Information Rigidities in Survey Data: Evidence from Dispersions in Forecasts and Forecast Revisions*

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Abstract

Predictable forecast errors in survey data documented in the existing literature suggest a deviation from the rational expectations hypothesis, and are in favor of imperfect information models such as sticky and noisy information models. This article assesses the validity of the imperfect information models by establishing a linkage between dispersions in survey forecasts and survey forecast revisions. We find that the dynamics of dispersion in survey forecasts are consistent with the prediction of sticky information models, but at odds with that of conventional noisy information models as well as full information rational expectations models, both of which assume agents' continuous updating of their information sets.

Keywords: Sticky Information; Noisy Information; Dispersion in Forecasts; Forecast Revision
JEL Classifications: D84; E30; E37

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1 INTRODUCTION

Recently there has been renewed interest in testing the assumption of full-information rational expectations. Although the presence of information rigidities in macroeconomic aggregates has a venerable tradition—Lucas (1972) and Kydland and Prescott (1982), for example—much of the recent interest was spurred by Coibion and Gorodnichenko (2012), who document a substantial degree of information rigidities in U.S. survey data. They demonstrate that survey forecast errors are highly predictable, which suggests a rejection of full-information rational expectation models. Rather, the evidence is consistent with the prediction of imperfect information models such as sticky information or noisy information models.

Based on an additional test using dispersions in forecasts among survey respondents, they further argue that the deviation from the full-information rational expectation assumption is consistent with noisy information models, while sticky information models are hardly supported by the data. Sticky information models posit that an arrival of aggregate shocks raises dispersions in forecasts as it leads to different forecasts between informed and uninformed agents. Accordingly, they explore whether survey-measured dispersions in forecasts respond to various structural shocks such as technology, news, and oil shocks, but find a limited role of them.

This paper reexamines the robustness of their finding from the dispersion-based test by establishing an alternative test on information rigidities. Unlike to their framework, the alternative test utilizes the link between dispersions in forecasts and forecast revisions, suggested by sticky information models. As we show formally below, this class of models predicts that forecast revisions associated with the arrival of new information between $t-1$ and t should have explanatory power for fluctuations in dispersions at t. The primary advantage of our empirical procedure is to use forecast revisions that are readily available in the Survey of Professional Forecasters (SPF), and thus is not subject to identification of structural shocks which may affect the results substantially.

Our finding indicates a pivotal role of forecast revisions in accounting for dispersions in survey forecasts of a wide range of macroeconomic variables, such as inflation, GDP, industrial production, new housing starts, nonresidential investment, and residential investment. This reveals a substantial degree of information stickiness in the survey-measured dispersions in forecasts, contradicting the results of Coibion and Gorodnichenko (2012). Models allowing for agents' constant information updating, such as full-information rational expectation and noisy information models, tend to be inconsistent with the data.[1] Employing the Livingston Survey (LS) dataset, instead of the SPF, does not alter our main finding.

2 DISAGREEMENT AND TWO IMPERFECT INFORMATION MODELS

2.1 DISAGREEMENT AND STICKY INFORMATION

There are two key premises of the sticky information model in Mankiw and Reis (2002): (1) only a fraction of agents update their information sets, and they have the same forecasts about macroeconomic variables; and (2) agents who do not update their information sets forecast macroeconomic variables based on old information sets.

Sticky information models predict that dispersion in forecasts about economic activity across agents is mainly driven by the fraction of agents with updated information sets. As Mankiw et al.

[1] Our empirical results, however, do not rule out the possibility that agents infrequently update information contaminated with noise.

(2004) make explicit, the degree of dispersion among agents associated with sticky information models is defined as

$$\begin{aligned}\sigma^x_{t,t+h} &\equiv \sqrt{(1-\gamma_i^{si})\sum_{k=0}^{\infty}(\gamma_i^{si})^k\left[E_{t-k}x_{t+h}-F_tx_{t+h}\right]^2}\\ &= \sqrt{(1-\gamma_i^{si})\left[E_tx_{t+h}-F_tx_{t+h}\right]^2+(1-\gamma_i^{si})\sum_{k=1}^{\infty}(\gamma_i^{si})^k\left[E_{t-k}x_{t+h}-F_tx_{t+h}\right]^2}\end{aligned} \tag{1}$$

where the information stickiness parameter, $\gamma_i^{si} \in [0,1]$, represents the fraction of agents who do not update their information sets in a given period. $F_tx_{t+h} \equiv (1-\gamma_i^{si})\sum_{j=0}^{\infty}(\gamma_i^{si})^j E_{t-j}x_{t+h}$ denotes the average forecast, which is a weighted average of current and past expectations of the variable at time $t+h$, where $E_{t-j}x_{t+h}$ is the h-period-ahead forecast of the variable x conditional on information at time $t-j$. Since agents update information according to the Calvo scheme, the average forecast can be decomposed into two components as

$$F_tx_{t+h} = (1-\gamma_i^{si})E_tx_{t+h} + \gamma_i^{si}F_{t-1}x_{t+h} \tag{2}$$

The equation reveals that the presence of newly informed agents, captured by $1-\gamma_i^{si}$, leads to forecast revision from $F_{t-1}x_{t+h}$ to F_tx_{t+h}. Rearranging (2) yields:

$$E_tx_{t+h} - F_tx_{t+h} = \gamma_i^{si}(E_tx_{t+h} - F_{t-1}x_{t+h}) \tag{3}$$

Equation (2) also implies that $E_tx_{t+h} = \frac{1}{1-\gamma_i^{si}}\left(F_tx_{t+h} - \gamma_i^{si}F_{t-1}x_{t+h}\right)$. Plugging this into (3) delivers

$$E_tx_{t+h} - F_tx_{t+h} = \frac{\gamma_i^{si}}{1-\gamma_i^{si}}\left(F_tx_{t+h} - F_{t-1}x_{t+h}\right) \tag{4}$$

Equation (4) demonstrates that the current period's deviation of the rational expectations from the average forecast is driven solely by forecast revision associated with the arrival of new information between $t-1$ and t. Accordingly, the disagreement in (1) can be rewritten as

$$\sigma^x_{t,t+h} = \sqrt{(1-\gamma_i^{si})\left[\frac{\gamma_i^{si}}{1-\gamma_i^{si}}\left(F_tx_{t+h}-F_{t-1}x_{t+h}\right)\right]^2+(1-\gamma_i^{si})\sum_{k=1}^{\infty}(\gamma_i^{si})^k\left[E_{t-k}x_{t+h}-F_tx_{t+h}\right]^2} \tag{5}$$

Equation (5) makes precise how disagreement about economic activity evolves under the presence of inattentive agents: an arrival of new information raises disagreement among agents due to the agents with outdated information.

2.2 DISAGREEMENT AND NOISY INFORMATION

Another departure from full-information rational expectation models is noisy information models as in Lucas (1972), Woodford (2003), Collard et al. (2009), and Lorenzoni (2009), among many others. This class of models posits that agents update information continuously but macroeconomic aggregates are observed with noise. Thus, agents should solve a signal extraction problem to specify the status of the economy on which their optimization is based.

Suppose that agents receive both private and public signals about the variable x such as $S_{it} = \left[s_{it}^{private}, s_{t}^{public}\right]'$ where $s_{it}^{private} = x_t + v_{it}$, $s_{t}^{public} = x_t + \eta_t$, $v_{it} \sim N(0, \sigma_v^2)$, and $\eta_t \sim N(0, \sigma_\eta^2)$, respectively. As in Coibion and Gorodnichenko (2012), we further assume that the macroeconomic variable follows an AR(1) process, $x_t = \rho x_{t-1} + w_t$ where $w_t \sim N(0, \sigma_w^2)$. The forecast for the variable x_t conditional on the unobservable state variable evolves as

$$\begin{aligned} x_{t|t}(i) =& x_{t|t-1}(i) + P\left[S_{it} - S_{t|t-1}(i)\right] \\ =& (1 - PH)\, x_{t|t-1}(i) + PHx_t + P\begin{bmatrix} v_{it} \\ \eta_t \end{bmatrix} \end{aligned}$$

where $H = [1, 1]'$, $P = [P_\eta, P_v]$, and the parameter P is a function of the standard deviations of σ_v, σ_η, and σ_w.[2] Thus, as shown in Coibion and Gorodnichenko (2012), dispersion in forecasts can be written as

$$\begin{aligned} \sigma_{t,t+h}^x = \sqrt{Var_i\left[x_t(i)\right]} =& \sqrt{Var_i\left\{(1 - PH)\, x_{t|t-1}(i) + PHx_t + P\begin{bmatrix} v_{it} \\ \eta_t \end{bmatrix}\right\}} \\ =& \sqrt{\left[(1 - PH)\, \rho\right]^2 Var_i\left[x_{t-1|t-1}(i)\right] + (P_v)^2\, \sigma_v^2} \end{aligned} \tag{6}$$

Squared dispersion in forecasts hinges on its own lag as well as on the constant variance σ_v^2, indicating that the degree of dispersion is affected by the distribution of the noise v_{it}. More importantly, in contrast to sticky information models, forecast revision plays no role in determining the dispersion in forecasts. The subsequent section establishes an alternative test for information rigidity, based on the importance of forecast revision in accounting for disagreement in macroeconomic forecasts.

3 EMPIRICAL TESTS AND RESULTS

3.1 DATA The article mainly uses the dispersion data in the SPF ranged from 1969:Q1 to 2015:Q2.[3] This choice of dataset is different from that of Coibion and Gorodnichenko (2012), who analyze the dispersion measures from the LS and Michigan Survey of Consumers (MSC). There are several advantages of using the SPF dataset over these surveys. First, it is a quarterly dataset including not only one- to four-quarter-ahead forecasts but also nowcasts on macroeconomic variables. This enables to directly observe how the forecast revision, $F_t x_{t+h} - F_{t-1} x_{t+h}$, evolves over time for a variety of forecasting horizons. In contrast, the MSC provides only forecasts for the next 12 months so that forecast revisions cannot be computed out of the dataset. A downside of employing the LS is less frequent updating as it is conducted biannually rather than quarterly. Second, as pointed out by Coibion and Gorodnichenko (2012), professional forecasters are likely to be "some of the most informed agents." Therefore, their inattentiveness can be viewed as a lower bound for information rigidity borne out by the data. Finally, the SPF is the most popular survey, extensively studied in the existing literature such as Mankiw et al. (2004) and Coibion and Gorodnichenko (2015).

[2] See Coibion and Gorodnichenko (2012) for details.

[3] For some variables, we employ the data from 1984:Q3 due to their availability.

3.2 TEST OF MODELS WITH INFORMATION RIGIDITY Coibion and Gorodnichenko (2012) demonstrate that the U.S. survey forecast errors are highly predictable. This suggests a rejection of full-information rational expectation models, and is consistent with the prediction of imperfect information models such as sticky information or noisy information models. In order to examine which imperfect information model is favored by the data, Coibion and Gorodnichenko (2012) set up a regression-based test as

$$\sigma^x_{t,t+h} = c + \sum_{k=1}^{K} a_k \sigma^x_{t-k,t-k+h} + \sum_{j=0}^{J} \beta_j |\epsilon_{t-j}| \tag{7}$$

This equation is designed to test whether dispersion in survey forecasts about the variable x is accounted for by macroeconomic shocks, ϵ_t's. They demonstrate that sticky information models predict the responses of $\sigma^x_{t,t+h}$ to various structural shocks such as technology, news, and oil shocks since an arrival of shocks elevates the dispersion by inducing different forecasts among informed and uninformed agents. Accordingly, when $\beta_n = 0$ for all $n \geq 1$, the sticky information model is not relevant in accounting for the dispersion in survey forecasts. Their estimates attribute almost no role of the aggregate shocks to fluctuations in the dispersion measure, which contrasts the prediction of sticky information models, while it is in favor of noisy information models.

As made clear in (5), an alternative way of validating the presence of sticky information in the survey data is based on forecast revisions. In particular, we establish a regression-based test as

$$\sigma^x_{t,t+h} = c + a_1 \sigma^x_{t-1,t-1+h} + a_2 \sigma^x_{t-2,t-2+h} + \beta |F_t x_{t+h} - F_{t-1} x_{t+h}| \tag{8}$$

and consider various variables (x's) for the test, including GDP inflation, growth in real GDP, growth in industrial production, growth in new housing starts, growth in nonresidential investment, and growth in residential investment. Notice that the selection of the variables nests that of Coibion and Gorodnichenko (2012), who only document results for inflation forecasts. Like above, the combination of $a_2 = 0$ and $\beta = 0$ when associated with $h = 0$ advocates the noisy information model in (6). The primary advantage of the test over that of Coibion and Gorodnichenko (2012) lies in its unnecessity of identifying structural shocks since forecast revisions are readily available from the SPF. Rather, in our framework, macroeconomic shocks hitting the economy simultaneously are approximated by the forecast revisions. In this regard, another key difference between (7) and (8) is that the former is based on a single shock, whereas the latter is associated with multiple shocks.[4]

3.3 EMPIRICAL RESULTS Table 1 summarizes the estimation results for (8). Except for the case of GDP inflation associated with h=1, the a_1 coefficients are statistically significant at the 5% level or below. The results for a_2 are a bit more mixed across types of variables and forecasting horizons. The a_2 estimates are not statistically different from zero for GDP inflation with h=0, industrial production with h=3, new housing starts with h=$0, 1, 3$, and nonresidential fixed investment with h=$0, 3$. The majority of the estimates, however, are statistically significant at the 10% level or below. More importantly, with the exceptions of GDP growth (h=3) and residential fixed

[4] It is worth mention that the difference can have profound impacts on the empirical results. Suppose that two types of shocks, driving the variable x in the opposite direction, occur simultaneously. The test in (8) predicts that the arrival of the shocks results in a somewhat weak response of the dispersion since the effects of each shock are mutually offset. By isolating the effects of single shocks, however, the test in (7) is likely to overestimate the aggregate magnitude of structural shocks at each period, which tends to underestimate the β coefficients.

investment (h=$1, 3$), the estimates for β are signed positive and statistically significant at the 5% level or below. Figure 1 confirms the positive correlation between the dispersions of the survey forecasts and the absolute values of forecast revisions by plotting the former against the latter. The relationship is consistently observed regardless of the variables and horizons. This underscores the importance of sticky information in accounting for dispersion in forecasts, coherent with (5). In addition, the fact that a_2 and β are jointly statistically significant lacks the support for noisy information models in which agents continuously update their information sets. Notice that these findings are consistent with Andrade and Le Bihan (2013). They document a substantial degree of information stickiness in the ECB SPF data, based on a microeconomic study that tracts the responses of individual professional forecasters.[5]

In order to examine whether the results are sensitive across different survey datasets, Table 2 documents the results for (8) associated with the Livingston Survey. As mentioned above, one of the major differences between the SPF and LS is the survey frequency: the SPF is conducted every quarter whereas the LS is surveyed biannually. Accordingly, the results demonstrated in the table correspond to the case in which h=1 and the length of each time period is six month. The a_1 estimates are statistically significant at the 5% level or below, except for the investment variable. In a sharp contrast to the SPF-based results, the a_2 coefficients are not statistically different from zero for all the variables considered. By construction, however, $\sigma^x_{t-2,t-2+h}$ captures three- to four-quarter lagged dispersions, instead of two-quarter lagged ones, and the difference in results across the survey datasets may be attributable to the setup. Nevertheless, the β estimates are signed positive and statistically at the 10% level or below, with an exception for the CPI case. This finding is in favor of sticky information models by highlighting a significant role of forecast revisions in fluctuations in the dispersion measures.

4 CONCLUSION

This article studies the implications of the two most prominent imperfect information models on dispersion in survey forecasts. Our finding indicates that survey data are consistent with models with inattentive agents, whereas it gives less empirical support for noisy information and rational expectation models, in which agents continuously update their information sets. In modeling information frictions, our results suggest that allowing for economic agents' infrequent information updating is a crucial setup, even if the information set contains noisy signals.

[5]The same type of study is impracticable with the U.S. SPF, which does not provide the historical responses of individual professional forecasters.

A TABLES

Panel A: GDP inflation and GDP growth								
	GDP inflation				GDP growth			
	a_1	a_2	β	$adj. R^2$	a_1	a_2	β	$adj. R^2$
$h = 0$	0.439**	−0.000	0.332**	0.37	0.475**	0.262**	0.186**	0.62
	(0.087)	(0.095)	(0.098)		(0.052)	(0.059)	(0.055)	
$h = 1$	0.053	0.351**	0.501**	0.39	0.462**	0.305**	0.202**	0.60
	(0.135)	(0.097)	(0.114)		(0.086)	(0.102)	(0.066)	
$h = 2$	0.554**	0.119*	0.303**	0.56	0.566**	0.139**	0.326**	0.68
	(0.082)	(0.070)	(0.100)		(0.079)	(0.070)	(0.133)	
$h = 3$	0.477**	0.164**	0.288**	0.52	0.537**	0.211**	0.139	0.57
	(0.073)	(0.054)	(0.080)		(0.082)	(0.086)	(0.125)	
Panel B: Industrial production and new housing starts								
	Industrial production				New housing starts			
	a_1	a_2	β	$adj. R^2$	a_1	a_2	β	$adj. R^2$
$h = 0$	0.290**	0.179**	0.372**	0.47	0.328**	0.138	0.300**	0.37
	(0.090)	(0.066)	(0.056)		(0.094)	(0.089)	(0.086)	
$h = 1$	0.317**	0.280**	0.484**	0.50	0.695**	0.031	0.394**	0.60
	(0.087)	(0.094)	(0.174)		(0.113)	(0.094)	(0.112)	
$h = 2$	0.426**	0.209**	0.485**	0.54	0.415**	0.266**	0.641**	0.63
	(0.090)	(0.074)	(0.133)		(0.072)	(0.067)	(0.142)	
$h = 3$	0.532**	0.085	0.612**	0.59	0.613**	0.060	0.619**	0.63
	(0.093)	(0.078)	(0.182)		(0.067)	(0.085)	(0.137)	
Panel C: Nonresidential and residential fixed investments								
	Nonresidential fixed investment				Residential fixed investment			
	a_1	a_2	β	$adj. R^2$	a_1	a_2	β	$adj. R^2$
$h = 0$	0.318**	0.109	0.288**	0.36	0.492**	0.210*	0.564**	0.64
	(0.096)	(0.085)	(0.081)		(0.071)	(0.117)	(0.193)	
$h = 1$	0.304**	0.185**	0.364**	0.39	0.312**	0.375**	0.085	0.45
	(0.104)	(0.077)	(0.081)		(0.130)	(0.098)	(0.160)	
$h = 2$	0.420**	0.182**	0.418**	0.46	0.445**	0.213**	0.307**	0.57
	(0.092)	(0.077)	(0.112)		(0.093)	(0.071)	(0.088)	
$h = 3$	0.330**	0.154	0.444**	0.30	0.390**	0.263**	0.220	0.49
	(0.086)	(0.113)	(0.108)		(0.084)	(0.054)	(0.186)	

Table 1: Forecast revision and dispersion in survey forecasts from the Survey of Professional Forecasters data. This table reports the estimates for the regression $\sigma^x_{t,t+h} = c + a_1\sigma^x_{t-1,t-1+h} + a_2\sigma^x_{t-2,t-2+h} + \beta|F_t x_{t+h} - F_{t-1}x_{t+h}|$. The numbers in parenthesis indicate standard errors for the corresponding coefficient. Statistical significance at * 10% and ** 5% or below.

	a_1	a_2	β	$adj. R^2$
Real GDP growth	0.266**	−0.103	0.273**	0.50
	(0.078)	(0.140)	(0.044)	
Nominal GDP growth	0.445**	0.018	0.318**	0.46
	(0.157)	(0.145)	(0.053)	
Real business fixed investment	0.085	0.105	0.559**	0.56
	(0.091)	(0.087)	(0.102)	
Industrial production index	0.536**	−0.017	0.211*	0.33
	(0.195)	(0.185)	(0.111)	
Producer price index	0.190**	0.046	0.777*	0.12
	(0.093)	(0.190)	(0.394)	
Consumer price index	0.295**	0.212	−0.027	0.11
	(0.120)	(0.170)	(0.207)	

Table 2: Forecast revision and dispersion in survey forecasts from the Livingston Survey data. This table reports the estimates for the regression $\sigma^x_{t,t+h} = c + a_1\sigma^x_{t-1,t-1+h} + a_2\sigma^x_{t-2,t-2+h} + \beta|F_t x_{t+h} - F_{t-1}x_{t+h}|$. The numbers in parenthesis indicate standard errors for the corresponding coefficient. Statistical significance at * 10% and ** 5% or below.

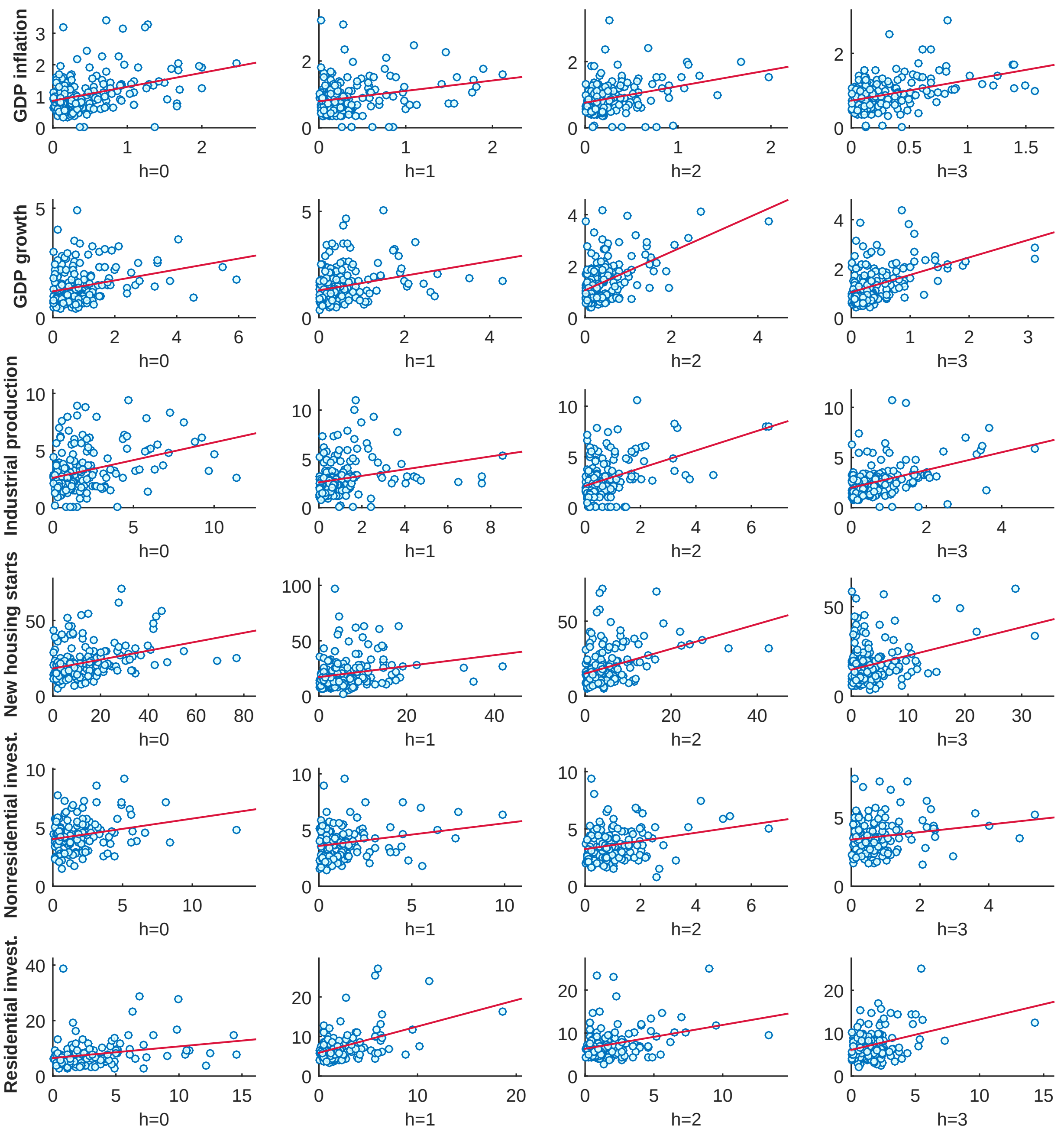

Figure 1: Scatter plots of disagreements (y-axis) against forecast revisions (x-axis). In each plot, the solid line displays the linear regression line of disagreements against forecast revisions.

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