Micro Information Dynamics: Decomposing the Forecasting Power of Aggregate Indicators

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Current forecasting literature

- large data sets
- factor models
- forecast combinations
- mixed-frequency issues
- Bayesian VARs
- *methodological focus*
- What kind of data helps forecasting e.g. GDP (survey data vs. financial indicators)?
- **This paper is different!**

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Motivation

Forecasting German industrial production with Ifo Indicators with an standard distributed lag model. Benchmark is an AR model.

Table : Forecasting Performance of Benchmark Indicators - Relative RMSFE

	h=0	h=1	h=3	h=6
ifo Business Climate	0.943	0.949	0.740	0.568
Situation	0.895	0.913	0.778	0.816
Expectations	0.881	0.882	0.700	0.593
AR-Benchmark	1.000	1.000	1.000	1.000

Motivation

Research Questions

- What makes survey indicators (e.g. Ifo) a good predictor?
  - Can we get answers by looking at micro data?
  - Is it the size or the industry sector?
  - What role does the situation and the expectation questions play for different forecasts horizons?
  - Do reliable firms drive the accuracy?
- Are there any new micro-based measures that can improve the forecasting accuracy?

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- *Go beyond the standard balance statistics*
- Take a look at the micro data and compute the balance statistics for different subcategories (others than sectors)
- Calculate various 'disagreement' and 'uncertainty' measures
- Does the answering behaviour play a role?

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Table of Contents

Outline

Business Situation and Expecations

> *We evaluate our state of business with respect to XY as:*
> *"good", "satisfactory", "bad",*

which we code as $s_{i,t} = \{+1, 0, -1\}$.

Analogously, the question on its expectation for the next six months is

> *With regard to the business cycle our business situation for XY will be:*
> *"rather more favorable", "the same", "rather less favorable",*

coded as $e_{i,t} = \{+1, 0, -1\}$.

Balance Statistics

Definition

Balance

$$\eta_t^B = p_{t,+} - p_{t,-}.$$

where

$$p_{t,\chi} = \frac{\sum_i \omega_{t,i} 1(z_{t,i} = \chi)}{\sum_i \omega_{t,i}},$$

for $\chi \in \{-1, 0, +1\}$. $\Rightarrow$ **this is our benchmark**

Higher-Order Measures

Definition (Shannon Entropy)

$$\eta_t^{ETY} = -\sum_{\chi \in \{-,0,+\}} p_{t,\chi} \cdot \log_2(p_{t,\chi})$$

Definition (Cross-sectional Standard Deviation)

$$\eta_t^{CSD} = \sqrt{p_{t,+}(1-\eta_t^B)^2 + p_{t,0}(\eta_t^B)^2 + p_{t,-}(1+\eta_t^B)^2}$$

Definition (Disagreement)

$$\eta_t^{DIS} = \sqrt{p_{t,+} + p_{t,-} - (p_{t,+} - p_{t,-})^2} \tag{1}$$

Higher-Order Measures

We can define an ex-post measure of uncertainty of each participant based on the forecast error at horizon h, captured by the individual's forecast errors . Denoting $s_{i,t}$ as the situation and $e_{i,t}$ as the expectation at time t we define

Definition (h-Period Realized Uncertainty)

$$\eta_t^{RU,h} = \frac{1}{\sum_i \omega_{i,t}} \sum_i \omega_{i,t} \left| [sgn(s_{i,t} - s_{i,t-h}) - e_{i,t-h}] \, min(1 - s_{i,t} e_{i,t-h}, 1) \right|,$$

where the first factor inside the absolute value captures the forecast error on an unbounded scale, and the second term corrects for the constraints effective when the previous situation was not neutral. We employ the average uncertainty given the mean of h periods ranging 1 one to 6.

Weighted Measures

Definition (Proportional Entropy-Weighted Balance)

$$\eta_t^{B,ETY} = \eta_{t,c}^{B} \cdot \eta_{t,c}^{ETY}$$

and

Definition (Inverse Entropy-Weighted Balance)

$$\eta_t^{B,IETY} = \eta_{t,c}^{B} / \eta_{t,c}^{ETY}.$$

$\Rightarrow$ We do the same for the cross-sectional standard deviation, disagreement, and h-Period Realized Uncertainty

Outline

Basic Categories

Survey participants can be classified by various characteristics. The *Ifo* survey, for example, provides information on the size and sectoral affiliation of each responding business unit. We classify respondents along the following dimensions:

- Business Unit *Size* (5 categories, by number of employees[1])
- *Branch* (10 categories)[2]
- *Sector* (3 categories: consumer goods, basic materials, technology)
- Trade differentiation (Export vs. Import)
- Oil vs. non-oil
- Small vs Large for Electronics, Optics Engineering; and Vehicle Manufacturing.

[1] The cutoffs between categories are 1-49, 50-199, 200-499, 500-999, and >1000 employees, respectively.

[2] The ten categories are Food and Tobacco; Textiles and Clothing; Timber, Furniture and Jewelry; Paper and Publishing; Electronics and Optics; Chemical Industry and Petroleum; Glass and Ceramics; Metal Industry; Engineering; and Vehicle Manufacturing.

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Categories based the past Answering Behavior I

Unconditional Switching Frequency (US Freq., $c = 3$ categories, omitted category: only one participation ever): Participants are assigned to categories based on how often they have changed their response relative to the previous survey since the beginning of our forecasting period. The categories are switching with a frequency of:

- less than $1/12$ of all surveys,
- of at least $1/12$ but not more than $1/6$ of all surveys,
- and of more than $1/6$ of all surveys.

Categories based the past Answering Behavior II

Conditional Switching Frequency (CS Freq., $c = 3$ categories, omitted category: only one participation during previous 24 months): At each point in time, survey participants belong to one of the following groups:

1. *Infrequent Switchers*, which switched less than 3 times during the previous 24 months,
2. *Medium-term Switchers*, which switched at least 3 but not more than 5 times during the previous 24 months,
3. *Frequent Switchers*, which switched more than 5 times during the previous 24 months.

Categories based the past Answering Behavior II

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Categories based the past Answering Behavior III

Conditional Switching Status (CS Stat, $c = 5$ categories):
At each point in time, survey participants belong to one of the following groups:

1. *New Entries*, which did not participate in the survey in the previous month,
2. *Reliable Switchers*, which changed their response this month relative to the previous month and which switched between 1 and 4 times during the previous 24 months,
3. *Reliable Non-Switchers*, which did not change their response this month relative to the previous month and which switched between 1 and 4 times during the previous 24 months,
4. *Unreliable Switchers*, which changed their response this month relative to the previous month and switched either not at all or more than 4 times during the previous 24 months,
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Categories based the past Answering Behavior IV

Given the firms' assessment of their current and expected future business situation we evaluate whether their expectations are consistent with their appraisal of their situation up to six months later. We define accuracy analogous to realized uncertainty given by Definition 5:

Definition (Accuracy)

The survey responses are accurate at horizon h if

$$A_h: \quad e_{t-h} = sgn(s_t - s_{t-h}) \quad \vee \quad e_{t-h} = s_t = s_{t-h}. \qquad (2)$$

Categories based the past Answering Behavior V

Unconditional Short-term Accuracy (US Acc., $c = 4$ categories): We count the number of periods for which $\exists h \in \{1, 2, 3\}$ with A_h being true. Participants are assigned to categories depending on how often their expectation in $t - h$ materialized in at least one of the subsequent three months.

1. *No Accuracy*, if the expectation was followed by a corresponding change in situation in less than 50% of surveys,
2. *Low Accuracy*, if the expectation was followed by a corresponding change in situation in 50%-75% of surveys,
3. *Medium Accuracy*, if the expectation was followed by a corresponding change in situation in 75%-90% of surveys,
4. *High Accuracy*, if the expectation was followed by a corresponding change in situation in more than 90% of surveys.

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Categories based the past Answering Behavior VI

Unconditional Long-term Accuracy (UL Acc., $c = 4$ categories): We count the number of periods for which $\exists h \in \{1, 2, 3, 4, 5, 6\}$ with A_h true. Participants are assigned to categories depending on how often their expectation in $t - h$ materialized in at least one of the subsequent six months.

1. *No Accuracy*, if the expectation was followed by a corresponding change in situation in less than 50% of surveys,
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Categories based the past Answering Behavior VII

Conditional Short-term Accuracy (CS Acc., $c = 2$ categories): At each point in time t, survey participants belong to one of the following groups:

1. *Some Accuracy*, if $\exists h \in \{1, 2, 3\}$ for which A_h is true,
2. *No Accuracy*, if $\neg A_h \; \forall h \in \{1, 2, 3\}$.

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Categories based the past Answering Behavior IX

Horizon of Maximum Conditional Accuracy (HMC Acc., $c = 4$ categories): At each point in time t, survey participants belong to one of the following groups:

1. 1-2 Months, if $\exists h \in \{1, 2\}$ for which A_h is true,
2. 3-4 Months, if $\neg A_h\ \forall h \in \{1, 2\}$ and $\exists h \in \{3, 4\}$ for which A_h is true,
3. 5-6 Months, if $\neg A_h\ \forall h \in \{1, 2, 3, 4\}$ and $\exists h \in \{5, 6\}$ for which A_h is true,
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Outline

The Ifo Survey

- since 1989
- micro data available from 1980
- 12 regular monthly questions, we focus on the two main questions: Situation and Expectations
- Until December 2001 the participants were surveyed at the beginning of each month (survey and publication month) about their situation in the previous month (reporting month).
- Since January 2002 survey and reporting month are identical. Due to this change no micro data are available for December 2001.
- To resolve this we shift all responses prior December 2001 forward by one month, so that survey and reporting month coincide in the whole sample.

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A look at the data

Table : Profile of Survey Responses by Firm Size

business unit size	total		unconditional switching frequency			sector		
			$<1/12$	1/12-1/6	$> 1/6$	cons. goods	basic mat	tech-nology
headcount	thousands	%	% of all firms			% of all firms		
1-49	365	27	8	24	68	9.5	12.7	5.2
50-199	487	37	11	34	56	11.0	15.8	9.9
200-499	253	19	17	39	44	4.7	7.5	6.8
500-999	114	9	27	40	34	1.5	3.0	4.0
$\geq$1000	109	8	34	44	22	1.0	2.5	4.7
overall	1328	100	11	36	53	27.7	41.6	30.7

The table lists the total number of responses from each sector during the entire sample period 1985:01 – 2012:12

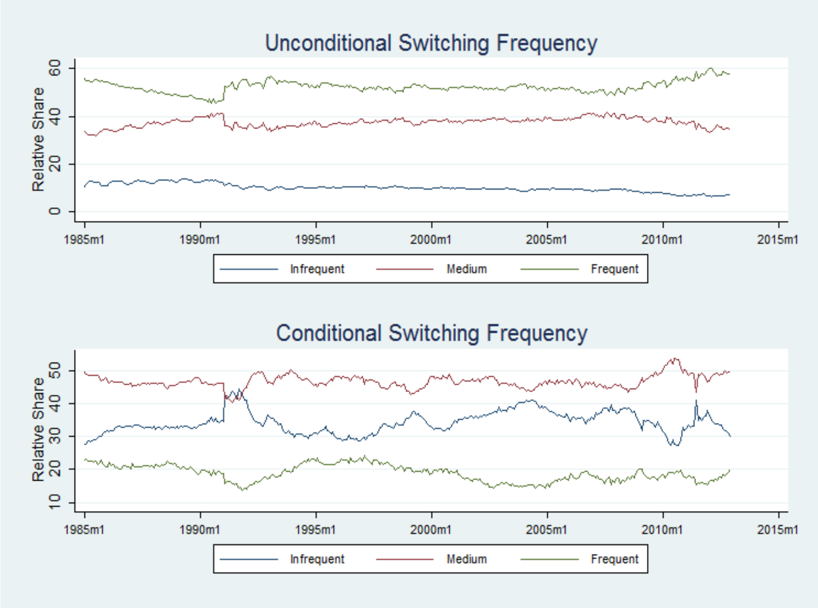
A look at the data

Table : Profile of Survey Responses by Sector

(% of all responses)		basic materials	cons. goods	technology
		sector		
share		57	17	26
unconditional	<1/6	9	9	14
switching	1/12-1/6	34	34	41
frequency	>1/6	57	57	44
unconditional	<50%	3	3	3
short-term	50-75%	8	7	7
accuracy	75-90%	23	23	24
	>90%	67	67	67
unconditional	<50%	2	2	2
long-term	50-75%	4	4	4
accuracy	75-90%	10	10	10
	>90%	84	84	84

The first row of the table lists the breakdown of all responses by sector during the entire sample period 1992:01 – 2010:12.

Switching Behaviour



Outline

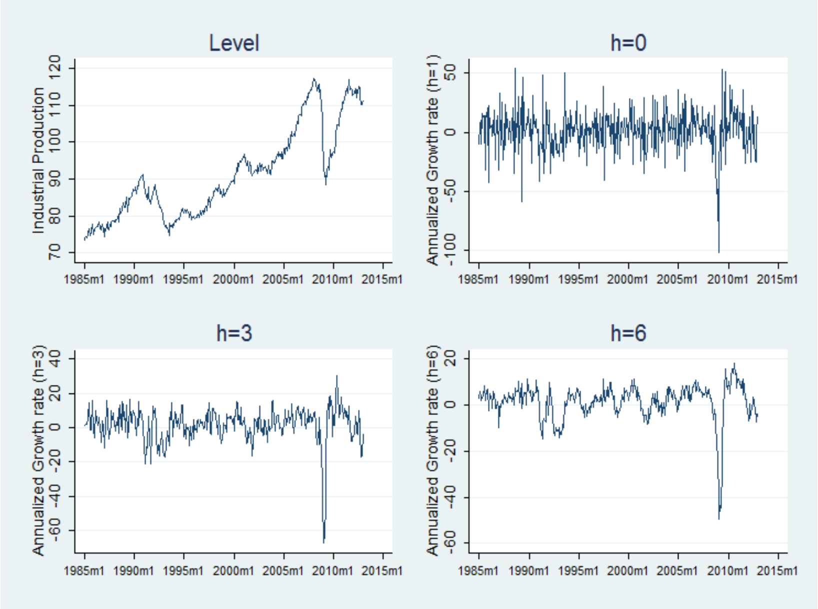
Target Variable

We forecast the h-month growth of **Industrial Production** at an annual rate (Stock and Watson 2006)

$$y_{t+h}^{h} = \frac{1200}{h} \ln \left(\frac{IP_{t+h}}{IP_t} \right), \tag{3}$$

where $h = 1, 3, 6$

The target variable



Empirical Approach

Our forecasting model is the standard autoregressive distributed lag model. Denoting the indicator series by η_t, we have for forecasting horizon $h > 0$

$$y_{t+h}^{h} = \alpha + \sum_{i=1}^{p} \beta_i y_{t-i}^{1} + \sum_{j=1}^{q} \gamma_j \eta_{t-j} + \varepsilon_t, \tag{4}$$

where we assume ε_t to be white noise.

Under nowcasting ($h = 0$) and defining $y_t^0 \equiv y_{t-1}^1$ equation (4) becomes

$$y_t^{1} = \alpha + \sum_{i=1}^{p} \beta_i y_{t-i}^{1} + \sum_{j=0}^{q} \gamma_j \eta_{t-j} + \varepsilon_t. \tag{5}$$

The lag length in this and all subsequent models is determined by the Bayesian Information Criterion (BIC) with $p, q \leq 6$.

Empirical Approach

1. Sample: 1985:01 - 2012:12
2. Forecasting window: 1991:01 - 2012:12
   $\Rightarrow$ 264 forecasts for each horizon
3. direct forecasting approach
4. Rolling scheme
5. Forecast horizons: $h = 0, 1, 3, 6$
6. Benchmarks: AR(p) and ADL models with ifo indicators
7. Forecast evaluation: MSE
8. Statistical Test: Model Confidence Set (Hansen et al. 2011, *Econometrica*)
   $\Rightarrow$ still problematic: computational intensive, handles only a small set of models, cannot discriminate between very simliar models

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Number of Models

1. 2 questions: Situation and Expectations
2. 14 different measures (balance, entropy, etc.)
3. 31 classification categories (size, branches, etc.)
4. 28 categories based on the past answering behaviour
5. in total: **24303** models
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Organization of the results

- Unweighted vs. Weighted balances
- Explaining the forecasting power of the ifo
  $\Rightarrow$ anatomy of the balances statistics
- Higher Order Measures
- Integrated regressions
- 1+1 Regressions

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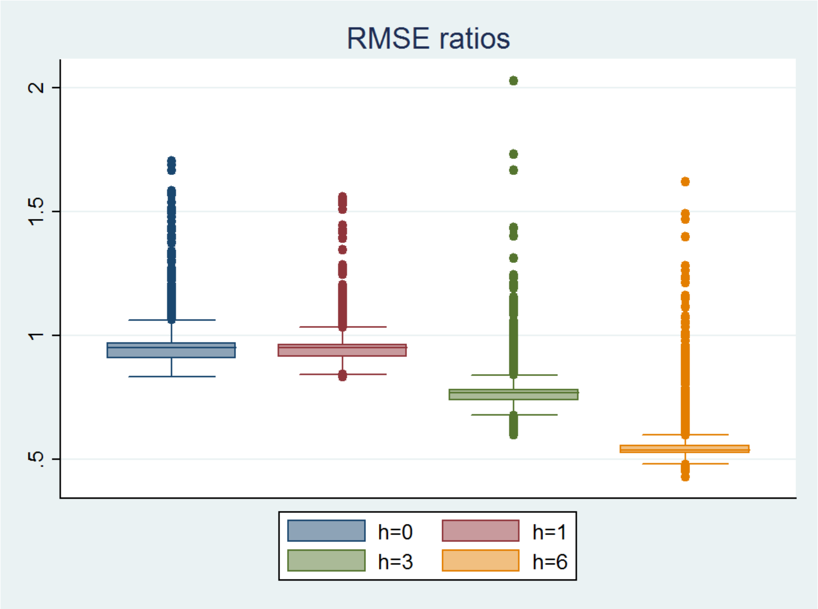

Results I:Does weighting matter?

Table : Forecasting Performance unweighted vs. weighted Ifo Indicators

	Weighting?	h=0	h=1	h=3	h=6
Ifo Business Climate	NO	0.944	0.931	0.753	0.849
Situation	NO	0.907	0.923	0.756	0.892
Expectations	NO	0.893	0.895	0.743	0.594
Ifo Business Climate	YES	0.943	0.949	0.740	0.568
Situation	YES	0.895	0.913	0.778	0.816
Expectations	YES	0.881	0.882	0.700	0.593
AR-Benchmark		1.000	1.000	1.000	1.000

Results II: Explaining the forecasting power of the ifo

- better than the aggregated ifo benchmark
- Expectations matter much more than situation over all horizons
- medium sized firms and basic materials enterprises

Results II: Higher Order Measures

- again, expectations matter
- consideration of uncertainty measures improves forecasting accuracy
- size and sector play again an important role
- Medium switchers at the top

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- include in every regression the balance statistic (1) and a uncertainty measure (+1)
- as before, look at the expectations
- further improvement especially in the short-run, but not in the long-run ($h = 6$)
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- We do this by forming many subcategories
- medium sized firms and enterprises from the basic material sector play an important role
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- rolling evaluation of the indicators
- forecast combinations
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- We can repeat the whole exercise for the production question

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