + \sum_{i=M+1}^{N} \eta_{it} \tag{9}$$

Substituting (9) into (6) and rearranging produces

$$Y_t = c_0 + c_S S_t + \mathbf{c}_x' \mathbf{x}_t + \varepsilon_{Y,t} \tag{10}$$

where we have defined

$$\begin{aligned} c_0 &\equiv \frac{\gamma + \gamma_L N \sum_{i=M+1}^{N} a_i}{1 - \gamma_L N\, (N - M)\, a_Y} \\ c_S &\equiv \frac{\gamma_L N M}{1 - \gamma_L N\, (N - M)\, a_Y} \\ \mathbf{c}_x &\equiv \frac{\boldsymbol{\gamma}_x + \gamma_L N\, (N - M)\, \mathbf{a}_x}{1 - \gamma_L N\, (N - M)\, a_Y} \end{aligned}$$

The error term is given by

$$\varepsilon_{Y,t} \equiv \frac{\gamma_L N}{1 - \gamma_L N\, (N - M)\, a_Y} \sum_{i=M+1}^{N} \eta_{it} + \frac{1}{1 - \gamma_L N\, (N - M)\, a_Y} \varepsilon_t \tag{11}$$

Equations (8) and (10) describe the relationship between business sentiment and economic activity. Since the business sentiment index S_t is published after production decisions have been taken, S_t itself cannot causally influence output in the same period. However S_t reflects the underlying expectations of many firms across the economy, and these expectations do influence production contemporaneously in equation (10). Economic activity in turn cannot contemporaneously *influence* business sentiment because output figures are only published after expectations have been formed; however since it will never be possible to account for all variables in firms' information sets, business sentiment will systematically *reflect* aggregate activity if firms' expectations are unbiased. Therefore if the contemporaneous comovement between economic activity Y_t and business sentiment S_t is restricted to zero so that the structural model described by equations (8) and (10) are estimated directly with imposing $a_Y = c_S = 0$, (i) an interesting channel for self-fulfilling expectations is neglected, and (ii) the remaining estimated coefficients will be biased.

For the econometric analysis in section 4 below, note that the errors in (8) and (10) will be unrelated, $cov\left(\varepsilon_{Y,t}, \varepsilon_{S,t}\right) = 0$ if we have

$$cov\left(\varepsilon_{it}, \eta_{jt}\right) = 0 \text{ for all } i, j \tag{12a}$$

$$cov\left(\eta_{it}, \eta_{jt}\right) = 0 \text{ for all } i \neq j \tag{12b}$$

Since ε_t captures fluctuations in production which are not explained by the model, it appears sensible to assume that such fluctuations are not correlated with firms' forecast errors, so that condition (12a) is likely to hold. Condition (12b) requires that forecast errors are unrelated across firms.

4 Empirical Analysis

4.1 Data

We analyze the relationship between business sentiment and economic fluctuations in Germany using monthly data from January 1991 to March 2008. As a measure of economic activity we use industrial production, which (unlike GDP data) is published on a monthly basis. This data is available from the web site of Deutsche Bundesbank. Every month, local statistical offices collect data from firms with more than 50 employees. From these data, the German Federal Statistical Office releases an industrial production indicator for month t, typically 38 days after month t. Thus, the figure for January, to take an example, becomes available roughly at the beginning of the second week of March. Upon the first release, the data contains approximately 10% estimations, and is revised four weeks after publication, at the end of every quarter (up to that quarter), and finally at the end of each year.

We employ the Ifo business situation index as a measure of business sentiment, available from the Ifo institute web site. The Ifo research institute conducts monthly surveys of about 7000 firms, which are asked a series of qualitative questions concerning their assessment of current and future business conditions. Several indicators are then derived from the survey results.

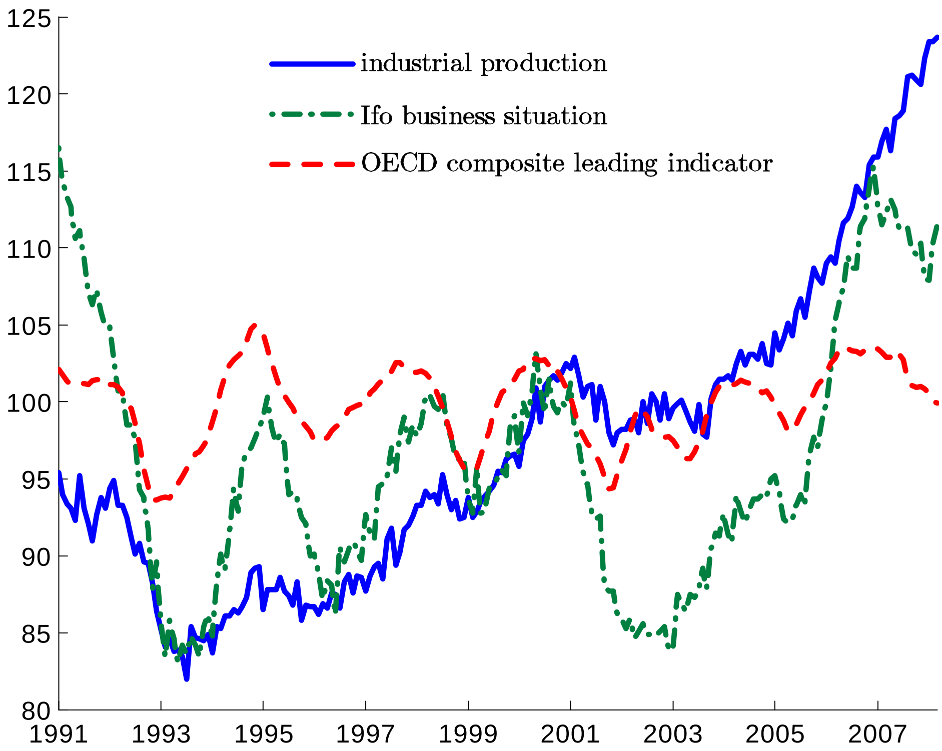

Figure 2: Business sentiment, economic activity and OECD leading indicator for Germany

The business situation index used in this study is compiled from responses to the question "We judge our current business situation for product group XY to be ...", with possible answers good, satisfactorily, or bad; these qualitative responses are then transformed into a quantitative business confidence index. Table 1 reports various correlations of the Ifo business situation index and industrial production. The index is released around the third or fourth week each month, and revised only in the process of seasonal adjustment, with typically very minor adjustments.

In addition to business sentiment and industrial production, we include the OECD composite leading indicator for Germany as a third endogenous variable in the VAR (available from the OECD web site). We use this indicator to capture various fundamental variables that are likely to influence both firms' expectations and economic activity. The problem with including relevant control variables individually is that with a relatively short dataset, including a sufficiently large number of control variables will limit the degrees of freedom. Furthermore, most control variables should themselves be treated as endogenous. For example, interest rates and exchange rates are likely to influence economic activity, but also to react themselves to changes in economic activity and to the publication of sentiment indices.

A further advantage of using the OECD composite leading indicator is that this index is constructed to forecast the industrial production series used in this paper, and thus provides a good summary of various relevant control variables. The components of the OECD leading indicator include the tendency of orders inflow or demand, the Ifo business climate indicator, the level of finished goods stocks, the level of export order books (all collected by the Ifo research institute in its monthly survey), interest rate spreads (provided by the European Central Bank) and total new orders in manufacturing (supplied by the Federal Statistical Office). These series are chosen because they exhibit a leading relationship with industrial production at the turning points. To construct the indicator, the individual component series are detrended, smoothed, normalized (to exhibit fluctuations of similar magnitude) and weighted equally. The OECD composite leading indicator with data from month t is published on the Friday of the first full week in month $t + 2$, and subsequently revised.

One drawback of using the OECD composite leading indicator for Germany as a control- and additional endogenous variable is that the Ifo business *climate* index entering the leading indicator is closely related to the Ifo business *situation* index that we use as endogenous variable. In particular, the business climate indicator is compiled by combining the business situation index with responses to a question concerning firms' expectations about their business situation over the following 6 months.[9] This can lead to possible multicollinearity problems, inducing larger standard errors, when using both the Ifo business situation index and the OECD composite leading indicator for Germany in the same regression.

To ensure stationarity we use the growth rate of all variables for the econometric analysis below. While business sentiment appears to be borderline stationary, our intuition is that changes in sentiment should matter for changes in output.[10]

4.2 Methodology

To analyze the relationship between business sentiment and economic activity, we want to estimate regressions along the lines of equations (8) and (10) derived in section 3. However, for the econometric analysis we generalize the model in equations (8) and (10) in two ways. As discussed in the previous subsection, we include the OECD composite leading indicator for Germany as the sole control variable, and add a third equation to the VAR to account for the possibility that the fundamental variables captured by this leading indicator are themselves influenced by business sentiment and economic activity. Furthermore, we include lagged values of sentiment and industrial production in all equations. Output is persistent, and therefore past values of economic activity are likely to have an influence on firms' expectations of current business conditions as well. Also, the effects of business sentiment on economic activity are likely to be persistent as investment and hiring decisions tend to affect production over several periods. Letting C_t denote the OECD composite leading indicator, equations (8) and (10) can

[9] To be precise, firms are asked "We judge our business situation over the next 6 months to be...", with possible answers "somewhat better", "somewhat worse", or "more or less the same". Let GL denote the balance of positive and negative responses to the question concerning the judgement of business conditions in the current period (the business situation index), and let GE denote the balance of responses to the question concerning expectations about the next 6 months. Then the Ifo business climate index is computed as $\sqrt{(GL + 200)(GE + 200)} - 200$.

[10] In an augmented Dickey-Fuller test with a constant and 5 lags (as suggested by the Schwarz Information Criterion) the null hypothesis that the Ifo business situation index has a unit root can be rejected at the 10% level (p-value: 0.0813).

Table 1: Correlations of business confidence and industrial production

j (month)	S_t^l, Y_{t-j}^l	S_t^l, Y_{t+j}^l	$S_t^l, \widehat{Y}_{t-j}$	$S_t^l, \widehat{Y}_{t+j}$	S_t, Y_{t-j}	S_t, Y_{t+j}
0	0.5636	0.5636	0.7277	0.7277	0.2744	0.2744
1	0.5520	0.5472	0.7472	0.6868	-0.0182	0.1237
2	0.5406	0.5317	0.7616	0.6342	0.1135	0.0866
3	0.5268	0.5191	0.7672	0.5785	0.1541	0.1409
4	0.5105	0.5032	0.7576	0.5078	0.0331	0.0101
5	0.4949	0.4846	0.7424	0.4456	0.0763	0.2096
6	0.4771	0.4591	0.7178	0.3719	0.1688	0.0446
7	0.4552	0.4346	0.6779	0.3029	-0.0903	-0.0468
8	0.4352	0.4099	0.6369	0.2389	0.1591	0.1591
9	0.4135	0.3833	0.5853	0.1670	-0.0580	0.1294
10	0.3931	0.3513	0.5351	0.0978	-0.0012	-0.0271
11	0.3731	0.3163	0.4839	0.0417	-0.0224	0.0207
12	0.3551	0.2809	0.4330	-0.0137	-0.0314	0.0959

Note: S_t^l and S_t denote, respectively, the levels and monthly growth rate of the Ifo business situation index (seasonally adjusted); Y_t^l, Y_t and $\widehat{Y}_t$ denote, respectively, the levels, monthly growth rate, and year-on-year growth rate of German industrial production (seasonally adjusted and excluding construction). The sample includes monthly data from 1991-01 to 2008-03.

then be generalized to

$$S_t = b_{S0} + b_{SY} Y_t + b_{SC} Y_t + \mathbf{b}_S' (L) \cdot \begin{bmatrix} S_{t-1} & Y_{t-1} & C_{t-1} \end{bmatrix}' + \varepsilon_{S,t} \tag{13a}$$

$$Y_t = b_{Y0} + b_{YS} S_t + b_{YC} C_t + \mathbf{b}_Y' (L) \cdot \begin{bmatrix} S_{t-1} & Y_{t-1} & C_{t-1} \end{bmatrix}' + \varepsilon_{Y,t} \tag{13b}$$

$$C_t = b_{C0} + b_{CS} S_t + b_{CY} Y_t + \mathbf{b}_C' (L) \cdot \begin{bmatrix} S_{t-1} & Y_{t-1} & C_{t-1} \end{bmatrix}' + \varepsilon_{C,t} \tag{13c}$$

where $\mathbf{b}_S(L)$, $\mathbf{b}_Y(L)$ and $\mathbf{b}_C(L)$ are 3x1 vectors of coefficients in the lag operator L.

From (13a) and (13b) it is clear that Y_t in equation (13a) and S_t in equation (13b) should be treated as endogenous variables: if (13a) and (13b) were estimated directly then the estimated coefficients would be subject to endogeneity bias. We can rewrite equations (13a) to (13c) as a structural VAR,

$$\begin{bmatrix} 1 & -b_{SY} & -b_{SC} \\ -b_{YS} & 1 & -b_{YC} \\ -b_{CS} & -b_{CY} & 1 \end{bmatrix} \cdot \begin{bmatrix} S_t \\ Y_t \\ C_t \end{bmatrix} = \begin{bmatrix} b_{S0} \\ b_{Y0} \\ b_{C0} \end{bmatrix} + \begin{bmatrix} \mathbf{b}_S'(L) \\ \mathbf{b}_Y'(L) \\ \mathbf{b}_C'(L) \end{bmatrix} \begin{bmatrix} S_{t-1} \\ Y_{t-1} \\ C_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{S,t} \\ \varepsilon_{Y,t} \\ \varepsilon_{C,t} \end{bmatrix} \tag{14}$$

where, following the analysis in section 3, we expect the error terms of output and sentiment to be unrelated,

$$cov\left(\varepsilon_{S,t}, \varepsilon_{Y,t}\right) = 0$$

if the errors in firms' expectations are unrelated. Furthermore, we assume that

$$\begin{aligned} cov\left(\varepsilon_{S,t},\varepsilon_{C,t}\right) &= 0 \\ cov\left(\varepsilon_{Y,t},\varepsilon_{C,t}\right) &= 0 \end{aligned}$$

We need to impose appropriate parameter restrictions to ensure that in the first equation of (14), describing how firms form expectations in month t, only data that is available at the time expectations were formed is included in the regression. The Ifo survey is conducted in the second week of each month t. At this point in time, the latest figures available for industrial production and the OECD composite leading indicator concern month $t-2$. Therefore, we restrict the coefficient corresponding to the contemporaneous effect of the leading indictor on business sentiment to zero, $b_{SC}=0$, and furthermore restrict the effects of Y_{t-1} and C_{t-1} in the business sentiment equation to zero.[11] Note that the coefficient b_{SY}, capturing the contemporaneous effect of industrial production on business sentiment, is allowed to be non-zero even though industrial production is not observed at the time firms form expectations. This is because, as argued above, expectations are formed on the basis of information that is unobserved by the econometrician; as seen in equation (8), expectations are therefore likely to *reflect* current economic activity even after controlling for economic fundamentals. In contrast, because the OECD leading indicator is constructed to provide information about *future* economic activity, rather than current economic conditions, firms' business situation in t is not linked to the composite leading indicator of the same month, C_t. Therefore firms' expectations about their business conditions in t, captured through business sentiment S_t do not reflect C_t, and hence we impose $b_{SC}=0$.

The estimation procedure is as follows. In a first step, we use seemingly unrelated regression (SUR) to estimate the reduced-form version of (14),

$$\begin{bmatrix} S_t \\ Y_t \\ C_t \end{bmatrix} = \mathbf{B}_0 + \mathbf{B}_1\left(L\right)\begin{bmatrix} S_{t-1} \\ Y_{t-1} \\ C_{t-1} \end{bmatrix} + \begin{bmatrix} u_{S,t} \\ u_{Yt} \\ u_{C,t} \end{bmatrix} \tag{15}$$

where

$$\begin{aligned} \mathbf{B}_0 &= \mathbf{A}^{-1}\left[\begin{array}{ccc} b_{S0} & b_{Y0} & b_{C0} \end{array}\right]' \\ \mathbf{B}_1\left(L\right) &= \mathbf{A}^{-1}\left[\begin{array}{ccc} \mathbf{b}'_S\left(L\right) & \mathbf{b}'_Y\left(L\right) & \mathbf{b}'_C\left(L\right) \end{array}\right]' \\ \left[\begin{array}{ccc} u_{S,t} & u_{Yt} & u_{C,t} \end{array}\right]' &= \mathbf{A}^{-1}\left[\begin{array}{ccc} \varepsilon_{S,t} & \varepsilon_{Y,t} & \varepsilon_{C,t} \end{array}\right]' \end{aligned}$$

[11] Note that although the OECD composite leading indicator for Germany corresponding to month t is published with a two-month lag in month $t+2$, some of the individual components of the index are known earlier. Therefore, we also estimated the model with C_{t-1} included in the business sentiment equation. The results were nearly identical to the results reported in the paper.

with

$$\mathbf{A} = \begin{bmatrix} 1 & -b_{SY} & -b_{SC} \\ -b_{YS} & 1 & -b_{YC} \\ -b_{CS} & -b_{CY} & 1 \end{bmatrix} \tag{16}$$

Then in a second step we use the residuals from this regression to identify the coefficients in matrix **A** using 'identification through heteroskedasticity'. This identification scheme, made popular by Rigobon (2003), exploits the heterogeneity of the data to obtain a sufficient number of moment conditions from which the structural parameters of the model can be estimated.

The basic idea behind 'identification through heteroskedasticity' is as follows. Assume that we can identify periods within our sample in which the volatility of the underlying structural shocks $\varepsilon_{S,t}$, $\varepsilon_{Y,t}$ and $\varepsilon_{C,t}$ changes. Specifically, assume that we can identify a subsample in which the volatility of sentiment shocks $\varepsilon_{S,t}$ is higher than in the rest of the sample, while the volatility of the other two structural shocks has not increased correspondingly. In such a period, the influence of sentiment shocks on output is likely to dominate in the data, because relatively large sentiment shocks are observed on average. Consequently, this period can be used to identify the influence of sentiment on output. Similarly, during periods of high $\varepsilon_{Y,t}$ and $\varepsilon_{C,t}$ volatility the data is likely to reflect a direction of causation running from those shocks to the other variables, making it possible to identify the corresponding contemporaneous effects from the data. The main assumption of this methodology is that the volatility of the error terms in (14) changes over the sample period, while the coefficients of the model are constant. This assumption is similarly maintained in the literature testing for the effect of self-fulfilling expectations on economic activity. Further details on the identification procedure, including the identified periods of changing volatility, are provided in the appendix.

4.3 Results

The results from the estimation of the reduced-form VAR are presented in Table 2. As discussed in the previous subsection, to account for the limited data availability at the time firms' form their expectations, the effects of the first lag of both industrial production and the OECD leading indicator in the business sentiment equation have been restricted to zero. In Table 2, note that the coefficients describing the effect of past business sentiment on economic activity are all positive and significant at the 5% level, and that the null hypothesis that the coefficients of business sentiment in the industrial production equation are jointly equal to zero can be rejected comfortably. This suggests that firms' expectations - as measured by the Ifo business situation index - seem to have a significant lagged effect on economic activity, which in turn implies that 'animal spirits', errors in firms' expectations such as 'irrational' waves of optimism and pessimism can affect the real economy.

Building on the results from the reduced-form model, we can then use 'identification through heteroskedasticity' to identify the structural parameters of the model. From equation (14), it is clear that the contemporaneous effects of the underlying structural shocks $\varepsilon_{S,t}$, $\varepsilon_{Y,t}$ and $\varepsilon_{C,t}$ on the endogenous variables are captured by the inverse of matrix **A**, defined in (16). More

Table 2: Results from reduced-form VAR

dependent variable	S_t	Y_t	C_t
const.	0.0001 [0.9292]	0.0025*** [0.0009]	−0.0001 [0.6852]
S_{t-1}	−0.2059*** [0.0014]	0.1221** [0.0148]	0.0478*** [0.0002]
S_{t-2}	−0.1053 [0.1071]	0.1289** [0.0139]	−0.0224* [0.0920]
S_{t-3}	0.3963*** [0.0000]	0.1027** [0.0418]	−0.0405*** [0.0016]
Y_{t-1}		−0.4571*** [0.0000]	0.0151 [0.4031]
Y_{t-2}	0.0591 [0.5141]	−0.2532*** [0.0008]	−0.0040 [0.8349]
Y_{t-3}	0.0355 [0.6910]	0.0435* [0.05372]	0.0285 [0.1120]
C_{t-1}		−0.0378 [0.8853]	0.9608*** [0.0000]
C_{t-2}	0.9965*** [0.0034]	0.4419 [0.2348]	0.0149 [0.8749]
C_{t-3}	0.1305 [0.7139]	0.0255 [0.92699]	−0.2005*** [0.0042]
$\overline{R}^2$	0.3494	0.2212	0.7572

	$H_0 : b^i_{YS} = 0 \ \forall i$
Wald test statistic (χ^2)	10.7008
P-value	0.0135
$\sum_i \widehat{b}^i_{YS}$	0.3537

Note: S_t, Y_t and C_t denote, respectively, the growth rates of the Ifo business situation index (seasonally adjusted), German industrial production (seasonally adjusted, excluding construction), and the OECD composite leading indicator for Germany. Sample includes monthly data from 1991-01 to 2008-03.
3 lags were included, as suggested by the Schwarz and Hannan-Quinn information criterion. Estimation using SUR. $\sum_i \widehat{b}^i_{YS}$ denotes the sum of all estimated coefficients corresponding to lagged business sentiment in the industrial production equation, capturing the combined effects of past business sentiment on industrial production. ***,** and * denote significance at the 1%, 5% and 10% level, respectively. P-values in square brackets.

specifically, the effect of a shock to variable j on variable i is given by the (i, j)th coefficient in $\mathbf{A}^{-1}$.

The results are reported in Table 3. The coefficient describing the contemporaneous effect of business sentiment on industrial production is positive and highly significant, suggesting that firms' expectations about their current business conditions have a strong immediate effect on economic activity. Furthermore, the contemporaneous effect of shocks to industrial production on business sentiment is also positive, highly significant, and of roughly similar magnitude to the estimated coefficient for the reverse effect. This suggests that firms have access to some information which has not been controlled for in the regressions, and that firms' resulting

Table 3: Results from identification procedure

contemporaneous feedback effects (matrix $\mathbf{A}^{-1}$)			
From...	$\varepsilon_{S,t}$	$\varepsilon_{Y,t}$	$\varepsilon_{C,t}$
...to			
S_t	1.0842***	0.2962***	0.0743***
	[0.0000]	[0.0000]	[0.0000]
Y_t	0.3273***	1.1522***	0.2891***
	[0.0000]	[0.0000]	[0.0000]
C_t	0.2635***	0.3222***	1.0808***
	[0.0000]	[0.0000]	[0.0000]

Note: S_t, Y_t and C_t denote, respectively, the growth rates of the Ifo business situation index (seasonally adjusted), German industrial production (seasonally adjusted, excluding construction), and the OECD composite leading indicator for Germany. Sample includes monthly data from 1991-01 to 2008-01.
***,** and * denote significance at the 1%, 5% and 10% level, respectively. P-values (in square brackets) are computed from 1000 bootstrap replications, following Rigobon (2003). Coefficient (i, j) describes the contemporaneous effect of a shock to variable j on variable i. The contemporaneous effects of the OECD leading indicator on business sentiment and industrial production were restricted to zero to reflect the timing of the publication of the leading indicator.

expectations reflect current economic activity. Note that shocks to the OECD composite leading indicator also have a significant positive contemporaneous effect on both business sentiment and economic activity. The OECD leading indicator cannot have a *direct* contemporaneous effect on business sentiment, because the indicator has not been released when firms form their expectations; however, the indicator reflects a variety of fundamental variables which do have an immediate effect on economic activity, which in turn is reflected in firms' expectations.

We can use impulse response functions and forecast error variance decompositions to investigate how the underlying *structural* shocks to expectations affect economic activity over various time horizons. Since all parameters of the structural model have been estimated, impulse responses and variance decompositions do not depend on the ordering of the endogenous variables. This is a major advantage of the identification method used in this paper. Figure 3 plots the response of each of the endogenous variables (listed in the columns) to one standard deviation realizations of different shocks (listed in the rows). The shocks to business sentiment analyzed here correspond to 'animal spirits' - 'true' expectational errors, changes in firms' expectations which are not justified by actual changes in business conditions. The effects of a shock to business sentiment on industrial production are positive and significant for several months, and die off after approximately one year. Shocks to industrial production similarly have a positive and significant effect on business sentiment, taking about a year to subside. Shocks to the OECD composite leading indicator - representing shocks to a variety of fundamentals which are not explicitly included - have a strong positive effect on both industrial production and sentiment for also about one year.

Forecast error variance decompositions for various forecast horizons are presented in Figure 4. As with the impulse responses, these variance decompositions do not depend on the ordering

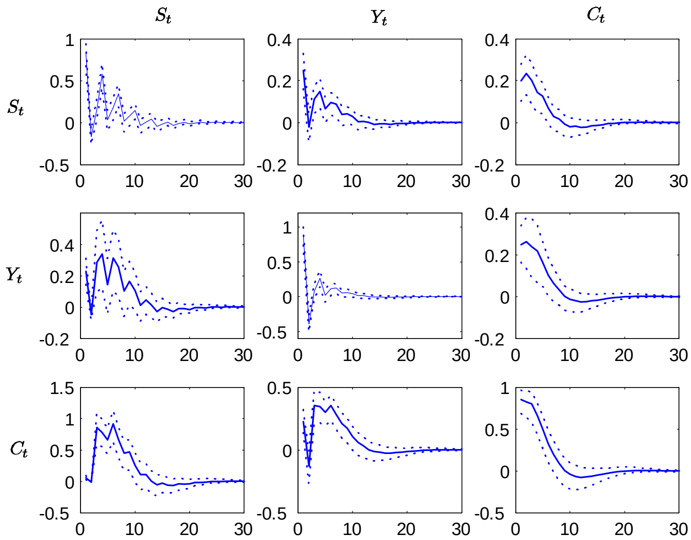

Figure 3: Impulse response functions.
Response of the variables listed in columns to one-standard deviation shocks to variables listed in the rows. Dotted lines are 95% confidence bands obtained from 1000 bootstrap replications. S_t denotes the Ifo business situation index, Y_t denotes German industrial production, and C_t denotes the OECD composite leading indicator for Germany. All variables are in log first differences. Sample includes monthly data from 1991-01 to 2008-03.

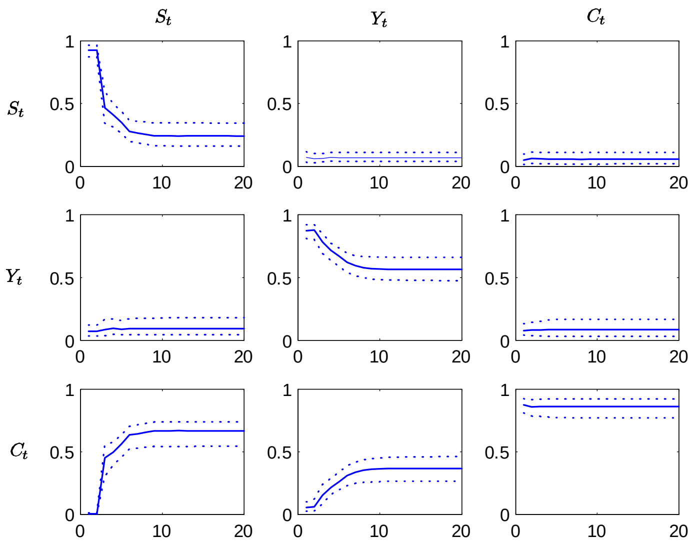

Figure 4: Forecast error variance decomposition.
Fraction of the forecast error variance of the variables listed in columns, explained by shocks to variables listed in the rows. Dotted lines are 95% confidence bands obtained from 1000 bootstrap replications. S_t denotes the Ifo business situation index, Y_t denotes German industrial production, and C_t denotes the OECD composite leading indicator for Germany. All variables are in log first differences. Sample includes monthly data from 1991-01 to 2008-03.

of the variables since the model is fully identified. Note that the forecast error variance of industrial production is explained almost exclusively by shocks to industrial production itself, and by shocks to the leading indicator. Therefore, while the impulse responses show that the influence of shocks to business sentiment on industrial production is significant for several periods, the forecast error decompositions show that these sentiment shocks are small on average and therefore can not contribute much to explaining the variance of economic activity. It is surprising that the contribution of industrial production shocks to the forecast error variance of business sentiment is fairly small. Over longer horizons the forecast error of business sentiment is mostly explained by past shocks to the OECD leading indicator, suggesting that firms use a variety of fundamental variables to form expectations.

5 Discussion

In this paper, we have used the Ifo business situation index to identify shocks to investors' expectations. This index captures firms' expectations, formed at the beginning of each month, about their business situation in that month. Thus our results shed light on the relationship between economic activity and firms' expectations about *current* business conditions.

While firms are likely to face some uncertainty about their current economic situation, clearly this uncertainty becomes much greater over longer horizons - with more scope to analyze the relevance of 'animal spirits' affecting economic outcomes. It would therefore be interesting to use data on expectations about economic activity - or business conditions - further in the future. For example, the Ifo research institute publishes a monthly business expectations index, compiled from the responses of German firms that are asked about their expectations concerning their individual business conditions over the next 6 months.

However the problem is that when analyzing a forward looking indicator which contains expectations about several future periods, the econometric analysis of the relationship between sentiment and economic activity becomes much more difficult. Again linking the business situation of individual firms to aggregate economic activity, and assuming that firms' expectations are akin to unbiased, but noisy signals about actual realizations - because firms have access to private information which cannot be controlled for by the econometrician -, today's business confidence then depends on (expectations about) economic activity over several future months. At the same time, business confidence may also influence output in the same periods, so that business confidence and economic activity at several lags cannot be treated as predetermined. Solving the endogeneity problems associated with indicators that reflect expectations of economic activity over several future periods, and at the same time possibly influence economic activity over the same time horizon, remains an interesting avenue for future research. The advantage of the business situation index used in this study is that it reflects expectations about the current period only, so that the econometric procedure is much cleaner.

The effect of business sentiment on economic activity in this paper was interpreted as reflecting the influence of firms' expectations on their hiring and investment decisions. These decisions determine the production and demand of individual firms, and hence affect aggregate economic activity. However, the release of statistics on business confidence itself could also have a direct effect on firms' production decisions, and hence economic activity. Firms are likely to invest when they expect other firms to do the same - namely, when they expect an economic boom; thus, investment decisions are based on firms' expectations about the expectations of other firms. Information that is widely reported, commented and observed is a useful indicator of aggregate expectations and is therefore likely to have an impact on firms' hiring and investment decisions. This would be a further advantage of using the Ifo business *climate* index, which is more widely reported in the press than the business *situation* index used in this paper.[12]

6 Conclusion

This paper studied the relationship between business sentiment and economic activity. Using monthly data on a well known index of German business sentiment compiled by the Ifo research institute, as well as industrial production in Germany as a measure of aggregate economic activity, we found that firms correctly anticipate economic activity; moreover, we found that firms' expectations about their current business situation have a positive and significant contemporaneous effect on industrial production. However, shocks to firms' expectations - 'animal spirits' on explain only a very small fraction of the variation of industrial production, suggesting that the quantitative importance of the effect of business sentiment (reflecting firms' expectations about current business conditions) on economic activity is limited.

The main contribution of this study was that, in contrast to some of the previous literature, our empirical analysis carefully accounted for the way in which firms form expectations. We specified a simple model where firms' expectations are aggregated into a publicly observed business confidence index. Since it is impossible for the econometrician to control for all information that firms might have, business sentiment indices are likely to be akin to noisy signals about business conditions, potentially leading to endogeneity problems. We avoided the resulting endogeneity bias by using a two-step procedure to estimate the empirical model. Employing a relatively novel identification method following Rigobon (2003), we were able to estimate the structural coefficients of the model without imposing the *ad-hoc* constraints typically imposed in the literature.

This paper produced interesting evidence supporting the intuitive notion that waves of optimism and pessimism may have an effect on economic activity, and made some progress towards an empirical strategy that accounts for the way in which measures of sentiment reflect survey participants' expectations about the future. One challenge in solving the endogeneity problems that arise when forecasts both reflect some variable (such as economic activity), and

[12]For example, Abberger (2006) finds that more vague questions concerning business situation and expectations of the Ifo business climate index produce better forecasts for economic activity in individual business branches than more concrete questions about current and expected production. Similarly, Lamla, Lein and Sturm (2007) find that expectations - as measured by the Ifo indicator - of firms in individual sectors are influenced more by information about the aggregate economy than by information about individual sectors.

If the survey results are observed by firms and affect their investment decisions, the role of higher-order expectations in investment decisions, and the importance of public information in such higher-order beliefs following the argument by Morris and Shin (2002) can explain these seemingly paradoxical empirical findings.

affect the subject of the forecast, is the time horizon. In this study we used an indicator which reflects firms' expectations about economic activity in the current period only. With forward-looking indicators the econometric analysis becomes a lot more difficult, as business confidence and economic activity at several lags cannot be treated as predetermined. Solving the endogeneity problems associated with indicators that reflect expectations about several future periods remains an interesting avenue for future research.

References

[1] Abberger, Klaus (2006), "Qualitative Business Surveys in Manufacturing and Industrial Production – What Can be Learned from Industry Branch Results?" *Ifo Working Paper* No. 31.

[2] Abberger, Klaus and Klaus Wohlrabe (2006), "Einige Prognoseeigenschaften des Ifo-Gechäftsklimas - Ein Überblick über die Neuere Wissenschaftliche Literatur," *Ifo Schnelldienst* 22, pp. 19-26.

[3] Barsky, Robert B. and Eric R. Sims (2006), "Information Shocks, Animal Spirits, and the Meaning of Innovations in Consumer Confidence," mimeo, University of Michigan.

[4] Batchelor, Roy and Pami Dua (1998), "Improving Macro-Economic Forecasts - The Role of Consumer Confidence," *International Journal of Forecasting* 14(1), pp. 71-81.

[5] Beaudry, Paul and Franck Portier (2004), "An Exploration into Pigou's Theory of Cycles," *Journal of Monetary Economics* 51(6), pp. 1183-1216.

[6] Beaudry, Paul and Franck Portier (2006), "Stock Prices, News, and Economic Fluctuations," *American Economic Review* 96(4), pp. 1293-1307.

[7] Beaudry, Paul and Franck Portier (2007), "When Can Changes in Expectations Cause Business Cycle Fluctuations in Neo-Classical Settings?" *Journal of Economic Theory* 135(1), pp. 458-477.

[8] Caporale, Guglielmo Maria, Andrea Cipollini and Panicos O. Demetriades (2005), "Monetary Policy and the Exchange Rate During the Asian Crisis: Identification through Heteroskedasticity," *Journal of International Money and Finance* 24(1), pp. 39-53.

[9] Carroll, Christopher D., Jeffrey C. Fuhrer and David C. Wilcox (1994), "Does Consumer Sentiment Forecast Household Spending? If So, Why?" *American Economic Review* 84(5), pp. 1397-1408.

[10] Chamley, Christophe and Douglas Gale (1994), "Information Revelation and Strategic Delay in a Model of Investment," *Econometrica* 62(5), pp. 1065-1085.

[11] Chauvet, Marcelle and Jang-Ting Guo (2003), "Sunspots, Animal Spirits, and Economic Fluctuations," *Macroeconomic Dynamics* 7(1), pp. 140-169.

[12] Choy, Keen Meng, Kenneth Long and Anthony S. Tay (2006), "Non-Fundamental Expectations and Economic Fluctuations: Evidence from Professional Forecasts," *Journal of Macroeconomics* 28(2), pp. 446-460.

[13] Claveria, Oscar, Ernest Pons and Raúl Ramos (2007), "Business and Consumer Expectations and Macroeconomic Forecasts," *International Journal of Forecasting* 23(1), pp. 47-69.

[14] Cooper, Russel and Andrew John (1988), "Coordinating Coordination Failures in Keynesian Models," *Quarterly Journal of Economics* 103(3), pp. 441-463.

[15] Den Haan, Wouter and Georg Kaltenbrunner (2007), "Anticipated Growth and Business Cycles in Matching Models," mimeo.

[16] Dohmen, Thomas, Armin Falk, David Huffman and Uwe Sunde (2006), "Seemingly Irrelevant Events Affect Economic Perceptions and Expectations: The FIFA World Cup 2006 as a Natural Experiment," *IZA Working Paper* No. 2275.

[17] Ehrmann, Michael, Marcel Fratzscher and Roberto Rigobon (2007), "Stocks, Bonds, Money Markets and Exchange Rates: Measuring International Financial Transmission," *NBER Working Paper* No. 11166.

[18] Eppright, David R., Nestor M. Arguea and William L. Huth (1998), "Aggregate Consumer Expectations Indexes as Indicators of Future Consumer Expenditures," *Journal of Economic Psychology* 19(2), pp. 215-235.

[19] Farmer, Roger E. A. and Jang-Ting Guo (1994), "Real Business Cycles and the Animal Spirits Hypothesis," *Journal of Economic Theory* 63(1), pp. 42-62.

[20] Gale, Douglas (1996), "Delay and Cycles," *Review of Economic Studies* 63(2), pp. 169-198.

[21] Jacobs, Jan P.E.M. and Jan-Egbert Sturm (2005), "Do Ifo Indicators Help Explain Revisions in German Industrial Production?" in: J.E. Sturm and T. Wollmershäuser (eds.), *Ifo Survey Data in Business Cycle and Monetary Policy Analysis*, Physica-Verlag, Heidelberg, pp. 93-114.

[22] Jaimovich, Nir and Sergio Rebelo (2006), "Can News about the Future Drive the Business cycles?" *NBER Working Paper* No. 12537.

[23] Keynes, John M. (1936), *The General Theory of Employment, Interest and Money.* London: Macmillan.

[24] Lamla, Michael J., Sarah M. Lein and Jan-Egbert Sturm (2007), "News and Sectoral Comovement," *KOF Working Paper* No. 183.

[25] Lee, Kevin and Kalvinder Shields (2000), "Expectations Formation and Business Cycle Fluctuations: an Empirical Analysis of Actual and Expected Output in UK Manufacturing, 1975-1996," *Oxford Bulletin of Economics and Statistics* 62(4), pp. 463-490.

[26] Lorenzoni, Guido (2008), "A Theory of Demand Shocks," mimeo, MIT.

[27] Matsusaka, John G. and Argia M. Sbordone (1995), "Consumer Confidence and Economic Fluctuations," *Economic Enquiry* 33(2), pp. 296-318.

[28] Morris, Stephen and Hyun Song Shin (2002), "The Social Value of Public Information," *American Economic Review* 92(5), pp.1521-1534.

[29] Oh, Seonghwan and Michael Waldman (1990), "The Macroeconomic Effects of False Announcements," *Quarterly Journal of Economics* 105(4), pp. 1017-1034.

[30] Oh, Seonghwan and Michael Waldman (2005), "The Index of Leading Economic Indicators as a Source of Expectational Shocks," *Eastern Economic Journal* 31(1), pp. 75-95.

[31] Pigou, Arthur (1926), *Industrial Fluctuations*, MacMillan, London.

[32] Potter, Simon (1999), "Fluctuations in Confidence and Asymmetric Business Cycles," *Federal Reserve Bank of New York Staff Report* No. 66.

[33] Rigobon, Roberto (2003), "Identification through Heteroskedasticity," *Review of Economics and Statistics* 85(4), pp. 777-792.11-523.

[34] Rigobon, Roberto and Brian Sack (2003), "Measuring the Response of Monetary Policy to the Stock Market," *Quarterly Journal of Economics* 118(2), pp. 639-669.

[35] Rigobon, Roberto and Brian Sack (2004), "The Impact of Monetary Policy on Asset Prices," *Journal of Monetary Economics* 51(8), pp.1553-2004.

[36] Salyer, Kevin D. and Steven M. Sheffrin (1998), "Spotting Sunspots: Some Evidence in Support of Models with Self-Fulfilling Prophesies," *Journal of Monetary Economics* 42(3), pp. 511-523.

[37] Schöler, Klaus (1994), "Business Climate as a Leading Indicator? An Empirical Investigation for West Germany from 1978 to 1990," *Empirical Economics* 19(1), pp. 165-169.

[38] Sentana, Enrique and Fiorentini, Gabriele (2001), "Identification, estimation and testing of conditional heteroskedastic factor models," *Journal of Econometrics* 102(2), pp. 143-164.

[39] Shleifer, Andrei (1986), "Implementation Cycles," *Journal of Political Economy* 94(6), pp. 1163-1190.

[40] Taylor, Karl and Robert McNabb (2007), "Business Cycles and the Role of Confidence: Evidence from Europe," *Oxford Bulletin of Economics and Statistics* 69(2), pp. 185-208.

[41] Veldkamp, Laura and Justin Wolfers (2007), "Aggregate Shocks or Aggregate Information? Costly Information and Business Cycle Comovement," *Journal of Monetary Economics* 54, Supplement 1, pp. 37-55.

[42] Woodford, Michael (2003), "Imperfect Common Knowledge and the Effects of Monetary Policy," in *Knowledge, Information and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps*, P. Aghion, R. Frydman, J. Stiglitz and M. Woodford (eds), Princeton University Press, pp. 25-58.

[43] Wright, Philip G. (1928), *The Tariff on Animal and Vegetable Oils*, New York: Macmillan.

Appendix: identification though heteroskedasticity

This appendix discusses in more detail how the coefficients capturing the contemporaneous feedback effects in equation (14) can be identified from the heteroskedasticity of the data. Denote the error terms of the reduced-from model in (15) by $\mathbf{u}_t$,

$$\mathbf{u}_t = \mathbf{A}^{-1}\boldsymbol{\varepsilon}_t \tag{17}$$

where $\boldsymbol{\varepsilon}_t \equiv \begin{bmatrix} \varepsilon_{S,t} & \varepsilon_{Y,t} & \varepsilon_{C,t} \end{bmatrix}'$. To see why the structural model in equation (14) is not identified, let $E\left(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'\right) \equiv \boldsymbol{\Omega}_\varepsilon$ and use (17) to compute the variance-covariance matrix of $\mathbf{u}_t$ as

$$\boldsymbol{\Omega}_u = \mathbf{A}^{-1}\boldsymbol{\Omega}_\varepsilon\mathbf{A}^{-1\prime}$$

Assume that the structural shocks are independent, so that $\boldsymbol{\Omega}_\varepsilon$ is diagonal. While $\boldsymbol{\Omega}_u$ is unknown, it can be proxied by the variance-covariance matrix of the residuals from the SUR estimation of the reduced-from model in (15). The model is not identified since from 6 equations (given by the unique elements in the 3x3 variance-covariance matrix $\boldsymbol{\Omega}_u$), 9 parameters need to be estimated: the 6 off-diagonal elements in $\mathbf{A}$, and the 3 diagonal elements in $\boldsymbol{\Omega}_\varepsilon$.

To identify the model we use 'identification through heteroskedasticity', an identification scheme made popular by Rigobon (2003). Assume that the structural error terms $\varepsilon_{S,t}$, $\varepsilon_{Y,t}$ and $\varepsilon_{C,t}$ are heteroskedastic. In particular, assume that it is possible to identify N volatility periods or 'regimes', where the variance and covariances of the errors are constant within each regime, but differ across regimes. Letting $\boldsymbol{\Omega}_{\varepsilon,s}$ and $\boldsymbol{\Omega}_{u,s}$ denote the covariance matrices of $\boldsymbol{\varepsilon}_t$ and $\mathbf{u}_t$ in regime s we can write

$$\mathbf{A}\boldsymbol{\Omega}_{u,s}\mathbf{A}' = \boldsymbol{\Omega}_{\varepsilon,s} \tag{18}$$

Suppose that we can identify $N = 4$ volatility regimes. Then equation (18) provides 24 moment conditions (for each volatility regime there are 6 unique elements in $\boldsymbol{\Omega}_{u,s}$), from which 18 parameters need to be estimated: the 6 off-diagonal elements in $\mathbf{A}$, and 12 shock variances (one per shock and per volatility regime): the model is now (over-)identified. Note that the crucial assumption for this identification procedure is that while the volatility of the structural shocks is allowed to change over time, the underlying structural relationships of the variables, captured by the coefficients in $\mathbf{A}$, are assumed to be constant. This ensures that as the number of volatility regimes N increases, the number of moment conditions increases by more than the number of unknown parameters.

What then remains is to identify the periods in which the volatilities of the underlying structural shocks change. Several studies using 'identification through heteroskedasticity' have used exogenous events to identify volatility regimes. Since no such natural regime choices are available in our case, we follow Ehrmann, Fratzscher and Rigobon (2005) in using a simple threshold rule to determine volatility regimes. Whenever the volatility of the residual corresponding to business sentiment (to take an example) in a given period - computed over moving windows of a fixed size - is above the chosen threshold, while the volatility of the other residuals is not, we

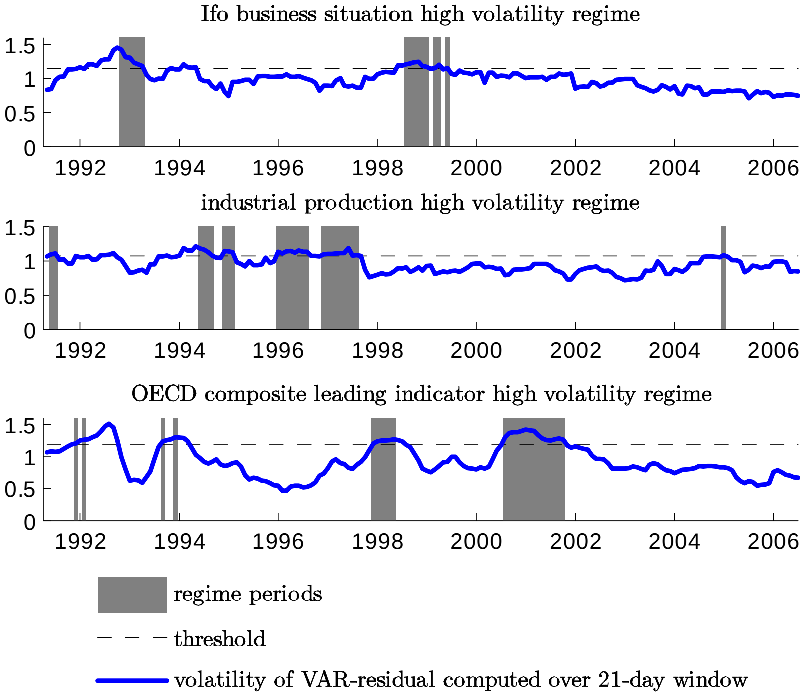

Figure 5: High volatility regimes with threshold rule

classify the structural shock to business sentiment in that period as being excessively volatile.[13] In this way, we identify periods in which the residuals, as proxies for the underlying structural shocks, are uniquely volatile, and periods when the volatility of all residuals is below the threshold. This gives 3 high volatility regimes and one 'tranquility' regime, which are sufficient to identify the model.

The distribution of high volatility regimes for our sample is reported in Figure 5. Although the changes in volatility are not as extreme as often observed with financial data, they are sufficient to provide identification. Moreover, most of the sample is characterized by increases in the volatility of one variable at a time, which helps to identify the source of the underlying shocks and hence the direction of causation.

[13] To be precise, we compute the volatility of the residual of variable j in period t, $\sigma^2_{j,t}$, over fixed windows of 21 days, centered around t. The threshold used is $E\left(\sigma^2_{j,t}\right) + c \cdot Var\left(\sigma^2_{j,t}\right)$ where we set $c = 1$. Decreasing the threshold level through decreasing c increases the number of observations that are classified as reflecting volatility states, but it also increases the number of periods where more than one variable is volatile.