The Early News Catches the Attention: On the Relative Price Impact of Similar Economic Indicators*

Dieter Hess and Alexandra Niessen

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*The authors are at the Corporate Finance Seminar and the Centre for Financial Research (CFR), University of Cologne, Albertus-Magnus Platz, D-50923 Cologne, Germany, Tel: +49 (0)221 470 7876, email: hess@wiso.uni-koeln.de and niessen@wiso.uni-koeln.de. We have benefited from comments by Louis Ederington, Felix Huefner, Mahendrarajah (Nimal) Nimalendran, Lars Norden, Stefan Ruenzi, participants at the FMA European Conference 2007, participants at the Annual Meeting of the German Academic Association for Business Research (VHB) and seminar participants at the University of Cologne. All errors are our own.

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Abstract

There is strong evidence that macroeconomic releases influence prices in financial markets. However, why do markets react to some announcements while they ignore others with a similar content? Based on a Bayesian learning model, we show that market impact is mainly determined by information quality and timeliness of a release. To test the model's implications, we analyze the successive introduction of the two largest German business surveys: the well-known IFO index and the recently introduced ZEW economic indicator. In line with the model's prediction, we find a diminishing market impact of the IFO index after the ZEW indicator was introduced.

1 Introduction

In recent years the information demand of financial markets has stimulated the creation of several new economic indicators. However, only a few of them have actually gained widespread attention. Stock and Watson (1999) examine 168 economic indicators to forecast inflation, but financial markets only react to a small fraction of them (see, e.g., Ederington and Lee (1993), Fleming and Remolona (1999) and Balduzzi, Elton, and Green (2001)). The large number of economic indicators is therefore puzzling, especially since many of them provide information that is already available to the market. This paper analyzes the properties an economic indicator needs to gain market impact if a similar indicator already exists. We provide both theoretical and empirical evidence that timeliness and information quality are the two main determinants of an economic indicator to obtain market participants' attention, and thus, to gain market impact.

Proposing a sequential Bayesian learning model, we first analyze how the information provided by two similar economic indicators is processed at financial markets from a theoretical point of view. The model shows that the magnitude of the market reaction to the release of an economic indicator depends primarily on two factors. First, its market impact is directly related to the quality of the released information, in particular, to the extent to which this information allows to obtain more precise estimates of the underlying information subject. Second, the market impact of an economic indicator is stronger the earlier it is released, i.e., the earlier market participants can update their expectations of economic conditions. This disadvantage of a late release results primarily from the fact that market participants have more precise prior expectations due to similar information they already have obtained from earlier released economic indicators. Overall, the model suggests that an economic indicator that is released more timely and provides more or equally precise information should have a stronger market impact than an otherwise comparable indicator.

A unique opportunity to test the model implications empirically provides the analysis of the two largest German business surveys, i.e. the IFO business climate indicator and the ZEW economic indicator: First, both indicators contain similar information. They are based on surveys among market participants about their expectation regarding economic conditions within the next six months.[1] Thus, they have a similar information content, i.e. both provide information about future economic conditions, but might differ in terms of information quality. Second, the indicators were introduced to the market one after another. The IFO business climate index published by the Institute for Economic Research was introduced for West Germany in 1969 whereas the ZEW economic indicator, published by the Centre for European Economic Research, was introduced in 1991. Both indicators are published monthly but the ZEW indicator is released one to two weeks before the IFO indicator. This structural break in information flows offers an opportunity to test the implications of our model empirically: Before 1991 market participants could only use survey information provided by IFO to update their expectations regarding real economic conditions. With the release of the ZEW indicator in 1991, a second information source emerged that allows an earlier update of economic expectations as compared to the IFO indicator. We take this structural break as a natural experiment to test the influence of timeliness and information quality on the market impact of two similar economic indicators.

In the first step, we investigate whether the information quality of both indicators is indeed comparable. As a benchmark to measure their information quality, we follow Huefner and Schroeder (2002) and relate both indicators to the growth rate of industrial production. We evaluate the information quality of the indicators in terms of predictability of industrial production and conduct out-of-sample forecasts obtained from different forecasting models. We find that both indicators have a similar information quality, i.e. both indicators are useful to forecast industrial production. A difference in market impact should therefore be driven by timeliness.

[1] Since the IFO indicator also provides information about the current economic situation, we use its subindex "IFO expectations" to compare it with the ZEW index.

In the second step, we investigate the market impact of both indicators. According to our sequential Bayesian learning model the ZEW indicator should have a stronger market impact since it is released earlier than the IFO indicator. Analyzing the price impact of both economic indicators on the German bund futures market supports the model's predictions. We observe a significant price reaction to the release of both indicators within the first release minute. However, the price reaction is significantly stronger for the ZEW indicator than for the IFO indicator. To gain further insight if the difference in timeliness accounts for this result, we investigate how the price impact of the IFO indicator changes after the ZEW indicator was introduced to the market. If timeliness is the reason for the different market impact, the introduction of the ZEW indicator should lead to a decreasing price impact of the IFO indicator. Indeed, we find that the price impact of IFO was stronger before the ZEW indicator was introduced to the market and decreased significantly after the introduction of ZEW.[2]

Overall, the empirical results strongly support the implications of our sequential Bayesian learning model: timeliness and information quality are the main determinants of an economic indicator's market impact. In particular, the relative price impact of the two largest German business surveys shows that even a large and well-established economic indicator like the IFO indicator can loose part of its impact, if a similar indicator is introduced to the market and released earlier. These results provide important implications for statistical agencies. If a new economic indicator is developed, these agencies face the problem of a trade-off between information quality and release time: a higher information quality requires more (precise) information to be included in the indicator while an early release time usually forces the agency to issue less precise information. We show that it is harder to achieve a superior information quality than to simply choose an early release time. Thus, it might be easier to follow a publication strategy that ensures that the indicator is released as timely as possible from a statistical agency's point of view.

[2] If the price reaction after the release of IFO was still equal or stronger, IFO would contain more or different information even after ZEW has published part of it.

Our paper contributes to the literature on the dynamics of information processing at financial markets (see, e.g., Ederington and Lee (1993), Fleming and Remolona (1999), and Boyd, Hu, and Jagannathan (2005)) by investigating the determinants of the relative price impact of two similar economic indicators theoretically and empirically. We also contribute to the literature testing the implications of Bayesian learning (see, e.g., Krueger and Fortson (2003) and Hautsch and Hess (2007)) and provide empirical evidence that Bayesian updating best describes information processing at the German bund futures market. Overall, the results allow for a better understanding how fundamental economic information is incorporated into asset prices.

The paper proceeds as follows. In Section 2 we derive the determinants of an economic indicator's market impact from a sequential Bayesian learning model. Section 3 provides a description of our data and the model implementation. The impact of a timely release on the market impact of the two German business surveys is analyzed in Section 4. Section 5 concludes.

2 Determinants of Market Impact - Conclusions from a Sequential Bayesian Learning Model

We first derive the determinants of the relative attention market participants pay to two similar economic indicators. Typically, data on market participants' attention are not available. However, from a Bayesian learning perspective market participants' attention is directly related to the shift in their mean expectations after some information is released. This shift in expectations is reflected by the strength of price adjustments at financial markets. Thus, a reasonable proxy variable for the attention that market participants pay to the release of an economic indicator is the market impact of this indicator. We propose a Bayesian updating framework to analyze how two sequentially released economic indicators with similar information content affect asset prices at financial markets. In particular, we investigate what determines the relative strength of the price impact of these indicators.

In financial markets research a wide variety of Bayesian learning models has been applied (see, e.g., Holthausen and Verrecchia (1988), Kim and Verrecchia (1991), Blume, Easley, and O'Hara (1994), Veronesi (2000)). In the following we extend the Bayesian learning model of Hautsch and Hess (2007) for the case of sequential information arrival. In line with standard Bayesian learning models our sequential model produces two fundamental results: first, the price reaction is driven by the amount of unanticipated information. Second, the precision of the released information acts as a catalyst in determining the strength of this price reaction. Moreover, our sequential model allows us to analyze the relative strength of the price reactions to two successively announced economic indicators.

Assume that two announcements regarding some economic variable X (e.g., some survey estimates of the 'true' economic conditions) are made at time $t = 1$ and $t = 2$. Furthermore, assume that market participants form homogeneous and normally distributed expectations with respect to X before the outcome of the first announcement at $t = 1$. Let μ_{F1} denote the mean expectation and ρ_{F1} its precision (i.e., the inverse of the variance).[3]

At time $t = 1$ the first announcement, A_1, is made, i.e., a noisy estimate of X (e.g., derived from a survey among experts) with an additive, zero mean normally and distributed error ε_{A1} that is independent of X. Let $\mu_{A1} = X + \epsilon_{A1}$ denote this announced estimate and ρ_{A1} the corresponding precision.[4]

After this first release market participants update their expectations regarding X, with mean posterior belief μ_{P1} (i.e. the updated belief)

$$\mu_{P1} = \mu_{F1}\frac{\rho_{F1}}{\rho_{F1}+\rho_{A1}} + \mu_{A1}\frac{\rho_{A1}}{\rho_{F1}+\rho_{A1}} \tag{1}$$

and precision ρ_{P1} of this posterior

$$\rho_{P1} = \rho_{F1} + \rho_{A1} \tag{2}$$

[3]To be precise, we assume that prior expectations are normally distributed, i.e. $N(\mu_{F1}, 1/\rho_{F1})$, and that they contain all relevant public information available before the release of the first announcement.

[4]Hence we assume that $\mu_A = X + \varepsilon_{A1}$ with $Var[\varepsilon_{A1}] = 1/\rho_{A1}$ and $E[X \cdot \varepsilon] = 0$. Then, the conditional probability density function of μ_{A1} given X is $f(\mu_{A1}|X)$, is $N(X, 1/\rho_{A1})$.

It is important to note that the announcement influences both market participants' mean beliefs and the precision of their beliefs,

$$\mu_{P1} - \mu_{F1} = (\mu_{A1} - \mu_{F1})\frac{\rho_{A1}}{\rho_{F1} + \rho_{A1}} \tag{3}$$

$$\rho_{P1} - \rho_{F1} = \rho_{A1}, \tag{4}$$

as long as the announcement is not perceived to be completely uninformative (or noisy), i.e. as long as $\rho_{A1} > 0$. In particular, the implication for the precision of market participants expectations is important. Even if the information in the announcement is completely anticipated (i.e. if there is no surprise at all, $\mu_{A1} - \mu_{F1} = 0$), the announcement would nevertheless change market participants expectations by enhancing the precision of their beliefs (i.e., $\rho_{P1} > \rho_{F1}$) given that the released information is not completely noisy.

Now, prior to the second announcement at $t = 2$, market participants again form expectations about its outcome. Correspondingly, let μ_{F2} and ρ_{F2} denote the mean expectation and the precision as well as μ_{A2} and ρ_{A2} the announced second estimate and its precision. We assume that this second announcement provides another noisy estimate of X, i.e., $\mu_{A2} = X + \varepsilon_{A2}$ where ε_{A2} is another mean zero normally distributed disturbance that is independent of both X and ε_{A1}.

Again, after this second release market participants update their expectations. Correspondingly to the updating after the first announcement, we get

$$\mu_{P2} - \mu_{F2} = (\mu_{A2} - \mu_{F2})\frac{\rho_{A2}}{\rho_{F2} + \rho_{A2}} \tag{5}$$

and

$$\rho_{P2} - \rho_{F2} = \rho_{A2}, \tag{6}$$

Note that we abstract from information asymmetries and assume that all market participants receive the announced information at the same time. In addition, we suppose that the precision parameters of the model are all known.[5]

For simplicity assume now that no other (relevant) information arrives besides the two announcements. In this case, the prior beliefs regarding the outcome of the second announcement are equal to the posterior beliefs after the first release, i.e. $\mu_{F2} = \mu_{P1}$ with $\rho_{F2} = \rho_{P1}$, and we may rewrite (5) as

$$\mu_{P2} - \mu_{F2} = \mu_{P2} - \mu_{P1} = (\mu_{A2} - \mu_{P1}) \frac{\rho_{A2}}{\rho_{P1} + \rho_{A2}} \tag{7}$$

Furthermore, under the standard assumption of a linear relation between asset prices P and traders expectations with respect to X, e.g.,[6]

$$P = \begin{cases} \nu \cdot \mu_{F1} & \text{before the first announcement} \\ \nu \cdot \mu_{P1} = \mu_{F2} & \text{after the first announcement} \\ \nu \cdot \mu_{P2} & \text{after the second announcement} \end{cases}$$

one obtains a linear relation between the price changes and changes in market participants expectations, i.e.,

$$\Delta P_t = \nu \cdot \pi_t \cdot S_t, \tag{8}$$

with $S_t = \mu_{A1} - \mu_{F1}$ and $\pi_t = \rho_{A1}/\rho_{P1}$ for $t = 1$ and $S_t = \mu_{A2} - \mu_{F2}$ and $\pi_t = \rho_{A2}/\rho_{P2}$ for $t = 2$. From the preceding analysis it can be seen that (under the standard assumptions) the usual results of Bayesian learning models hold, (1) price changes are proportional to the unanticipated information component in an announcement, i.e., the surprise S_t at time t, and (2) the strength of this price reaction is determined by the relative precisions of the released data and posterior beliefs (i.e., the aggregated precision of forecasts and data). In addition, this analysis yields a first answer to our initial question, i.e., whether

[5] Bayesian Learning under unknown precision is analyzed, for example, by Hautsch, Hess, and Mueller (2007).

[6] See, e.g., Kim and Verrecchia (1991) and Kandel and Pearson (1995). In these models traders even receive direct signals of the asset's fair value and, thus, $\nu = 1$.

the strength of the price reaction to the sequentially made announcements differs. From Equations (3), (7), and (8) it follows that

$$\Delta P_t = \begin{cases} \nu \cdot (\mu_{A1} - \mu_{F1}) \cdot \frac{\rho_{A1}}{\rho_{P1}} & \text{after the first announcement} \\ \nu \cdot (\mu_{A2} - \mu_{P1}) \cdot \frac{\rho_{A2}}{\rho_{P1}+\rho_{A2}} & \text{after the second announcement} \end{cases}$$

To obtain a straightforward interpretation of this result consider the special case that both economic indicators are equally informative, i.e., $\rho_{A1} = \rho_{A2}$, and that they both release exactly the same (although independent) estimate $\mu_{A1} = \mu_{A2} \neq \mu_{F1}$. This case can arise if two competing agencies publish an economic indicator with a comparable information content (but derived from independently taken surveys). In this case

$$\Delta P_1 = \nu \cdot (\mu_{A1} - \mu_{F1}) \cdot \frac{\rho_{A1}}{\rho_{P1}}$$

while

$$\Delta P_2 = \nu \cdot (\mu_{A1} - \mu_{P1}) \cdot \frac{\rho_{A1}}{\rho_{P1} + \rho_{A1}} = \nu \cdot \left((\mu_{A1} - \mu_{F1}) \cdot \frac{\rho_{F1}}{\rho_{F1} + \rho_{A1}} \right) \cdot \frac{\rho_{A1}}{\rho_{P1} + \rho_{A1}}$$

Overall, from the above analysis it follows that the price impact of the second announcement is lower due to two effects: Firstly, the surprise component of the second announcement is smaller, i.e.,

$$(\mu_{A2} - \mu_{F2}) = (\mu_{A1} - \mu_{P1}) = (\mu_{A1} - \mu_{F1}) \cdot \frac{\rho_{F1}}{\rho_{F1} + \rho_{A1}} < (\mu_{A1} - \mu_{F1}),$$

since market participants have adjusted their mean expectations after the first announcement. Secondly, the relative precision of the second announcement is lower, i.e.,

$$\frac{\rho_{A2}}{\rho_{P2}} = \frac{\rho_{A1}}{\rho_{P1} + \rho_{A1}} < \frac{\rho_{A1}}{\rho_{P1}},$$

since market participants' beliefs have become more precise due to the information provided by the first announcement. [7]

[7]Consider a simple numerical example: Let $\mu_{F1} = 100$ while $\mu_{A1} = \mu_{A2} = 115$ and $\rho_{F1} = 0.1$ in contrast to $\rho_{A1} = \rho_{A2} = 0.2$. Moreover, assume $\nu = 1$. Given these figures we would observe a price change of 10 from 100 ($= \mu_{F1}$) to 110 ($= \mu_{P1} = \mu_{F2}$) as a reaction to the release of the first economic indicator, but only a price change of 2 after the release of the second economic indicator. However, also the

If the releasing agency aims to attract more attention, or equivalently, increase the market impact of the second economic indicator, it could try to enhance the information precision. However, in order to obtain the same market impact (per unit of surprising information) as the first announcement, i.e.,

$$\frac{\rho_{A1}}{\rho_{P1}} = \frac{\rho_{A2}}{\rho_{P1} + \rho_{A2}} \quad \text{or} \quad \rho_{A2} = \rho_{A1}\left(1 + \frac{\rho_{A1}}{\rho_{F1}}\right),$$

the precision of the second announcement would need to be increased by the factor $(1 + \rho_{A1}/\rho_{F1})$. This may be hard to achieve in practice.[8]

This suggests a clear-cut "first mover advantage": the first release receives more attention because it has a stronger impact on market participants' expectations: Therefore it has a stronger price impact, given a similar content and precision of the released information. The disadvantage of the second economic indicator results primarily from the fact that it is confronted with more precise prior expectations. It is rather difficult to compensate for this disadvantage by increasing the precision of the second economic indicator.[9]

For the subsequent empirical analysis, the model yields the following testable implications:

H1: Relative price impact in a static framework

Consider the case of two existing economic indicators with a comparable information content. Then, the influence of the later announced indicator should be smaller the more valuable information is provided by the first indicator.

Given approximately equal precisions of two sequentially announced indicators with

surprise components in the announcement are different although both release the same figure (115). While the surprise component in the first announcement is 15, the surprising information reduces to 5 for the second announcement since traders have already adjusted their expectations. In addition, the surprising information component in the second announcement receives a lower weight (i.e., $\pi_2 = 2/5$ in contrast to $\pi_1 = 2/3$), since the precision of market participants expectations increases after the first economic indicator is released (from $\rho_{F1} = 0.1$ to $\rho_{F2} = \rho_{P1} = 0.3$) due to the additional information provided by this economic indicator.

[8]In the previously given numerical example the precision of the second announcement c.p. would need to be tripled (from 0.2 to 0.6) in order to obtain the same market impact as the first announcement.

[9]Although there is certainly a trade-off between timeliness of the release and its precision, such a substantial increase in the precision is hard to achieve in practice.

a comparable information content, we should observe that the strength of the price impact of the later announced indicator is significantly lower.

H2: Relative price impact in a dynamic framework

Consider the case that at some point in time a new economic indicator is introduced which has a comparable information content as an already existing indicator and assume that this newly introduced indicator is released earlier than the previously existing indicator.

In this case we would expect a significant decrease in market participants' attention to the 'older' indicator and thus a significant decrease in its price impact, primarily due to the fact that the older indicator is confronted with more precise prior expectations.

H3: Change of analyst forecast dispersion

The introduction of a second (and earlier released) indicator should also affect market participants prior expectations before the release of the older indicator. If the new indicator provides valuable information (i.e., $\rho_{A1} > 0$), its introduction should increase the precision of market participants' prior beliefs with respect to the later announcement (i.e., ρ_{F2}).

Hence, after the introduction of the new indicator, the precision of observable analysts' forecasts (as a proxy for market participants prior expectations) for the later announced indicator should be higher as compared to the period before.

3 Data and Implementation of the Model

3.1 Information Components of the ZEW and IFO Indicator

Our analysis is based on the two largest German business surveys, i.e. the ZEW and IFO indicators, that were introduced to the market one after another. Both indicators have a similar information content, i.e. they capture market participants expectations with respect to future economic conditions.

The ZEW economic indicator is a monthly survey conducted among 350 financial analysts including experts from banks, insurance companies and investment companies. Participants are asked about their six-months expectations concerning the economy. Furthermore, they are asked to evaluate the development of 13 different German industries. They only have to give qualitative estimations regarding the expected development, i.e. they evaluate if conditions will improve (+), deteriorate (-) or remain unchanged (=) in the following 6 month. The indicator reflects the difference between positive and negative expectations.[10]

The IFO business climate indicator is based on a survey of approximately 7000 industrial companies in manufacturing, construction, wholesaling and retailing. The future conditions are labeled as better (+), poor (-) or unchanged (=). In addition to their expectations regarding economic conditions in 6 months, participants are asked for an assessment of the current economic situation.[11] The balanced value of the indicator reflects the difference between positive and negative expectations. The IFO index includes both information components, current conditions and expectations, as a geometric average. Besides the overall index, the individual components are published as well. Until 2004, the index was published exclusively for West-Germany. Then, the index was extended to cover the reunited German country.

Overall, the two indicators used in our analysis seem to be very similar with respect to their information content. To further illustrate the properties of both indicators, we calculate summary statistics in Table 1.

— Please insert TABLE 1 approximately here —

[10]Specifically, the indicator is calculated as the difference of participants who believe in an improvement of economic conditions and those who believe in a deterioration. If 70% of all participants forecast an improvement of economic conditions, 20% think that there will be no change at all and 10% believe that economic conditions will deteriorate, the value of the indicator would be 60.

[11]The current situation can be labeled as "good", "satisfactory" or "poor". Answers are weighted due to the relative importance of an industry.

The minimum and maximum values indicate that the ZEW indicator has a stronger variation as compared to the IFO indicator. Since the IFO indicator is calculated with respect to the base year 2000, its standard deviation is lower as compared to the ZEW indicator. The large differences in the means and standard deviations of the indicators point out the need to rescale both indicators in order to make them comparable for further analysis. Our sample begins in 1991 and ends in 2005. All numbers used in our study are as initially announced at the day of the news release, i.e. we use unrevised time series of all indicators.

3.2 Rescaling of Indicators to achieve Comparability

Since the ZEW indicator is a balanced indicator, we also use the balanced values of the IFO indicator to achieve comparability. We transform the index values of IFO to balanced values based on the following equation provided by the IFO institute:

$$BAL_{i,t}^{IFO} = \frac{IDX_{i,t}^{IFO}}{100} \cdot (MeanBAL_{baseyear}^{IFO} + 200) - 200 \tag{9}$$

$BAL_{i,t}^{IFO}$ denotes the balanced value of the IFO indicator and $IDX_{i,t}^{IFO}$ denotes the corresponding index value. As a proxy for the market's expectation concerning the development of the two indicators we use data from Money Market Services, (MMS, now Informa Global Markets) obtained from the Bureau of Labor Statistics.[12] These forecasts are available from 1996 on for the IFO indicator and from 2001 on for the ZEW indicator. Since forecasts for the IFO indicator refer to index values, we also transform them to balanced values based on (9). We then compute the surprise component of announcement i in month t, $S_{i,t}$, as the difference between the released value of the indicator, $A_{i,t}$, and the forecasted value of this announcement, $F_{i,t}$:

$$S_{i,t} = A_{i,t} - F_{i,t} \tag{10}$$

[12] Each Friday, MMS polls analysts' forecasts of several economic indicators to be released in the following week. Survey responses are received over a 3 to 4-hour period every Friday morning via fax or phone.

Transforming IFO data according to (9) guarantees that surprise components in both indicators are measured on the same scale. Summary statistics for the surprise components used in our analysis are given in Table 2.

— Please insert TABLE 2 approximately here —

Summary statistics of the surprise components show that the transformed values of both indicators are directly comparable for further analysis. Note that this transformation is superior to the usual standardization, i.e. dividing surprises by their standard deviation or by the standard deviation of announcements, since comparability is achieved without deleting dispersion information.[13]

3.3 Benchmark to measure Information Quality of both Indicators

In order to measure the information quality of the ZEW and the IFO indicator we need to define a benchmark, i.e. a forecast target against which we can benchmark the information provided by the indicators. Survey based economic indicators are often interpreted as leading indicators or proxies for changes in real economic activity. Bram and Ludvigson (1998) find that improvements in US consumer sentiment are positively related to an increase in the consumption growth rate. This finding is also supported for European data by Nahuis (2000). Golinello and Parigi (2003) find that consumer confidence across various countries is useful to forecast GDP. Huefner and Schroeder (2002) find that the ZEW and IFO indicators are useful to predict the year-over-year growth rate of German industrial production. Therefore, we follow Huefner and Schroeder (2002) and benchmark both indicators against the growth rate of industrial production.[14]

[13] Nevertheless, we calculate surprises with index values of the IFO indicator and standardize surprises by the standard deviation of the corresponding announcement. Results (not reported) remain similar. All results not reported in this paper can be obtained from the authors upon request.

[14] Alternatively, the gross domestic product (GDP) could be used as a benchmark. However, GDP information is provided only on a quarterly basis while industrial production is released monthly, i.e. with the same frequency as our economic indicators.

The year-over-year growth rate of German industrial production is published with a delay of two months within the monthly reports of the German Centralbank, i.e. the figure for January is published in March. We hand-collected two time series out of these reports to get the initially announced (unrevised) figures for West-Germany and for the whole country (labeled as Pan-Germany). In addition to data for Pan-Germany, we use data for West-Germany because the IFO indicator was published for West-Germany up to 2004. Thus, the correct reference series for this indicator would be the industrial production of West-Germany during this time.[15]

Figure 1 illustrates how the economic indicators develop during our sample period.[16]

— Please insert FIGURE 1 approximately here —

The ZEW and IFO indicator exhibit a contemporaneous development over time and seem to reflect business cycle movements. For example, both indicators increased strongly during the last economic expansion of 1999 and decreased significantly in the following recession. Thus, the indicators seem to contain similar information. However, the IFO indicator contains two components, the current economic situation as well as expectations about future economic conditions. In contrast, ZEW is exclusively based on expectations about future economic conditions and has no component on current conditions. To ensure a fair comparison of both indicators, we include the subindicator "IFO-expectations" in our further analysis. To investigate how the indicators are correlated with their reference series of industrial production, we calculate the cross-correlations for six lags of both indicators with the year-over-year growth rate of industrial production Pan and West Germany in Table 3.

— Please insert TABLE 3 approximately here —

[15]Results (not reported) remain stable if we use the Pan-German series as a benchmark for both indicators.

[16]To make the indicators comparable, the values are normalized by subtracting the mean and dividing by their standard deviation.

We find that the ZEW- and IFO indicators are positively correlated with the year-over-year growth rate of industrial production Pan and West Germany in t=0. Overall, surveys of financial analysts and industrial companies regarding real economic changes provide similar results, i.e. real economic conditions are perceived similarly by both survey groups. The cross-correlations support the view that a fair comparison of both indicators requires to extract the expectations component of the IFO indicator. The IFO indicator is correlated more contemporaneously with industrial production, whereas ZEW is correlated on higher lead-levels. Since IFO also contains information about the current economic situation, this finding is not very surprising. We therefore compare the cross-correlations between the subindex "IFO expectations" and industrial production to correlation between the ZEW indicator and industrial production. Here we can also see that ZEW is still leading industrial production on the sixth lag whereas the IFO expectations series has its highest correlation at the third (IP West) to the fourth (IP Pan) lag.

To investigate the leading properties of both indicators with respect to industrial production, granger causality tests are conducted as well. The results (given in the Appendix) are in line with earlier findings of Huefner and Schroeder (2002) who also report that both indicators improve forecasts of industrial production with the ZEW indicator being significant on higher lead orders.[17] However, even if the ZEW indicator has a higher leading order over industrial production, this does not necessarily mean that it contains more information. A more meaningful criterion is the out-of-sample forecast quality of both indicators which will be conducted in the following section.

3.4 Evaluation of Information Quality

One reason for the existence of only a few model tests of Bayesian updating is the problem to measure information precision indicated by the parameter ρ in our model. We argue that

[17] We also examine if industrial production provides additional explanatory power for both economic indicators and regress each indicator on its optimal number of autoregressive lags and different numbers of lags of industrial production. The results (not reported) show no clear pattern and are insignificant.

the information disclosed by the ZEW and IFO indicator is equally precise. To investigate if this is indeed the case, we assume that the indicators' information quality is determined by their usefulness in forecasting future economic conditions. Hence, we analyze their forecast performance conducting rolling window estimations of different time series models to forecast industrial production with and without including the indicators' information.[18] We use a rolling window of eight years.[19] The basic equation used to forecast industrial production reads:

$$IP_t^{Pan,West} = \alpha + \sum_i AR(i) + MA(1) + Trend + \sum_j SIN_j + \sum_j COS_j + \epsilon \qquad (11)$$

We estimate different AR(MA) models varying from AR(1) up to AR(12) and successively add a moving average component, $MA(1)$, seasonal polynoms (i.e. flexible Fourier transforms of order j=1...5 with $SIN_j = SIN(j \cdot \bar{m} \cdot 2\Pi)$ and $COS_j = COS(j \cdot \bar{m} \cdot 2\Pi)$ and $Trend$ defined as the normalized elapsed time within our estimation window). Furthermore, we estimate the models with and without accounting for GARCH effects and seasonal volatility effects.

We then re-estimate every model specification and successively include the IFO-expectations series or the ZEW indicator from 1 up to 8 lags. Overall, we estimate 540 different equations. In the next step, we conduct out-of-sample forecasts for every model and evaluate the forecasting quality based on the root mean squared forecast error (RMSFE). Results are given in Table 5.

— Please insert TABLE 5 approximately here —

The following conclusions emerge from this comprehensive forecasting exercise: Most importantly, the forecasting quality evaluated on the basis of the root mean squared forecast

[18] We employ the Pan-German as well as the West-German series for both indicators. However, our results do not depend on one of these series.

[19] This is a compromise between maximizing the number of out-of-sample estimates and the in-sample estimation window. Alternatively, we use a rolling window of five years. Results (not reported) remain similar.

error (RMSFE) increases if the ZEW or IFO-expectation indicator is included into the regression equation. Forecast errors based on the autoregressive models in column 1 and 4 are larger as compared to forecasts errors after the inclusion of the ZEW (IFO) indicator in columns 2 (3) and 5 (6). Thus, the inclusion of both indicators improves forecasts of industrial production. Furthermore, the improvement of forecasts does not differ largely between the indicators. While the inclusion of the ZEW indicator decreases the RMSFE from 2.8 to 2.76, the inclusion of the IFO-expectations series decreases it to 2.78. Overall, our analysis suggests that the information quality of the ZEW indicator is comparable to the IFO indicator. At least we do not find significant differences with respect to their out-of-sample forecast performance.

According to Bayesian Learning, indicators with a similar information quality should have a comparable market impact if the indicators were released at the same time. However, the ZEW indicator is released about two weeks before the IFO indicator. Summary statistics of the release dates of the ZEW indicator and the IFO indicator are given in Table 4.

— Please insert TABLE 4 approximately here —

Table 4 shows that the ZEW indicator is always released before the IFO indicator: While the ZEW indicator is usually published in the first half of the month (with a minimum of the seventh calendar day), the IFO indicator is published in the second half of the month (with a minimum of the sixteenth calendar). The minimum time lag of the IFO indicator is one day, the maximum time lag is 16 days. Hence during our sample period, the ZEW indiator is always released earlier than the IFO indicator. Thus, according to the sequential Bayesian learning model, the ZEW indicator has a publication advantage over the IFO indicator since it is released earlier and provides information of a similar quality. The question whether this publication advantage leads to a stronger market impact of the ZEW indicator is investigated in the following section.

4 Empirical Results: Determinants of the relative Market Impact

To analyze the market impact of both indicators, we use high frequency data of one of the most actively traded government bond markets, i.e. the German bund futures market. We calculate log returns (multiplied by 10,000) for 1 minute intervals within an event window starting 30 minutes before the release of an indicator and ending 60 minutes after the release.

According to the efficient market hypothesis, market reactions to macroeconomic announcements should only be observable if the announcement contains unanticipated news. To separate the effect of unanticipated news on bund future prices from the already expected part of the announcement, we calculate the difference of the released economic indicator and its expected value proxied by MMS analysts' forecasts as described in (10). Analyst coverage of IFO begins in 1996, whereas the ZEW indicator is covered since 2001. It seems reasonable to assume that the emergence of analysts' forecasts is a sign for an increased awareness of market participants to these indicators. Therefore, we restrict our sample for IFO to the period 1996-2005 and for ZEW to the period 2001-2005.

We employ the following equation to estimate how bund future prices react to unanticipated news of both indicators, we estimate the following equation:

$$\Delta P_{\tau,t} = \alpha + \sum_{m} \beta_m \cdot S_{i,t} \cdot D_m + \epsilon_{\tau,t} \tag{12}$$

On announcement day t we relate the price change, $\Delta P_{\tau,t}$, within one minute intervals in our event window from $\tau = -30... + 60$ to the surprise component of announcement i, $S_{i,t}$, multiplied by a dummy variable D_m with $m = 1...5$ for the first five minute intervals after the release. To account for differences in market volatility after the release of both indicators we also estimate the following Garch(1,1) model:

$$
\begin{aligned}
\Delta P_{\tau,t} &= c + \beta \cdot \Delta P_{\tau-1,t} + \sum_m \delta_m S_{i,t} \cdot D_m + \epsilon_{\tau,t} \\
\epsilon_{\tau,t} &= \mu_{\tau,t} \sigma_{\tau,t} \\
\sigma^2_{\tau,t} &= \omega + \alpha \epsilon^2_{\tau-1} + \sum \gamma_j D_j
\end{aligned} \tag{13}
$$

The mean equation contains dummy variables for the first five minutes after the release ($m = 1...5$), interacted with the surprise component of the announcement, $S_{i,t} \cdot D_m$. The variance equation is first estimated without dummy variables (model 1) and then reestimated with dummy variables (model 2) to allow for differences in volatility in the first five minutes, D_{1-5}, in contrast to the following five minutes, D_{6-10} and the next five minutes, D_{11-15}, after the release. Results are reported in Table 6:

— Please insert TABLE 6 approximately here —

The estimated coefficients given in Panel A show a significant price reaction at the German bund futures market to the release of the IFO and ZEW indicator: coefficients of the surprise component interacted with D_1 are large and highly significant. Both indicators are significantly negative related to the German bund futures market, i.e. an unexpected increase in future economic activity leads to price pressure, increasing interest rates and thereby lower prices at the bund futures market. However, the price reaction is only significant within the first release minute. This is in line with previous studies on the market impact of macroeconomic announcements (see e.g. Ederington and Lee (1993) as well as Jones, Lamont, and Lumsdaine (1998)) suggesting that market prices quickly incorporate the information provided by economic indicators within the first minutes after the release.[20] To obtain a test of hypothesis **H1**, i.e. to test whether the price impact of the earlier released indicator is stronger, both indicators are pooled together in one regression.

[20] There is a smaller effect for the ZEW indicator within the third minute after the release, but this effect is only significant at the 10% level.

Results are given in Column 3. We still find a highly significant negative price reaction for both indicators (Panel 1) that is basically completed after one minute. To test whether the difference between the coefficients of the price impact of both indicators is significant, we conduct a Wald coefficient test resulting in a p-value of 0.01481. We interpret this result ar supporting evidence in favor of **H1**, concluding that the German Bund Futures market reacts significantly stronger to the earlier released ZEW indicator as compared to the IFO indicator.

Panel B contains results from the GARCH(1,1) model. They also show a significantly negative price reaction at the German bund futures market within the first minute after the release of the ZEW and IFO indicator. As before, the result of a Wald coefficient test supports **H1** suggesting that the ZEW indicator has a significantly stronger price impact than the IFO indicator (with a p-value of 0.01577 for the model given in Column 3).

Volatility patterns of both indicators are quite similar. The dummy variables of the variance equations reveal that volatility rises sharply within the first five minutes after the release of the ZEW and IFO indicator and returns to normal levels after approximately ten to fifteen minutes.

To sum up, our findings show that the German bund futures market reacts significantly to the release of the IFO and ZEW indicator independent of the model specification we use. Furthermore, our results strongly support Hypothesis 1 by showing that the price reaction to the release of the ZEW indicator is significantly stronger than the price reaction to the release of the IFO indicator. According to the sequential Bayesian learning model given in Section 2, this result may be attributable to the difference in release time between the indicators.

To test whether a first mover advantage in terms of a more timely release accounts for the stronger market impact of the ZEW indicator, we now investigate the market impact of IFO indicator before and after the ZEW indicator was introduced to the market. If market participants are aware of the timeliness effect, we should find a decreasing market impact of IFO after the introduction of the ZEW indicator, since more precise prior expectations (due to the release of the ZEW indicator) should decrease the weight of the surprise component in their updating equation (see Hypothesis 2).

We analyze the market reaction to the release of the indicators from the beginning of 2001 where the first analyst report for the ZEW indicator was issued. Splitting our sample in equally large subperiods of 1.5 years enables us to investigate changes in the market impact of IFO before and after ZEW was also covered by analysts. Since the previous results suggest that the price reaction is completed within the first minute after the release of an indicator, we now use returns within the first minute after the release and estimate the following equation:

$$\Delta P_{1,t} = \alpha + \sum_{y} \beta_y \cdot S_{i,t} \cdot D_1 \cdot D_y + \epsilon_{1,t} \tag{14}$$

We relate the price change, $\Delta P_{1,t}$, within the first minute interval, D_1 after the release of an indicator i on day t to a constant and the surprise component of the release, $S_{i,t}$ multiplied by dummy variables D_y indicating the subperiods y the announcement is attributed to. Again, we estimate this model with (Panel A) and without (Panel B) accounting for GARCH effects.[21] Results are given in Table 7.

— Please insert TABLE 7 approximately here —

Results in Panel A indicate that the market impact of the IFO indicator significantly decreased after the first analyst forecast for ZEW was published in 2001. In the first years of our subsamples, IFO had a significant price impact on the German Bund Futures market. Hypothesis **H2** argues that this is because IFO was the only economic indicator that enabled market participants to update their expectations with respect to real economic changes in an early stage, i.e. before other economic indicators had been released. In 2001,

[21] We again focus on the first release minute since prices only react significantly to the release within this time interval.

the first analyst forecast of the ZEW indicator was released indicating that market participants became increasingly aware of the ZEW indicator and began using this source of information for an earlier update of their expectations regarding future economic conditions. This results in more precise prior information and hence a decreasing market impact of the IFO information.[22]

Results of the GARCH(1,1) model (Panel B) also supports **H2** showing that the price impact of IFO on the German bund futures market decreased over time whereas the impact of ZEW increased. This effect is especially large between the years 2000 and 2001, when analysts started to cover the ZEW indicator. Thus we conclude that the market impact of the IFO indicator decreases due to the fact that the ZEW indicator which provides almost equal precise information is released earlier.[23] Accordingly, in line with **H2**, the price reaction to the release of the IFO indicator decreased while the price impact of the ZEW indicator constantly increased over time.[24]

To investigate whether market participants' prior information indeed becomes more precise after the introduction of the ZEW indicator (see Hypothesis 3), we compare the standard deviation of analysts' forecasts with respect to the IFO indicator before and after the ZEW indicator was introduced to the market.[25] Results are given in Table 8.

— Please insert TABLE 8 approximately here —

The standard deviation of analyst forecasts with respect to the IFO indicator decreases after the introduction of the ZEW indicator. If the data is split after the release of the first

[22]Since there is no similar information available when the ZEW indicator is released, market participants have less precise priors and surprises should thus be larger.

[23]We do not find a significant price reaction for the first 1.5 years in which IFO was covered by analysts. We argue that there have to be enough market participants reacting to the release of the indicator. This point is obviously first reached in 1998 where the market reacts significantly negative to the release of IFO. We observe a similar pattern after the first analyst report of ZEW, where the market reaction also became stronger after 1.5 years.

[24]An increasing impact of the ZEW indicator is to some extent surprising, if all market participants became aware of this information source at the same time. It indicates that it takes market participants some time to fully understand the ZEW indicator.

[25]Individual analyst forecasts for the ZEW indicator and the IFO indicator are obtained from Bloomberg.

analyst forecast of the ZEW indicator (Model 1), the standard deviation decreases about -0.06. However, the difference is not statistically significant. This is due to an increased volatility of forecasts within the first six months after both indicators exist at the market. If this time period is excluded from the sample, the standard deviation significantly decreases about -0.09. Generally, our results support Hypothesis 3 showing that the precision of market participants' expectations regarding the IFO indicator increases after the ZEW indicator has been introduced to the market.

Taken together, our findings are in line with the implications obtained from the Bayesian learning model showing that a timely release is an important determinant of the market impact of an economic indicator.

5 Conclusion and Implications

Both our theoretical and empirical analysis of the determinants of investor attention to new information reveal a clear result: the timeliness of an information release is an important factor to explain the strength of its price impact. According to a sequential Bayesian learning model, information quality as well as the rank in the release sequence are important. The disadvantage of a late release could in principle be compensated by a higher precision of the released information. In fact, it seems reasonable to assume that a later released report provides more precise information since additional time and effort could be put into the preparation and validation of the released information or that more (i.e., late) survey respondents could be included. Nevertheless, the model also implies that only a substantial – not just an incremental – increase in precision can compensate for being late. In addition, our empirical analysis suggests that such a substantial increase is hard to achieve in practice.

Our empirical analysis focusses on the intraday price reaction at the German bund futures market to the release of two similar but sequentially introduced German economic indicators, namely the ZEW and IFO indicator. Both indicators contain similarly precise information regarding future economic conditions but the monthly release of IFO occurs after the release of ZEW. First of all, we find that bund futures prices significantly react to the unexpected news component of both indicators. As predicted by our model, the price impact of the IFO indicator significantly changes by the time the ZEW indicator receives full market attention for the first time (i.e., when analysts start to provide forecasts). Providing at least the same information quality but being published around one to two weeks in advance, the ZEW indicator gains a significantly stronger market impact than the IFO index. Moreover, comparing the market impact of the IFO index over time we find a significant decrease coinciding with the time the ZEW indicator begins to receive market attention.

In addition, our Bayesian learning model implies that the ZEW information leads to an increase of the precision of market participants' expectations regarding the later released IFO information. In fact, we find that the dispersion of analysts' IFO forecasts decreases substantially after the introduction of the ZEW indicator.

Overall, our empirical findings strongly support the model implications, i.e., both timeliness and information quality of an indicator are important determinants of how much attention market participants pay. Nevertheless, timeliness seems to be more important, i.e. the disadvantage of coming late is hard to outweigh by providing more precise information. This has important implications for statistical agencies developing an economic indicator. When designing an economic indicator, it is important not only to ensure a high information quality provided by the indicator, but also to distinguish this indicator from other, already existing indicators, that might provide similar information from an investors' point of view. Most importantly, an early release time increases the attention the market pays to the indicator and is therefore crucial to gain market impact.

6 Appendix

Granger causality tests between the economic indicators and industrial production are conducted based on the following regression equation:[26]

$$IP_t = \alpha + \sum_j \beta_j IP_{t-j} + \delta_i X_{t-i} + \epsilon_t. \tag{15}$$

We relate the year-over-year growth rate of industrial production, IP_t, to the optimal number of autoregressive lags, $\sum_j IP_{t-j}$ in addition to different lag numbers of one of the two indicators, X_{t-i}. This allows us to investigate, if the inclusion of a given indicator provides additional explanatory power for the regression.[27] If the inclusion of an indicator provides additional explanatory power, the coefficient of this indicator should have a significant influence and the goodness-of-fit measure of the regression should increase. Estimation results are given in the following table:

[26] Augmented Dickey Fuller tests show that the normalized series of ZEW as well as IFO-expectations and the year-over-year growth rate of industrial production are stationary and can be used in our further analysis. The optimal number of autoregressive lags for each time series is determined based on the Bayes-Schwartz criterion.

[27] Since the IFO indicator is referred to West Germany up to 2004, we use an unrevised series of industrial production for West Germany as reference series for this indicator. However, results remain unchanged, if we use Industrial Production Pan Germany for IFO as well.

Granger causality among IFO/ZEW and Industrial Production

Panel 1		ZEW granger-causes Industrial Production PAN					
zew-lags	intercept	AR(1)	AR(2)	AR(3)	ZEW_{t-i}	adj. R^2	F-stat
i	0.00739	0.37410 ***	0.30056 ***	0.17035		0.5539	53.98
1	−0.04263	0.28436 ***	0.29429 ***	0.24374 **	**0.30869** ***	0.6064	50.31
2	−0.04997	0.26188 ***	0.27797 ***	0.24011 **	**0.33688** ***	0.6144	51.99
3	−0.06358	0.23505 ***	0.25529 ***	0.23157 ***	**0.39357** ***	0.6322	56.01
4	−0.07768	0.19429 **	0.24083 ***	0.21668 ***	**0.44725** ***	0.6432	58.68
5	−0.07896	0.19371 **	0.21541 **	0.19958 **	**0.43747** ***	0.6249	54.31
6	−0.06506	0.25485 ***	0.21240 **	0.15726	**0.34973** ***	0.5911	47.26
7	−0.04524	0.31639 ***	0.23685 **	0.12844	**0.23805** **	0.5671	42.91
8	−0.01489	0.35869 ***	0.27623 ***	0.14414	0.09400	0.5528	40.56

Panel 2		IFO^{exp} granger-causes Industrial Production WEST					
ifo-lags	intercept	AR(1)	AR(2)	AR(3)	IFO_{t-i}	adj. R^2	F-stat
i	0.01348	0.53613 ***	0.33659 ***	(-)		0.6879	156.35
1	0.11762	0.34382 ***	0.28274 ***	(-)	**1.35750** ***	0.7501	142.08
2	0.13569	0.31428 ***	0.25628 ***	(-)	**1.49935** ***	0.7476	140.19
3	0.11138	0.33988 ***	0.22598 ***	(-)	**1.41977** ***	0.7345	130.12
4	0.09754	0.40068 ***	0.21764 ***	(-)	**1.14703** ***	0.7164	118.06
5	0.06424	0.46412 ***	0.26158 ***	(-)	**0.67494** **	0.7005	108.60
6	0.00780	0.52564 ***	0.33197 ***	(-)	0.08556	0.6917	103.48
7	0.01185	0.55567 ***	0.38525 ***	(-)	−0.32011	0.7021	107.84
8	0.02006	0.54314 ***	0.38745 ***	(-)	−0.30552	0.7017	106.87

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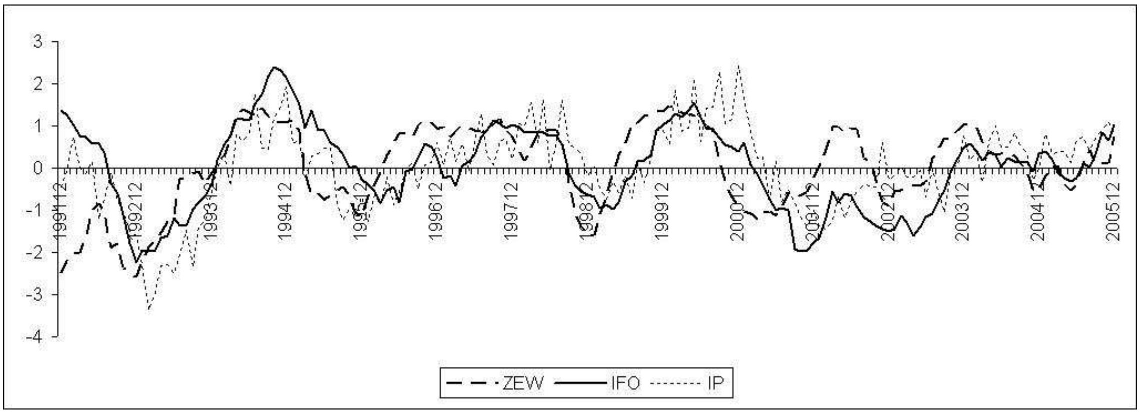
Figure 1: ZEW, IFO and Industrial Production



This Figure shows the development of the ZEW indicator, the IFO indicator as well as the year-over-year growth rate of industrial production over time. Our sample period starts in 1991 and ends in 2005. To make the indicators comparable, the values are normalized by subtracting the mean and dividing by their standard deviation.

TABLE 1

Summary Statistics: Indicators

	Mean	Min	Max	Stdv
ZEW	34.50	-62.20	89.60	37.43
IFO	95.12	85.10	108.30	4.77
IFO Expectations	96.17	83.50	105.10	4.12
IFO Current Situation	94.15	83.00	116.50	6.68

This table contains summary statistics for each indicator used in our analysis. Mean, minimum and maximum value as well as the standard deviations are given for ZEW, IFO, IFO expectations and IFO current situation indicators.

TABLE 2

Summary Statistics: Surprise Components

	$Surprise_{ZEW}^{resc}$	$Surprise_{IFO}^{resc}$
Mean	1.01	-0.55
Median	1.50	-0.81
Min	-23.60	-27.13
Max	19.80	27.13
Stdv	9.01	9.05

This table contains summary statistics for the surprise components of the ZEW indicator (Column 1) and the IFO indicator (Column 2). Surprises are computed according to the following equation $S_{i,t} = A_{i,t} - F_{i,t}$ where $A_{i,t}$ denotes the released balanced value of indicator i on day t and $F_{i,t}$ denotes the market expectation with respect to the release, proxied by MMS analyst forecasts. The IFO indicator has been transformed to its balanced value based on the following rule $BAL_{i,t}^{IFO} = \frac{IDX_{i,t}^{IFO}}{100} \cdot (MeanBAL_{baseyear}^{IFO} + 200) - 200$ with $BAL_{i,t}^{IFO}$ indicating the balanced value of IFO and $IDX_{i,t}^{IFO}$ indicating the index value.

TABLE 3

cross-correlations

	$IPPanGermany_t$			$IPWestGermany_t$		
j	ZEW_{t+j}	IFO_{t+j}	IFO_{t+j}^{exp}	ZEW_{t+j}	IFO_{t+j}	IFO_{t+j}^{exp}
-6	**0.6812**	0.4548	0.6305	0.7631	0.4459	0.6643
-5	0.6806	0.5416	0.6825	**0.7634**	0.5401	0.7341
-4	0.6340	0.5890	**0.6889**	0.7502	0.6121	0.7732
-3	0.5299	0.6312	0.6641	0.6983	0.6823	**0.7893**
-2	0.4092	0.6290	0.6230	0.6123	0.7219	0.7827
-1	0.3106	0.6653	0.5985	0.5357	**0.7316**	0.7449
0	0.1987	**0.6770**	0.5320	0.4468	0.7210	0.6758
1	0.0747	0.5966	0.4451	0.3570	0.6773	0.6006
2	−0.0365	0.5384	0.3488	0.2694	0.6316	0.5323
3	−0.1330	0.4781	0.2533	0.1805	0.5672	0.4505
4	−0.2430	0.4097	0.1524	0.0743	0.4949	0.3516
5	−0.3150	0.3321	0.0777	−0.0275	0.4144	0.2489
6	−0.3673	0.2595	−0.0013	−0.1046	0.3274	0.1367

This table contains cross-correlations between the indicators (ZEW, IFO and IFO expectations) and the year-over-year growth rate of industrial production Pan and West Germany. We calculated the correlation of the year-over-year growth rate of industrial production, IP_t with different lead and lag numbers of the indicators, ZEW_{t+j}, IFO_{t+j} or IFO_{t+j}^{exp}, respectively. The number of leads or lags is indicated by j.

TABLE 4
Release Dates

	ZEW	IFO	Timelag
Minimum	7.0	16.0	1.0
Maximum	24.0	29.0	16.0

This table contains summary statistics for the release dates of the ZEW indicator (Column 1) and the IFO indicator (Column 2). The minimum as well as the maximum calendar day of the release dates are given. Furthermore, the minimum and maximum timelag between the release of the ZEW indicator and the IFO indicator is calculated.

TABLE 5
Out of Sample Forecast Evaluation

	Benchmark: IP West			Benchmark: IP Pan		
	AR	$AR+ZEW$	$AR+IFO^{exp}$	AR	$AR+ZEW$	$AR+IFO^{exp}$
RMSFE	2.8633	**2.5859**	**2.8137**	2.8563	**2.7614**	**2.7800**
MAD	2.2532	2.0635	2.2943	2.2364	2.2584	2.1936
Mean Error	0.5730	0.4570	0.4228	1.1314	0.4629	0.9145
Mean (R-Sq)	0.9136	0.8888	0.9216	0.9258	0.9079	0.9417
Mean (AIC)	4.8034	5.0707	4.8274	5.0088	4.9502	4.5975

This table contains the minimum value of root mean squared forecast errors($RMSFE$), mean absolute deviations (MAD), mean errors, mean R-squared and mean Akaike Information Criteria ($Mean(AIC)$) for different forecast models as discussed in the text. The models have been estimated with rolling windows of 8 years. The benchmark of forecast errors reported in the first three columns is industrial production West Germany. The benchmark of forecast errors reported in the last three columns is industrial production Pan Germany. Column 1 and 4 contain the best autoregressive model (lowest RMSFE), results in Columns 2 and 5 contain the best forecast model in terms of the lowest RMSFE that includes the ZEW indicator and results in Columns 3 and 6 include contain the best forecast model that includes the IFO-expectations indicator.

The regressions are estimated with Newey-West autocorrelation and heteroskedasticity constant standard errors.

Table 6
Price Impact of ZEW and IFO indicator

Panel A: OLS

	ZEW	IFO	ZEW and IFO
Intercept	-0.0068	-0.0012	-0.0030
$S_{ZEW,t} \cdot D_1$	-0.3139^{***}		-0.3139^{***}
$S_{ZEW,t} \cdot D_2$	-0.0061		-0.0061
$S_{ZEW,t} \cdot D_3$	-0.0592^{*}		-0.0593^{*}
$S_{ZEW,t} \cdot D_4$	-0.0224		-0.0225
$S_{ZEW,t} \cdot D_5$	-0.0162		-0.0162
$S_{IFO,t} \cdot D_1$		-0.1509^{***}	-0.1509^{***}
$S_{IFO,t} \cdot D_2$		0.0255	0.0255
$S_{IFO,t} \cdot D_3$		-0.0016	-0.0016
$S_{IFO,t} \cdot D_4$		-0.0281	-0.0281
$S_{IFO,t} \cdot D_5$		-0.0087	-0.0087
R^2	5.64%	1.05%	2.19%
observations	$4,590$	$10,080$	$14,670$

Panel B: GARCH (1,1)

	ZEW	IFO	ZEW and IFO
Mean equation			
Intercept	-0.0004	0.0192	0.0128
$P_Ret(-1)$	-0.14333^{***}	-0.1042^{***}	-0.1158^{***}
$S_{ZEW,t} \cdot D_1$	-0.3436^{***}		-0.3388^{***}
$S_{ZEW,t} \cdot D_2$	-0.0620^{*}		-0.0518
$S_{ZEW,t} \cdot D_3$	-0.0444		-0.0452
$S_{ZEW,t} \cdot D_4$	-0.0403		-0.0369
$S_{ZEW,t} \cdot D_5$	-0.0138		-0.0138
$S_{IFO,t} \cdot D_1$		-0.1350^{***}	-0.1365^{***}
$S_{IFO,t} \cdot D_2$		-0.0127	-0.0145
$S_{IFO,t} \cdot D_3$		-0.0044	-0.0049
$S_{IFO,t} \cdot D_4$		-0.0125	-0.0134
$S_{IFO,t} \cdot D_5$		0.0090	0.0076
Variance equation			
Intercept	0.0174^{***}	0.033^{***}	0.0272^{***}
σ^2_{t-1}	0.9242^{***}	0.9401^{***}	0.9363^{***}
ϵ^2_{t-1}	0.0595^{***}	0.0423^{***}	0.0473^{***}
$ZEW \cdot D_{1-5}$	0.7527^{***}		0.6181^{***}
$ZEW \cdot D_{6-10}$	-0.4843^{**}		-0.4405^{**}
$ZEW \cdot D_{11-15}$	-0.0447		-0.0945^{*}
$IFO \cdot D_{1-5}$		1.0305^{***}	1.1093^{***}
$IFO \cdot D_{6-10}$		-0.8166^{***}	-0.8515^{***}
$IFO \cdot D_{11-15}$		-0.0938^{***}	-0.0694^{**}
R^2	6.16%	1.16%	2.46%
observations	$4,590$	$10,079$	$14,669$

Panel A of this table contains regression results of the following equation $\Delta P_{\tau,t} = \alpha + \sum_m \beta_m \cdot S_{i,t} \cdot D_m + \epsilon_{\tau,t}$. On announcement day t we relate the return within one minute intervals in our event window from $\tau = -30... + 60$ to the surprise of announcement i, $S_{i,t}$, multiplied by a dummy variable D_m with $m = 1...5$ for the first five minutes after the release. Column 1 contains results for the ZEW indicator. Column 2 contains results for the IFO indicator and Column 3 contains results for both indicators, respectively.

Panel B contains results for the following GARCH(1,1) model: $\Delta P_{\tau,t} = c + \beta \cdot \Delta P_{\tau-1,t} + \sum_m \delta_m S_{i,t} \cdot D_m + \epsilon_{\tau,t}, \epsilon_{\tau,t} = \mu_{\tau,t} \sigma_{\tau,t}\ and \sigma^2_{\tau,t} = \omega + \alpha \epsilon^2_{\tau-1} + \sum \gamma_j D_j$. We estimate the mean equation for $i = ZEW or IFO$, relating the returns of the German bund futures market, $R_{\tau,t}$ within the τ-time intervals in our event window, to its first order lag, $\Delta P_{\tau-1,t}$ and the surprise of the announcement,$S_{i,t}$ multiplied by dummy variables for the first five minutes after the release, $D_m with m = 1..5$. The variance equation always contains the squared lagged error, $\epsilon^2_{\tau-1,t}$ and dummy variables for the five minute intervals after the release, D_j. Column 1 contains results for the ZEW indicator. Column 2 contains results for the IFO indicator and Column 3 contains results for both indicators, respectively. Robust standard errors are estimated with heteroskedasiticy consistent covariance (Bollerslev-Wooldridge). Significance levels are indicated as follows: *** 1% significance, ** 5% significance and * 10% significance.

Table 7
Impact of Timeliness

Panel A: OLS	ZEW	IFO	Difference (ZEW-IFO)
Intercept	-1.2617^{***}	-0.5467	
$S_{i,t} \cdot D_{Jun1996-Dec1997}$		0.0168	
$S_{i,t} \cdot D_{Jan1998-Jun1999}$		-0.4770^{***}	
$S_{i,t} \cdot D_{Jul1999-Dec2000}$		-0.4673^{***}	
$S_{i,t} \cdot D_{Jan2001-Jun2002}$	-0.2053^{**}	-0.2015^{**}	-0.0038
$S_{i,t} \cdot D_{Jul2002-Dec2003}$	-0.3052^{**}	-0.0149	-0.2903^{**}
$S_{i,t} \cdot D_{Jan2004-Dec2005}$	-0.3308^{***}	-0.0604	-0.2704^{***}
R^2	46.35%	29.48%	
observations	51	112	

Panel B: GARCH(1,1)

	ZEW	IFO	ZEW and IFO
Mean equation			
Intercept	0.0007	0.0215^{*}	0.0153
$\Delta P_(-1)$	-0.1352^{***}	-0.0995^{***}	-0.1103^{***}
$S_{ZEW,t} \cdot D_{Jan2001-Jun2002}$	-0.2598^{***}		-0.2634^{***}
$S_{ZEW,t} \cdot D_{Jul2002-Dec2003}$	-0.3671^{***}		-0.3639^{***}
$S_{ZEW,t} \cdot D_{Jan2004-Dec2005}$	-0.3011^{***}		-0.2966^{***}
$S_{IFO,t} \cdot D_{Jun1996-Dec1997}$		-0.0057	-0.0042
$S_{IFO,t} \cdot D_{Jan1998-Jun1999}$		-0.4984^{***}	-0.4967^{***}
$S_{IFO,t} \cdot D_{Jul1999-Dec2000}$		-0.3506^{***}	-0.3527^{***}
$S_{IFO,t} \cdot D_{Jan2001-Jun2002}$		-0.1667^{*}	-0.1693^{**}
$S_{IFO,t} \cdot D_{Jul2002-Dec2003}$		0.0011	0.0023
$S_{IFO,t} \cdot D_{Jan2004-Dec2005}$		-0.0636^{*}	-0.0637^{*}
Variance equation			
Intercept	0.0307^{***}	0.1135^{***}	0.0748^{***}
σ^2_{t-1}	0.8879^{***}	0.8365^{***}	0.8590^{***}
ϵ^2_{t-1}	0.0794^{***}	0.0929^{***}	0.0884^{***}
$ZEW \cdot D_{Jan2001-Jun2002}$	2.7062^{**}		2.9461^{**}
$ZEW \cdot D_{Jul2002-Dec2003}$	2.8457^{***}		3.0685^{***}
$ZEW \cdot D_{Jan2004-Dec2005}$	1.2595^{***}		1.1655^{**}
$IFO \cdot D_{Jun1996-Dec1997}$		1.1464	1.0036
$IFO \cdot D_{Jan1998-Jun1999}$		1.1438^{**}	1.3527^{**}
$IFO \cdot D_{Jul1999-Dec2000}$		5.5159^{***}	4.8274^{***}
$IFO \cdot D_{Jan2001-Jun2002}$		5.7459^{***}	5.2503^{***}
$IFO \cdot D_{Jul2002-Dec2003}$		3.2120^{***}	2.9398^{***}
$IFO \cdot D_{Jan2004-Dec2005}$		1.3491^{**}	1.2896^{**}
$adj.R^2$	5.88%	2.55%	3.43%
observations	4,590	10,079	14,669

Panel A of this table contains regression results of the following equation $\Delta P_{1,t} = \alpha + \sum_y \beta_y \cdot S_{i,t} \cdot D_y + \epsilon_t$. We relate the return within the first minute interval after the release of an indicator, ΔP_t on day t to a constant and the surprise component of announcement i on day t, $S_{i,t}$ multiplied by dummy variables D_y

indicating the years of our subperiods. As subperiods we use equally large intervals of 1.5 years, beginning in June 1996 where the first analyst forecast for IFO was released.

Panel B contains results for the following GARCH(1,1) model: $\Delta P_{\tau,t} = c + \beta \cdot \Delta P_{\tau-1,t} + \sum_m \delta_m S_{i,t} \cdot D_y + \epsilon_{\tau,t}, \epsilon_{\tau,t} = \mu_{\tau,t}\sigma_{\tau,t}\ and \sigma^2_{\tau,t} = \omega + \alpha\epsilon^2_{\tau-1} + \sum \gamma_y D_y$. The mean equation relates the return of the German Bund Futures market, $\Delta P_{\tau,t}$, within the τ-time intervals of our event window to its first order lag, $\Delta P_{\tau-1,t}$ and the surprise of announcement i,$S_{i,t}$ with $i = ZEW, IFO$ multiplied by dummy variables D_y for each subperiod of 1.5 years. The variance equation always contains the squared lagged error, $\epsilon^2_{\tau-1,t}$. and dummy variables for the volatility in the first minute after the release within our subperiods of 1.5 years, D_y. Robust standard errors are estimated with heteroskedasiticy consistent covariance (Bollerslev-Wooldridge). Significance levels are indicated as follows: *** 1% significance, ** 5% significance and * 10% significance.

TABLE 8
Standard Deviation of Forecasts

	Model 1	Model 2
$IFO^{1998-2001}$	0.3052	0.3052
$IFO^{2002-2005}$	0.2452	0.2189
Difference	-0.06	-0.0863^{**}

This table contains standard deviation of analysts' forecasts of the IFO indicator. Standard deviations are computed over individual forecasts for the time period before the introduction of the ZEW indicator, $IFO^{1998-2001}$, and for the time period after the introduction of the ZEW indicator, $IFO^{2002-2005}$. Model 1 provides results for a cutoff in December 2001 (Column 1), while the data in Model 2 does not contain the first six months after the introduction of the ZEW indicator (Column 2). The difference is calculated based on a two-sided t-test. Significance levels are indicated as follows: *** 1% significance, ** 5% significance and * 10% significance.