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Discussion Paper No. 2012-E-6

IMES

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JAPAN

IMES Discussion Paper Series 2012-E-6
May 2012

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Abstract

We test whether professional forecasters forecast *rationally* or *behaviorally* using a unique database, *QSS Database*, which is the monthly panel of forecasts on Japanese stock prices and bond yields. The estimation results show that (i) professional forecasts are behavioral, namely, significantly influenced by past forecasts, (ii) there exists a *stock-bond dissonance*: while forecasting behavior in the stock market seems to be *herding*, that in the bond market seems to be *bold* in the sense that their current forecasts tend to be negatively related to past forecasts, and (iii) the dissonance is due, at least partially, to the individual forecasters' behavior that is influenced by their own past forecasts rather than others'. Even in the same country, forecasting behavior is quite different by market.

Keywords: Anchoring; Bold; Herding; Survey Forecasts
JEL classification: D03, G17

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The authors thank the QUICK Corporation for permission to use the panel data on each individual forecast. The authors also thank seminar participants at Waseda University and the staff of the Institute for Monetary and Economic Studies (IMES), the Bank of Japan, for their useful comments. Views expressed in this paper are those of the authors and do not necessarily reflect the official views of the Bank of Japan, the Federal Reserve Bank of Dallas or the Federal Reserve System.

1 Introduction

In this paper, we test whether professional forecasters forecast *rationally* or *behaviorally* using a unique database, *QSS database*. This survey includes forecasts on both stock prices and bond yields for various time horizons. The history of forecasts made by a particular individual forecaster can be also tracked.

Testing rationality of decision–making, including forecasting, is not a new subject. There have been a vast and growing number of studies from both theoretical and empirical perspectives. The seminal study by Tversky and Kahneman (1974) shows the possibility that the decision–making is not perfectly rational and rather *heuristic*. Decision makers tend to use a simple rule such as *anchoring*, where the decision is based on some *uninformative* targets.[1] In particular, Tversky and Kahneman (1974) report that answers to such a simple but unfamiliar question as "what percentage of African countries are in the United Nations" can be heavily influenced by the number suggested by the *Wheel of Fortune*. Kahneman and Knetsch (1993) and Wansink, Kent, and Hoch (1998) also show similar results on different economic activities. Beggs and Graddy (2009) find anchoring effects in art auctions.

Herding is a closely related concept.[2] According to Banerjee (1992), herding is defined as the behavior that "people will be doing what others are doing rather than using their information." Some economic activities, such as fertility decisions and voting, are heavily influenced by what other people are doing. Banerjee (1992) and Zhang (1997) point out that the strong complementarity on each decision making and asymmetric information could lead to herding behavior. As for the former, if some things are worthwhile when others are doing related things, network externalities can result in herding. On the latter, economic agents may think that other people should possess more valuable information.

Many studies herding behavior in the financial markets, particularly forecasting behavior taken by analysts or professional forecasters. Bondt and Forbes (1999) define *excessive agreement* among analyst predictions, that is, a surprising degree of consensus relative to the predictability of corporate earnings. Ehrbeck and Waldmann (1996) raise the possibility of *rational cheating*, a tendency to mimic able forecasters. Cooper, Day, and Lewis (2001) empirically support this rational cheating using analysts' performances, and Grinblatt, Titman, and Wermers (1995), Graham (1999),

[1]For the developments in studies on anchoring, see Chapman and Johnson (2002).

[2]For the comprehensive reference on modeling herding behavior, see Chamley (2004).

and Welch (2000) also report similar results for mutual fund managers. Park and Sabourian (2011) investigate the relationship between herding and contrarian behavior. Ichiue and Yuyama (2009) find irrationality of professional forecasts for the Fed Funds futures market. We revisit this problem with a new and unique database.

Estimation results in this paper show that (i) professional forecasts are behavioral, namely, significantly influenced by past forecasts, (ii) there exists a *stock–bond dissonance*: while forecasting behavior in the stock market seems to be *herding*, that in the bond market seems to be *bold* in the sense that their current forecasts tend to be negatively related to past forecasts, and (iii) the dissonance is due at least partially to the individual forecasters' behavior that is influenced by their own past forecasts rather than others'. We also show that contrary to the previous studies such as Hong, Kubik, and Solomon (2000) and Lamont (2002), the degree of such behavioral forecasting as herding or bold in the Japanese financial markets has little to do with individual experiences as professional forecasters.

These are new results and altogether imply a complex forecasting behavior in the Japanese financial markets. Even in the same country, forecasting behavior is quite different by market. This suggests that the nature of professionals in the stock market is fundamentally different from that in the bond market.

The remainder of this paper is structured as follows. Section 2 shows the details of the data used in this paper and estimation strategy. Then, we report estimation results in Section 3. Finally, Section 4 concludes.

2 Estimation

2.1 The QSS Data

The QSS monthly conducts the paper–based surveys of forecasts as well as attitudes made by professional forecasters in the Japanese financial markets. This survey includes forecasts on both stock prices and bond yields for various time horizons. We use forecasts on the stock prices (TOPIX) and newly–issued JGB yields (5–year, 10–year, and 20–year maturities) for the one–, three–, and six month horizons. We also use the data of realized stock prices and JGB yields at the end of month, since the QSS surveys are conducted around the end of each month. Each respondent is asked to answer a point forecast for each horizon. Surveys are collected from securities firms, asset managements, investment advisers, banks, trust banks, life insurances, general insurances, and pension funds. On average, we have 150 forecasts each month. We can also track the history of forecasts made by a particular individual forecaster.

The QSS launched surveys of TOPIX in June 2000. For bond yields, surveys of 20–year bond started in April 2003, those of 10–year bond in July 1998, and those of 5–year bond in May 2001. In this paper, we use the data up until November 2010. Figure 1 and Figure 2 illustrate the means and the one standard deviation confidence intervals of monthly survey forecasts on TOPIX and 10-year JGB yield for 3-month horizon, respectively. Figure 1 and Figure 2 indicate that *ex post* realized stock prices and JGB yields move within around one standard deviation of forecasts.

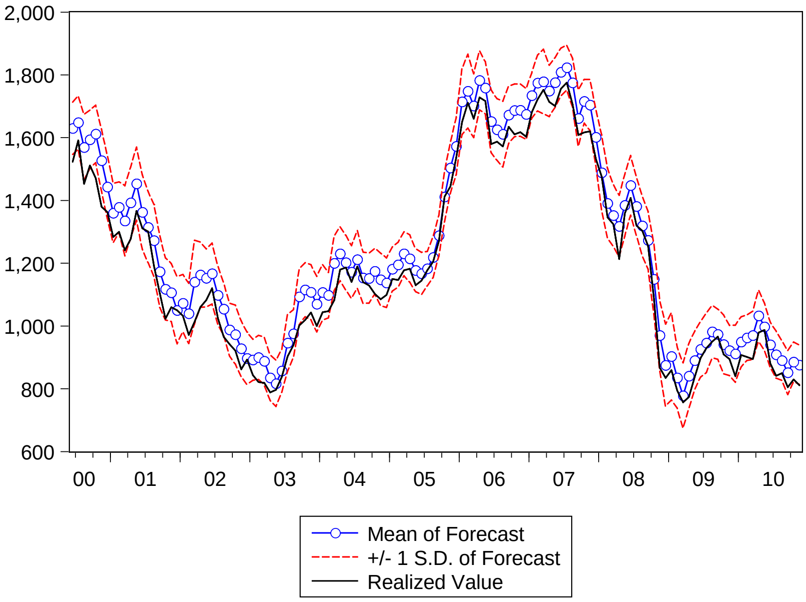

Figure 1: Forecast on TOPIX for 3-month horizon

2.2 Estimation Strategy

Do professional forecasters determine their own forecasts rationally or behaviorally relying on past forecasts? We first evaluate this question only using macro aggregated data. We then test how individual forecasts are influenced by their own past forecasts or publicly available past mean forecasts.

In this paper, $S_{t\to t+n}$ denotes a survey forecast conducted in period t of the stock price or bond yields in period $t+n$, and K_{t+n} denotes *ex post*

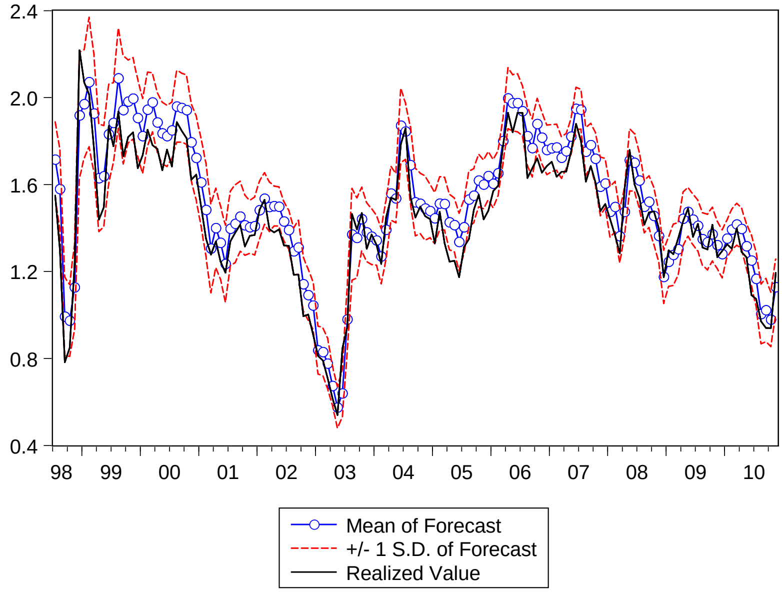

Figure 2: Forecast on 10-year JGB yield for 3-month horizon

realized value in period $t + n$. Since we have a panel data set, we have two definitions of survey forecasts. The first is what we call the aggregate mean forecast $\bar{S}$ and the second is the individual forecast $\tilde{S}$. $\mathbb{E}_t$ denotes the expectation operator under rational expectations.

Following Ichiue and Yuyama (2009), we consider a partial adjustment model:

$$S_{t \to t+n} = \rho S_{t-k \to t+n} + (1 - \rho)\mathbb{E}_t K_{t+n}, \tag{1}$$

where ρ measures the degree of the inertia in survey forecasts. If $\rho \neq 0$, current survey forecasts $S_{t \to t+n}$ are influenced by past surveys conducted k months before $S_{t-k \to t+n}$. Otherwise, current survey forecasts are equal to the rational expectations conditional on the information available in period t, namely $\mathbb{E}_t K_{t+n}$. Thus this model nests or is more generalized than a model which simply assumes the rational expectations, which are widely assumed in the macroeconomics and finance literature.

As Nordhaus (1987) points out, previous surveys are likely to play a very important role in determining current forecasts. It is plausible that many forecasters are aware of their own past forecasts and consensus forecasts. It is because this *anchoring* or *herding* helps forecasters' reputation intact. For example, Graham (1999) finds that analysts seem to be willing to sacrifice some prediction accuracy for protecting their reputation. Instead, some people might intend to make their forecasts *bold* in order to draw people's attention, as Clement and Tse (2005) show. Therefore, past forecasts are added to our model.

By using the definition of the forecast error, equation (1) can be transformed into

$$K_{t+n} - S_{t\to t+n} = \beta(S_{t\to t+n} - S_{t-k\to t+n}) + \eta_{t\to t+n}, \tag{2}$$

where

$$\beta = \frac{\rho}{1-\rho},$$

and

$$\eta_{t\to t+n} = K_{t+n} - \mathbb{E}_t K_{t+n}.$$

$\eta_{t\to t+n}$ denotes the forecast error, which is not predictable from information known in period t under rational expectations. As a result, we can test a null hypothesis of $\beta = 0$, which implies rational forecasts, by estimating equation (2).[3] When $\beta \neq 0$, forecasts are behavioral. Especially when $\beta > 0$, forecasts are pulled by past forecasts and therefore are considered herding. When $\beta < 0$, the current forecast tends to be revised more widely than the changes in the rational expectations, and toward opposite directions from past forecasts. According to the terminology defined in Clement and Tse (2005), such forecasting behavior is called bold.

When testing rationality of forecasts, we examine three cases depending on the definition of survey forecasts: (Case A) aggregate mean forecasts on aggregate past mean forecasts, namely $\bar{S}$ on $\bar{S}$; (Case B) individual forecasts on aggregate past mean forecasts, namely $\tilde{S}$ on $\bar{S}$; (Case C) individual forecasts on individual past forecasts, namely $\tilde{S}$ on $\tilde{S}$. Regarding the combinations of (n, k), we examine three cases: $(n, k) = (1, 2)$, $(3, 3)$ or $(1, 5)$.

We also evaluate the differences by professional experience for (Case B) and (Case C). We divide forecasts into three categories: (1) all, (2) more than 1 year of experiences, and (3) more than 2 years of experience. Since mean for each category (1), (2) and (3) is not publicly available, we always use $\bar{S}$ as reference forecasts.

[3]Note that a constant term is not included in the regression, as in Nordhaus (1987). This is because the forecast errors of market expectations $\eta_{t\to t+n}$ should be unbiased at least *ex ante*. Thus if the estimated forecast errors are biased, we interpret the biases as a sample artifact.

3 Results

3.1 Unit Root Tests

Before showing our main results, we examine whether the dependent and independent variables are stationary to justify our methodology. We use Augmented Dickey-Fuller(ADF) tests in Case A, and ADF-Fisher Chi-square tests in Case B and C. Table 1 shows that the unit root hypothesis is rejected for 35 cases out of 36 at the 5 percent level. This result shows that the variables we use are stationary and there is no estimation bias due to nonstationary variables.

Table 1: Unit root tests

	(n,k)	Case A		Case B		Case C	
		dep.	indep.	dep.	indep.	dep.	indep.
TOPIX	(1,2)	-8.215**	-5.174**	8568**	3991**	8568**	4175**
	(3,3)	-4.857**	-4.697**	3038**	2826**	3038**	2979**
	(1,5)	-8.215**	-2.129	8568**	1949**	8568**	1797**
20y	(1,2)	-6.913**	-3.574**	-222**	3241**	-222**	2924**
	(3,3)	-7.018**	-4.599**	2646**	2267**	2646**	2209**
	(1,5)	-6.913**	-4.333**	-222**	1832**	-222**	1715**
10y	(1,2)	-9.092**	-8.053**	9659**	5161**	8659**	4668**
	(3,3)	-9.958**	-4.988**	3988**	3852**	3988**	3585**
	(1,5)	-9.092**	-3.078*	9659**	2544**	9659**	2272**
5y	(1,2)	-7.918**	-7.258**	6562**	3721**	6562**	3402**
	(3,3)	-6.587**	-4.104**	2622**	2721**	2622**	2540**
	(1,5)	-7.918**	-4.610**	6562**	1829**	6562**	1695**

Note: * and ** denote significance at 5% and 1% level respectively. Unit root tests are conducted by ADF in Case A, and ADF-Fisher Chi-square in Case B and C, respectively. The dependent variable and the independent variable are abbreviated to 'dep.' and 'indep.', respectively.

3.2 Aggregate Data (Case A)

Table 2 shows the estimation results in (Case A), namely β and $\rho = \frac{\beta}{1+\beta}$ from

$$K_{t+n} - \bar{S}_{t\to t+n} = \beta(\bar{S}_{t\to t+n} - \bar{S}_{t-k\to t+n}) + \eta_{t\to t+n}.$$

Table 2: Estimation Results (Case A)

	(n,k)	β	ρ
TOPIX	(1,2)	0.229**	0.186
	(3,3)	0.443**	0.307
	(1,5)	0.101**	0.092
20y	(1,2)	0.097	0.089
	(3,3)	0.001	0.001
	(1,5)	-0.036	-0.037
10y	(1,2)	0.053	0.050
	(3,3)	-0.213	-0.271
	(1,5)	-0.047	-0.049
5y	(1,2)	0.105	0.095
	(3,3)	-0.042	-0.044
	(1,5)	-0.024	-0.025

Note: * and ** denote significance at 5% and 1% level respectively.

All β and ρ are positive and significant in forecasts on stock prices.[4] As have been reported in such previous studies as Ehrbeck and Waldmann (1996), forecasts on stock prices are judged behavioral and herding. On the other hand, all coefficients are not significant in forecasts on bond yields. This is not inconsistent with rational forecasting in the bond market. Below, we will check this rational or behavioral forecasts in both markets using individual forecasts.

3.3 Individual Data

3.3.1 Reliance on Aggregate Mean Forecast (Case B)

Table 3 shows the estimation results in (Case B), namely β and $\rho = \frac{\beta}{1+\beta}$ from

$$K_{t+n} - \tilde{S}_{t\to t+n} = \beta(\tilde{S}_{t\to t+n} - \bar{S}_{t-k\to t+n}) + \eta_{t\to t+n}. \tag{3}$$

Even when forecasting behavior is evaluated with micro individual forecasts, we can still find herding behavior in forecasts on stock prices.[5] On the

[4]Standard errors are computed using Newey and West (1987) estimator. Because samples are overlapped when $k \neq 1$, it is natural to have serial correlation in residuals at least when $k \neq 1$.

[5]Standard errors in Cases B and C are computed using the robust variance matrix estimator proposed by Arellano (1987).

Table 3: Estimation Results (Case B)

	(n,k)	β	ρ
TOPIX	(1,2)	-0.004	-0.004
	(3,3)	0.036**	0.035
	(1,5)	0.041**	0.039
20y	(1,2)	-0.108**	-0.121
	(3,3)	-0.264**	-0.359
	(1,5)	-0.119**	-0.135
10y	(1,2)	-0.093**	-0.102
	(3,3)	-0.357**	-0.554
	(1,5)	-0.105**	-0.118
5y	(1,2)	-0.082**	-0.090
	(3,3)	-0.271**	-0.372
	(1,5)	-0.090**	-0.098

Note: * and ** denote significance at 5% and 1% level respectively.

other hand, regarding forecasts on bond yields, all β and ρ are significantly negative. According to the results here, forecasting behavior in the bond market is considered bold. Professional forecasters have a tendency to revise their forecasts rather boldly to the opposite directions from the previous consensus.[6]

Results so far exhibit a stock–bond dissonance: while forecasting behavior in the stock market is considered herding, individual forecasters in the bond market are characterized bold. These results are new and altogether imply very complex forecasting behavior in the Japanese financial markets. For the QSS, many respondents do not report for both stock and bond markets. Due possibly to such market segmentation, forecasting behavior is quite different by market even in the same country.

3.3.2 Reliance on Individual Forecast (Case C)

We seek for the reason behind the stock–bond dissonance by looking into the individual forecasting behavior, namely estimating how individual forecasts are related to their own past forecasts. Table 4 shows the estimation results in (Case C), namely β and $\rho = \frac{\beta}{1+\beta}$ from

[6] For the intuitive explanation of the bold forecast, please refer to the Figure 1 in Clement and Tse (2005).

Table 4: Estimation Results (Case C)

	(n,k)	β	ρ
TOPIX	(1,2)	0.080**	0.074
	(3,3)	0.167**	0.143
	(1,5)	0.055**	0.052
20y	(1,2)	-0.012	-0.013
	(3,3)	-0.108**	-0.122
	(1,5)	-0.062**	-0.066
10y	(1,2)	-0.002	-0.002
	(3,3)	-0.164**	-0.196
	(1,5)	-0.039**	-0.041
5y	(1,2)	0.002	0.001
	(3,3)	-0.122**	-0.139
	(1,5)	-0.047**	-0.049

Note: * and ** denote significance at 5% and 1% level respectively.

$$K_{t+n} - \tilde{S}_{t\to t+n} = \beta(\tilde{S}_{t\to t+n} - \tilde{S}_{t-k\to t+n}) + \eta_{t\to t+n}. \tag{4}$$

Forecasts in the stock market are *sticky*, namely having a tendency to follow their past individual forecasts. On the other hand, those in the bond market are considered to have *excess sensitivity* to new available information. Consequently, forecasts tend to be revised drastically and quite often to the opposite directions from their own previous forecasts. These results altogether show that the stock–bond dissonance is due, at least partially, to the difference in the individual forecasting behavior between the stock and the bond markets: sticky forecasts in the stock market and excess sensitivity in forecasts in the bond market.

3.4 Differences by Experience

Hong, Kubik, and Solomon (2000) conclude that experienced forecasters are more likely to provide bold forecasts than inexperienced forecasters. Lamont (2002) also finds that with the more experiences, forecasts become more radical. We test whether forecasting behavior in the Japanese financial markets differs by experience.

Table 5 and 6 show the estimation results for (Case B) in equation (3) and (Case C) in equation (4) respectively by experience. We cannot observe any

Table 5: Estimation Results by Experience (Case B)

	(n,k)	all		more than 1y		more than 2y	
		β	ρ	β	ρ	β	ρ
TOPIX	(1,2)	-0.004	-0.004	-0.006	-0.006	-0.003	-0.003
	(3,3)	0.036**	0.035	0.034**	0.033	0.041**	0.039
	(1,5)	0.041**	0.039	0.039**	0.037	0.039**	0.037
20y	(1,2)	-0.108**	-0.121	-0.136**	-0.158	-0.141**	-0.164
	(3,3)	-0.264**	-0.359	-0.284**	-0.396	-0.288**	-0.404
	(1,5)	-0.119**	-0.135	-0.125**	-0.143	-0.120**	-0.137
10y	(1,2)	-0.093**	-0.102	-0.091**	-0.100	-0.093**	-0.102
	(3,3)	-0.357**	-0.554	-0.315**	-0.460	-0.294**	-0.417
	(1,5)	-0.105**	-0.118	-0.093**	-0.103	-0.085**	-0.093
5y	(1,2)	-0.082**	-0.090	-0.078**	-0.085	-0.068**	-0.073
	(3,3)	-0.271**	-0.372	-0.264**	-0.358	-0.268**	-0.366
	(1,5)	-0.090**	-0.098	-0.088**	-0.096	-0.087**	-0.096

Note: * and ** denote significance at 5% and 1% level respectively.

Table 6: Estimation Results by Experience (Case C)

	(n,k)	all		more than 1y		more than 2y	
		β	ρ	β	ρ	β	ρ
TOPIX	(1,2)	0.080**	0.074	0.078**	0.072	0.080**	0.074
	(3,3)	0.167**	0.143	0.168**	0.144	0.173**	0.148
	(1,5)	0.055**	0.052	0.054**	0.051	0.053**	0.050
20y	(1,2)	-0.012	-0.013	-0.029**	-0.030	-0.033**	-0.034
	(3,3)	-0.108**	-0.122	-0.114**	-0.128	-0.112**	-0.127
	(1,5)	-0.062**	-0.066	-0.064**	-0.068	-0.061**	-0.065
10y	(1,2)	-0.002	-0.002	0.001	0.001	0.010	0.010
	(3,3)	-0.164**	-0.196	-0.126**	-0.144	-0.092*	-0.101
	(1,5)	-0.039**	-0.041	-0.034*	-0.035	-0.025*	-0.025
5y	(1,2)	0.002	0.001	0.003	0.003	0.007	0.007
	(3,3)	-0.122**	-0.139	-0.120**	-0.136	-0.123**	-0.140
	(1,5)	-0.047**	-0.049	-0.047**	-0.049	-0.047**	-0.049

Note: * and ** denote significance at 5% and 1% level respectively.

clear difference by experience. Forecasting behavior in the Japanese financial market is characterized by market and not by experience.

While the past empirical studies about differences by experience show that forecasting behavior in the financial markets differs by experience, we see no evidence of that. One reason may come from the characteristics of data. Forecast rationality is analyzed using data on analysts' earnings forecasts of listed companies in Hong, Kubik, and Solomon (2000) and Clement and Tse (2005), and economists' macroeconomic forecasts in Lamont (2002). Earnings and macroeconomic forecasts are made public in a way that you can trace their forecasts and the outcome and evaluate whose performance is better or not. When it is considered that the forecasts data are published, analysts and economists weigh heavily on their career and reputation in predicting earnings or macroeconomic variables. Thus, it is possible that differences by experience affect forecasting behavior. On the other hand, the QSS asks professionals in the Japanese financial markets to make forecasts on asset prices, but individual forecasts are not published. Furthermore, the survey's respondents are not only "sell side" security firms' analysts but also "buy side" fund managers for pensions or investment trusts, etc. Although fund managers in the "buy side" are mainly responsible for finding money-making opportunities and reaping profits, "sell side" security firms' analysts and economists are likely to make consistent and/or bold forecasts for keeping their reputation intact. In sum, because the QSS survey does not publish individual forecasts and covers many types of respondents, many of whom do not have to care about their reputation, differences by experience may not affect the way of forecasting.

4 Conclusion

In this paper, we find that (i) professional forecasts are behavioral and significantly influenced by past forecasts, and (ii) there exists a stock–bond dissonance: while forecasting behavior in the stock market is considered herding, individual forecasters in the bond market are characterized bold in a sense that their current forecasts are negatively related to past forecasts. Forecasting behavior in the financial markets is not unique and different by market. Furthermore, the degree of such behavioral forecasting is not influenced by experience as professional forecasters.

We have shown that this dissonance stems, at least partially, from the difference in the individual forecasting behavior between the stock and the bond markets: sticky forecasts in the stock market and excess sensitivity in forecasts in the bond market. Yet, we have not investigated the structural reason behind this dissonance. This requires a microeconomic modelling of professional forecasters. Structural understanding of this dissonance is left for our future research.

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