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When are GDP forecasts updated? Evidence from a large international panel

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HIGHLIGHTS

- I analyze revisions of GDP forecasts from a large international survey panel.
- On average, less than half of the forecasts are revised each month.
- Revisions are more frequent in advanced economies compared to emerging economies.
- Revisions are affected by interactions between forecasters and the business-cycle.
- State-dependency is vital for micro-consistent theories of expectation formation.

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ABSTRACT

Based on a large international panel of surveyed GDP forecasts I analyze the frequency of forecast revisions and the factors that influence the likelihood of forecast revisions. I find that each month on average 40%–50% of forecasters revise their forecasts. In addition, I find that the likelihood of forecast revisions significantly depends on a number of factors such as the forecast horizon, the business-cycle, or strategic interactions between forecasters. My results suggest that a realistic modeling of expectations/forecasts of agents has to take into account cross-sectional heterogeneity, strategic interaction between agents, and effects of the economic environment—features that existing models such as the sticky information framework are missing.

1. Introduction

Macroeconomic forecasts are frequently updated to adjust for incoming news. But while a large body of literature analyzes if these revisions are made in a rational way (see e.g. Nordhaus, 1987), little is known about the frequency of forecast adjustment and about the factors that influence the likelihood of a forecast revision. Two recent exceptions are the contributions by Andrade and Le Bihan (2010) and Dovern et al. (2013) that use data on individual forecasts to show that macroeconomic forecasts are revised quite frequently. This evidence is in contrast to conventional estimates based on aggregate data and derived under the assumption of sticky information (e.g. Mankiw et al., 2004; Coibion and Gorodnichenko, 2012).[1]

In this paper I go one step further. I use data on individual GDP forecasts from a large international panel to analyze the cross sectional distribution of forecast revision frequencies and to analyze which factors influence the likelihood of forecast revisions.

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[1] The model of sticky information assumes that agents update their expectations only infrequently due to a limited capacity to process information (Sims, 2003) or due to costs of acquiring and processing information about the state of the economy (Reis, 2006); the updating process is assumed to be governed by an exogenous and constant probability of updating a forecast at each time period.

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2. Methodology

2.1. Unconditional probability of forecast revisions

Let $y_{i,t|h}$ denote the forecast for the yearly growth rate of GDP in year t made with a forecast horizon of h months by agent i. The unconditional probability for updating a forecast at a certain forecast horizon, $\lambda(h) = \Pr(y_{i,t|h} \neq y_{i,t|h+1})$ can be estimated under the assumption that the probability is the same for each individual:

$$\widehat{\lambda}(h) = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N_{t|h}}\sum_{i=1}^{N_{t|h}} I(y_{i,t|h} \neq y_{i,t|h+1}), \tag{1}$$

where T is the total number of different target years in the sample, $N_{t|h}$ denotes the number of observed forecasts for target year t and with forecast horizon h, and $I(y_{i,t|h} \neq y_{i,t|h+1})$ is an indicator function that is equal to 1 if $y_{i,t|h} \neq y_{i,t|h+1}$ and 0 otherwise. Likewise, an analogous estimate for each individual can be obtained by computing an average of $I(y_{i,t|h} \neq y_{i,t|h+1})$ across target years and forecast horizons.[2]

2.2. Conditional probability of forecast revisions

Binary choice models with duration dependence can be used to analyze which factors influence the conditional probability of forecast revisions. These are appropriate to model the probability that a forecast is altered at a certain point in time. Defining $\theta_{i,t,h} \equiv I(y_{i,t|h} \neq y_{i,t|h+1})$, the general form of these models is given by

$$P\left(\theta_{i,t,h} = 1|\boldsymbol{X_{i,t}}, c_i\right) = G(\boldsymbol{X_{i,t}}\boldsymbol{\beta} + c_i), \tag{2}$$

where $\boldsymbol{X_{i,t}}$ is a vector of exogenous covariates and c_i is an unobserved individual-specific effect. $G(\cdot)$ could in principle be any function that evaluates to values between 0 and 1; here I use the logistic function and the cumulative density function of the standard normal distribution. Under the assumption that $c_i|\boldsymbol{X_i} \sim N(0, \sigma_c)$, the model can be estimated using maximum likelihood techniques by integrating out c_i.

3. Data

My analysis is based on forecasts for annual GDP growth from a cross-country survey data set compiled by Consensus Economics Inc. The data set has a three-dimensional panel structure of the kind formalized in Davies and Lahiri (1995): For each target year, the data contain a sequence of 24 forecasts of each panelist made between January of the year before the target year and December of the target year. The forecasts are made by public and private economic institutions. I include all countries in the sample for which Consensus Economics Inc. reports individual forecasts.[3] A considerable degree of data cleaning is necessary due to the absence of unique identifiers for individuals in the survey; I follow the approach implemented by Dovern et al. (2013) to obtain a proper panel data set. In total, the data set contains 188,639 individual forecasts from 30 different countries, of which 104,894 are from 14 advanced economies.[4] These forecasts are made for target years between 1989 and 2011.

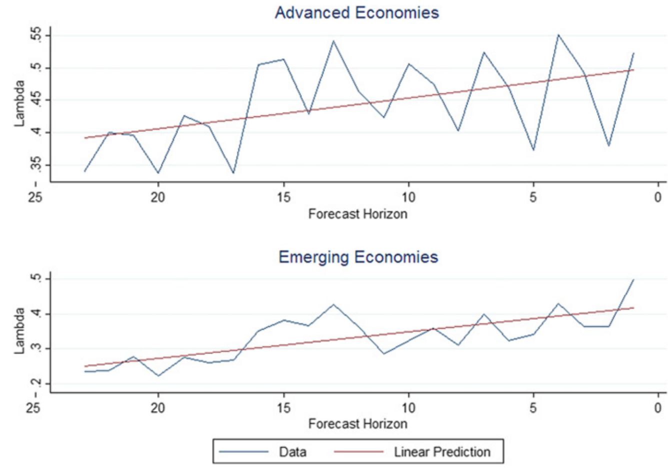

Fig. 1. Average revision probabilities as a function of the forecast horizon (color on web, black-and-white in print).
Source: Consensus Economics; author's calculations.

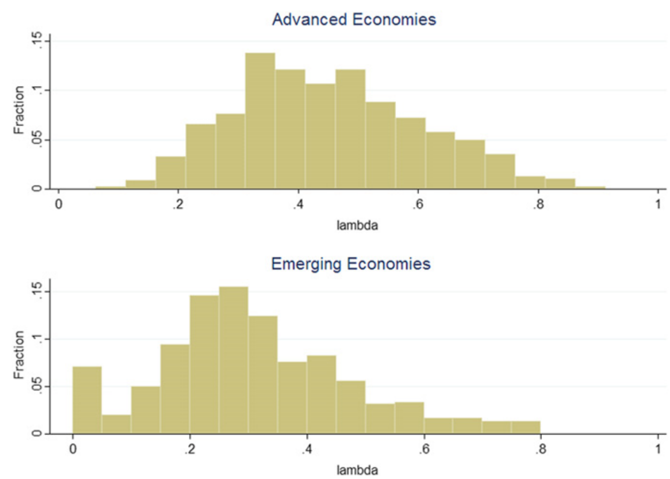

Fig. 2. Histogram of forecaster-specific unconditional revision probabilities (color on web, black-and-white in print).
Source: Consensus Economics; author's calculations.

4. Empirical evidence from international survey data

4.1. Unconditional probability for forecast revisions

Looking at estimates for the unconditional probability of updating for each of the different forecast horizons covered by the data sample, $\hat{\lambda}(h)$, is a good way to start a detailed analysis of the dynamics of forecast revisions. Four key lessons can be drawn from the estimates shown in Fig. 1. First, measured at a monthly frequency on average less than half of all forecasters update their information sets/forecasts at each point in time.[5] Second, the probability of forecast revisions in advanced economies (just under 0.5 on average) is considerably higher than in emerging economies (roughly 0.4). Third, attentiveness is increasing with shrinking forecast horizon. Finally, there seem to be some intra-quarterly seasonal patterns, especially for advanced economies.

I now turn to the distribution of $\lambda(i)$. Fig. 2 shows a histogram of the individual-specific unconditional updating probabilities. It

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2 Computing different updating probabilities for different forecast horizons for a single individual does not yield reliable estimates, since the number of observations is too small in many cases.

3 The survey process is essentially the same in all countries: During the first two weeks of each month the forecasters send their responses and the data are published in the middle of each month. Thus, panelists are aware of their competitors' forecasts from one month ago when making their new forecasts.

4 Due to the fact that the panel is heavily unbalanced a substantial fraction of data points cannot be used to compute revisions, because many of the observed forecasts are adjacent to missing values. Thus, estimations below are based on significantly fewer observations.

5 This is roughly in line with what Andrade and Le Bihan (2010) and Dovern et al. (2013) find based on individual forecast data, and it implies a degree of informational stickiness that is considerably lower than estimates derived from aggregate forecasts by Coibion and Gorodnichenko (2012) or Dovern et al. (2013).