A New Hedging Hypothesis Regarding Prediction Interval Formation in Stock Price Forecasting

Dan Zhu*, Qingwei Wang† and John Goddard‡

Abstract

We propose and test a simple hedging hypothesis for prediction interval formation in stock price forecasting. In the presence of uncertainty, forecasters hedge their forecasts by adjusting the bounds of the prediction interval in a way that reflects their forecast of the average forecast of others. This hypothesis suggests a positive relationship between the belief wedge, defined as the difference between the subject's forecast of the average forecast of others and the subject's own point forecast, and the asymmetry of the prediction interval. Empirical support for the hedging hypothesis is drawn from two in-class surveys, an experiment, and a large survey of professional analysts' forecasts of future stock prices.

Keywords: Prediction intervals; Forecast of average forecasts of others; Asymmetry; Forecasts; Decision making under uncertainty.

*Wu jinglian School of Economics, Changzhou University, Changzhou, Jiangsu, 213159, China Tel: +86 (0)519 88519206. E-mail: chongchong1016@hotmail.com

†Cardiff Business School, Aberconway Building, Colum Drive, Cardiff, CF10 3EU, United Kingdom Tel: +44 (0)2920 875514. E-mail: wangQ30@cardiff.ac.uk

‡Bangor Business School, Hen Goleg, College Road, Bangor, LL57 2DG, United Kingdom E-mail: j.goddard@bangor.ac.uk

A New Hedging Hypothesis Regarding Prediction Interval Formation in Stock Price Forecasting

Abstract

We propose and test a simple hedging hypothesis for prediction interval formation in stock price forecasting. In the presence of uncertainty, forecasters hedge their forecasts by adjusting the bounds of the prediction interval in a way that reflects their forecast of the average forecast of others. This hypothesis suggests a positive relationship between the belief wedge, defined as the difference between the subject's forecast of the average forecast of others and the subject's own point forecast, and the asymmetry of the prediction interval. Empirical support for the hedging hypothesis is drawn from two in-class surveys, an experiment, and a large survey of professional analysts' forecasts of future stock prices.

Keywords: Prediction intervals; Forecast of average forecasts of others; Asymmetry; Forecasts; Decision making under uncertainty.

1 Introduction

A rapidly growing literature, surveyed by Lawrence, Goodwin, O'Connor, and Onkal (2006), acknowledges the importance of incorporating judgments to improve the accuracy of forecasts or predictions. Forecast accuracy, however, is not the only consideration when making forecasting judgments (O'Connor, Remus, and Griggs 2001). Forecasters are often required to report a prediction interval that reflects the uncertainty associated with a point forecast. Prior literature typically assumed that the decision maker's judgmental prediction interval (JPI) is symmetric around the point forecast (e.g., Taylor and Bunn 1999). However, several studies have reported evidence of asymmetric JPIs (De Bondt 1993, O'Connor et al. 2001, Du and Budescu 2007). Despite this empirical evidence, why JPIs are often asymmetric remains an open question.

The primary goal of our study is to propose and test a new hypothesis that helps explain the asymmetry of the JPI. Keynes (1936), among others, claimed that market participants are likely to take others' forecasts into account when making financial decisions. We consider the viewpoint of a forecaster who faces the task of predicting future stock prices. Without knowing the opinions of others, the forecaster produces his own point forecast and his forecast of the average point forecast of others (hereafter "FAPFO"). We hypothesize that the JPI constructed by the forecaster around his point forecast may reflect a tendency for the forecaster to hedge his own forecast with his FAPFO.

Accordingly, we hypothesize that if the forecaster's point forecast diverges from his FAPFO,[1,2] he hedges his own belief by creating a JPI oriented in the direction of his FAPFO. Therefore, the JPI is asymmetric around the forecaster's own point forecast. Our principal hypothesis is that there is a positive association between the belief wedge and the asymmetry of the JPI,[3] where the belief wedge is the difference between the subject's FAPFO and his own point forecast, and the asymmetry of the JPI measures the relative proximity of the point forecast to the two bounds of the JPI.[4]

Figure 1 provides a graphical illustration of the principal hypothesis for three different scenarios. In Scenario 1, a subject's point forecast coincides with his FAPFO, making it unnecessary to adjust the bounds of the JPI. Therefore, the JPI is symmetric around the point forecast. In Scenario 2, the point forecast exceeds the FAPFO. Subjects hedge their forecasts by shifting the bounds of the JPI toward the FAPFO, causing their point forecasts to be closer to the upper bound than the lower bound of the adjusted JPI. Consequently, the asymmetry of the JPI measure becomes negative. In Scenario 3, conversely, the point forecast was below the FAPFO. Shifting the bounds of JPI toward the FAPFO leads to a point forecast closer to the lower bound of the JPI, hence, a positive asymmetry of the JPI.

[Insert Figure 1 about here]

We tested our hypotheses using data from several sources. First, we conducted an in-class survey by presenting the subjects (students) with charts of past stock prices and then asking them to forecast future prices and report their FAPFO in the same survey. Second, to take into account the potential effect of incentives on the accuracy of forecasts, we conducted a second survey that provided subjects with such incentives. Additionally, subjects in this survey were not presented with charts but were free to use any information to make real-time forecasting each week over a period of seven weeks. It was considered that the shorter forecast horizon in this survey might make the subjects more likely to hedge their JPIs toward their FAPFOs, as Froot, Scharfstein, and Stein (1992) claim that speculators have stronger incentives to think about the opinions of others in the short term than the long term.

Third, to alleviate the potential concern that students' beliefs/behaviors may not resemble those of market participants, we further analyzed a large panel data set drawn from a survey of professional analysts' monthly forecasts of the German stock market index (DAX). The data are sourced from the monthly ZEW Financial Market Survey data from the Center for European Economic Research (ZEW) in Germany. Although the survey participants were not prompted to consider the beliefs of others, we assumed that as professional financial market participants they do so unprompted, and we measured the belief wedge using a proxy for the FAPFO obtained by extrapolating from the most recent prior data produced by the same survey.

Fourth, to shed light on the causal relationship between belief wedge and the asymmetry of JPI, we conducted an in-class experiment in which some subjects were primed to adopt a "low-power" condition, conducive to taking others' beliefs into account, while others were primed to adopt a "high-power" condition, which is conducive to disregarding the FAPFO. Prior experimental evidence suggests that high-power subjects anchor more heavily on their own opinions, and are less likely to take others' perspectives into account (Galinsky, Magee, Inesi, and Gruenfeld 2006). We found that low-power subjects were more likely than high-power subjects to formulate their JPI in accordance with the hedging hypothesis. Such a pattern provides indirect evidence that the belief wedge causes JPI asymmetry.

Across several alternative surveys and experimental designs as outlined above, the empirical evidence is consistent with the hypothesized positive association between the belief wedge and the asymmetry of JPIs, after controlling for the personal characteristics of the forecasters and the structure of the observed (historical) stock price movement. The results are robust to the use of different model specifications, an alternative measure of the FAPFO, the logarithmic transformation of variables, and adjustments for nonlinearity and outliers, as well as the controls of salient features in the price charts displayed to the subjects.

Our study contributes to the literature in several ways. We provide a new explanation for the asymmetry of the JPI. As pointed out by O'Connor et al. (2001), two major circumstances can lead to asymmetric JPIs. The first source is contextual environment or information unrelated to the time series. For example, a forecaster's loss function may cause his forecast to deviate from the "most likely one", and has the potential to induce asymmetric JPIs. The second source stems from a forecaster's desire to convey information about his perceived risk (such as whether an observed trend will continue) through the JPI. Our explanation focuses on the second source, and we argue that a forecaster uses JPIs to convey the uncertainty about whether his own or others' forecasts are more likely to be right, and shifts the bounds of his JPI toward his FAPFO to hedge such a risk.

Our study also adds to the literature on anchoring and adjustment heuristics first theorized by Tversky and Kahneman (1974), which refers to the tendency for decision makers to rely too heavily on the first piece of information offered (the "anchor"). A number of studies have examined this heuristic in time-series forecasting (Bolger and Harvey 1993, Lawrence and O'Connor 1995). Closely related to our study, De Bondt (1993) argues that the asymmetric JPI arises from two anchors (perceived slope and the average observed price) during the formation of the JPI. Our approach differs from De Bondt (1993) in that it introduces a new anchor: the forecaster's FAPFO. Our hypothesis is therefore most relevant to situations where participants are likely to take others' beliefs into account (such as, but not limited to, financial markets).

Finally, our study attempts to understand how an FAPFO may affect individual's own judgmental forecasts. The relevance of others' forecasts is theoretically well founded in economics (Townsend 1983, Allen, Morris, and Shin 2006), and its application goes beyond financial forecasting (Allen et al. 2006). Indeed, since Keynes (1936) introduced the metaphor of the beauty contest, it is widely acknowledged by market participants and academic researchers that others' beliefs matter in financial markets because the equilibrium price is not only a function of one's own forecasts, but more importantly, also a function of the forecasts of others (Welch 2000, Allen et al. 2006, Borgsen and Weber 2008, among others). Therefore market participants are likely to take their estimates of others' opinions into account when forming their forecasts of future financial outcomes. Furthermore, the prior literature suggests that individual forecasts are likely to be subject to various behavioral biases (Budescu and Chen 2015). By invoking the wisdom-of-crowds principles, combining forecasts of different individuals improves forecast accuracy (Clemen and Winkler 1986, Timmermann 2006, Himmelstein, Atanasov, and Budescu 2021). This provides incentives for a forecaster to consider his FAPFO. Despite its importance, whether the FAPFO matters for various aspects of judgmental forecasting such as point and interval forecasts is rarely explored. Our empirical evidence suggests that it affects the asymmetry of the JPI.

The remainder of this paper is organized as follows. Section 2 provides a brief review of the literature. Section 3 describes the experimental design and presents the empirical results. Section 4 concludes.

2 Literature

This section discusses several strands of literature related to our study, including those concerning JPI, higher-order beliefs, and the effects of the salient features of time series on subjects' forecasts.

Much of the existing literature on JPI focuses on the determinants of interval width and incidence.

A common example of overconfidence comes from experiments that ask the subjects to form prediction intervals for the future value of a time series at a given probability level. Overconfidence (more specifically, overprecision or miscalibration) is indicated if the rate at which the stated prediction intervals fail to encompass the true values over a large number of predictions exceeds the probability level associated with the intervals.[5] A few papers have shown that salient features of observed time series influence the width of the prediction interval. Such features include the degree of randomness in the observed values of the series (O'Connor and Lawrence 1992), trend (Lawrence and Makridakis 1989, O'Connor and Lawrence 1992), degree of seasonality (O'Connor and Lawrence 1992) and the scaling of the graphs presented to subjects (Lawrence and O'Connor 1993). Other studies find that experts' advice and the use of statistical methods improves the calibration of JPI (Önkal, Goodwin, Thomson, Gönül, and Pollock 2009), and appropriate feedback to subjects reduces their overconfidence (Bolger and Önkal-Atay 2004).

Several studies have provided empirical evidence that JPIs do not fall symmetrically around the point forecast (De Bondt 1993, O'Connor et al. 2001, Du and Budescu 2007). Why is the JPI asymmetric? O'Connor et al. (2001) suggested two major sources of asymmetry. The first source is the contextual environment or information unrelated to the time series. One such explanation is that the intended use of JPI reflects asymmetries in the utility functions of the users of forecasts. For example, a user of value at risk analysis in finance might be primarily concerned with the probability of incurring a loss that results in insolvency (Lawrence et al. 2006), rather than with the entire distribution of possible profits or losses. The second source is the forecaster's desire to convey information about his perceived risk through the JPI. For instance, De Bondt (1993) proposes a hedging theory to explain his finding that the asymmetry of JPI varies inversely with the magnitude of the expected price change (the difference between the point forecast and the last observed value of the stock price, hereafter, EPC). In hedging theory, forecasters follow a three-step procedure to construct their prediction intervals under the influence of two anchors. The first anchor is a perceived slope measure based on past stock price changes, and the second is the average observed (historical) stock price. At the first step the forecaster forms a point forecast by applying the rate of past price change to the last observed price.[6] At the second step, he constructs a symmetric interval forecast around the point forecast. In the third step, he adjusts both bounds of the interval forecast toward the average price, leaving the point forecast unchanged. In general, the procedure introduces an asymmetric prediction interval. In a controlled experiment involving portfolio managers and novices, Muradoglu (2002) found that De Bondt (1993)'s hedging theory is not supported. Expert forecasters did not hedge, but they speculated on their optimistic forecasts.

Another example of the second source is the "hedge strategy" explained by O'Connor et al. (2001). They hypothesized that, similar to the role of EPC in producing an asymmetric JPI in De Bondt (1993), the difference between the point forecast and the last observed value of the time series is a key determinant of the direction and magnitude of the asymmetry. A decision maker who employs the hedge strategy targets the point forecast in one direction and biases the prediction interval in the opposite direction. Unlike De Bondt (1993) and O'Connor et al. (2001), the asymmetry of JPIs in our hypothesis arises when the decision maker is unsure whether his or others' forecasts are more likely to be correct, and hedges such a risk by shifting the bounds of JPI toward the FAPFO.

Spence (1996) proposes another explanation for asymmetric JPI that seems unrelated to the two sources summarized by O'Connor et al. (2001). He argues that a subject's best estimate is less likely to be the midpoint of his prediction interval when it is more difficult to forecast. Difficulty in forecasting creates a need to decompose the initial problem into a series of interrelated problems. Miscalculation on the part of a "contingency thinker" can result in an asymmetric or skewed subjective density function.

The emphasis on FAPFO links this study to the finance literature on higher-order beliefs.[7] A growing theoretical literature attempts to relate beliefs about others' beliefs to stylized facts, such as price bubbles (Balakrishnan, Schrand, and Vashishtha 2020), short-term momentum (Banerjee, Kaniel, and Kremer 2009), trading behavior (Egan, Merkle, and Weber 2014, Cespa and Vives 2015), return co-movements (Grissey 2008) and excess volatility (Monnin 2004). The opinions about others' beliefs are typically not directly observable, and empirical evidence is sparse. Notable exceptions include Egan et al. (2014), who observed first- and second-order expectations of returns from a longitudinal panel survey of private investors at Barclays Stockbrokers, finding that investors' second-order beliefs influenced their investment decisions. Monnin (2004) estimated a heterogeneous-expectations asset pricing model using US stock market data from 1871 to 2003, suggesting that higher-order beliefs could form part of the explanation of the excess volatility puzzle. Using data from a survey of professional investors, Rangvid, Schmeling, and Schrimpf (2013) present strong evidence that second-order beliefs influence investors' forecasts.

The FAPFO also links our paper to the literature on forecast combinations and the wisdom of crowds. This literature shows that a typical decision-maker often relies on simplifying heuristics to form a judgment, which is associated with behavioral biases such as overconfidence (Budescu and Chen 2015, Gilovich, Griffin, and Kahneman 2002). To improve forecast performance, the wisdom-of-crowds principle advocates the use of aggregated forecasts from multiple individuals (Budescu and Chen 2015, Himmelstein et al. 2021). Supporting this principle, the forecasting literature shows that simple consensus forecasts outperform those of individual forecasters, and more sophisticated statistical methods help improve the forecast accuracy further (Clemen and Winkler 1986, Timmermann 2006, Himmelstein et al. 2021). Therefore, when forecasts of others are unavailable, it is conceivable that a forecaster would consider his FAPFO when forming his own forecasts.

To test our hypotheses, we asked subjects to forecast future prices after observing a price chart in a class survey and an experiment. This relates our study to existing studies that have used a time-series task. Previous literature shows that various salient features of the presented time series affect subjects' forecasts/decisions. Such features include price path patterns (Grosshans and Zeisberger 2018, Huber and Huber 2019), extreme points (Mussweiler and Schneller 2003), crashes (Borsboom and Zeisberger 2020), last trade direction, uncertainty level (Duclos 2015, Sobolev and Harvey 2016), run length, local minima and maxima (Raghubir and Das 2010), and the mean absolute price change and irregularity (Duxbury and Summers 2018) of past price series. While these salient time series features have the potential to affect the length and asymmetry of JPI, our focus is on the role of the belief wedge to explain the asymmetry of JPI, and we control for these features, insofar as this is possible, in our empirical analysis.

3 Research Design and Results

We tested our hedging hypothesis of JPI formation by conducting two in-class surveys and one in-class experiment and utilizing a large panel of surveys of professional analysts. To ensure the validity of our in-class surveys/experiment design, we sought feedback from colleagues on our original survey questions and designs and incorporated them into the revised design. We also ran mock surveys before conducting Survey 1 and the experiment among a small group of subjects (about 10) who did not participate in the actual surveys/experiment later. We gathered their comments on the appropriateness of the survey questions for example, whether they understood the questions well and whether the allotted time for the survey/experiment was sufficient for them to answer all questions and adjusted our survey/experimental design accordingly. We also trained the experimenters before the formal survey/experiment to ensure that they followed the same protocol. For example, we required the experimenter to treat each subject in the same way to avoid the Pygmalion effect.[8] To ensure that the subjects understood the forecasting questions, the experimenters explained those questions at the beginning of the survey/experiment.

In this section, we present the motivation, research design, data, and results for each survey and experiment individually, and provide some general discussions at the end.

3.1 Survey 1

3.1.1 Motivation

We first took an in-class survey approach similar to that of De Bondt (1993) to examine the relationship between the belief wedge and the asymmetry of JPIs. Such an approach allows us to collect subjects' elicited point forecasts, prediction intervals, and, more importantly, their FAPFOs, which are usually unavailable from other data sources.

3.1.2 Subjects

The subjects in this survey were undergraduate finance students registered in a quantitative methods course at a business school. They received no reward for their participation or performance in the survey. The allotted class time for completion of the survey was 15 minutes. Of the 80 students registered for the course, 65 (25 males and 40 females) completed and returned the survey, yielding a response rate of 81.25%. The average age of respondents was 21. The participants were asked to provide the following information: gender, nationality, and GPA in the previous semester. None of the participants participated in the other survey or the experiment described below.

3.1.3 Stimuli

We followed the methods used by De Bondt (1993) to generate the stimulus series. The subjects were shown six charts, and each chart represents 48 consecutive monthly prices of an unnamed stock. The six charts are in fact selected segments of the FTSE 100 index between 1984 and 2011. The selected series were rescaled to minimize the possibility of recognition. Two of the six price series were upwardly trended, two series were downwardly trended, and two series appeared to be untrended. Figure 2 shows an example of each of the three cases.

[Insert Figure 2 about here]

To mitigate concerns that respondents might complete the questions for the first few charts and leave the rest blank, we assigned two different sets of six charts randomly among the subjects, with the ordering of the six charts reversed between the two sets. Reversal of the ordering also helped mitigate against practice effects, whereby a subject's forecasting performance would tend to improve over repeated attempts at a forecasting exercise.

We applied two different rescaling factors (1/100 and 3/100) to the original FTSE 100 index series within each set of six charts and generated two versions of each set with different degrees of volatility. Huber and Huber (2019) showed that the scale of the presented price series affects forecasters' future price forecasts. Rescaling enabled us to examine whether it affected the validity of our hedging hypothesis, as well as helping alleviate the concern that subjects might form their forecasts based on their memory of the historical FTSE 100 index (De Bondt 1993).

3.1.4 Procedures

Each subject received two pages containing the six charts and supplied handwritten answers to the survey questions. The subject was asked to forecast the price of each stock 13 months (56 weeks) ahead and provide a 90% prediction interval. The subject was then asked to estimate the average forecast of his or her classmates.[9,10] Subjects were asked to complete their responses without conferring with any other party. They were not asked to revise their point forecasts or prediction intervals after stating their FAPFO.

3.1.5 Analysis and Results

Our key variables of interest, the standardized[11] asymmetry and belief wedge measures, were defined as follows:

$$\textit{Asymmetry of JPI} \;=\; 100 \times \frac{\textit{Upper bound} + \textit{Lower bound} - 2 \times \textit{Point forecast}}{(\textit{Upper bound} - \textit{Lower bound}) \times \sqrt{\textit{Number of weeks ahead}}} \tag{1}$$

$$\textit{Belief wedge} \;=\; 100 \times \frac{\textit{FAPFO} - \textit{Point forecast}}{\textit{Last observed price} \times \sqrt{\textit{Number of weeks ahead}}} \tag{2}$$

In addition to the belief wedge and asymmetry measures, we followed De Bondt (1993) and controlled for a standardized EPC, measured as:

$$\textit{EPC} \;=\; 100 \times \frac{\textit{Point forecast} - \textit{Last observed price}}{\textit{Last observed price} \times \sqrt{\textit{Number of weeks ahead}}} \tag{3}$$

In the regressions, we included controls for several characteristics of the subjects, including gender, nationality (denoted *country*), and GPA in the previous semester (denoted *mark*), and salient features of the observed price series presented to the subjects, including trend and volatility. We defined the trend as the difference between the last and first prices shown in the chart, and measured volatility using the standard deviation of the daily prices shown in the chart. We also winsorized the measures of the asymmetry of the JPI, belief wedge, and EPC at the 1% and 99% levels (in this survey and the surveys/experiment below) to remove the outliers.[12]

[Insert Table I about here]

Panel A of Table I reports the summary statistics. Consistent with the findings of O'Connor et al. (2001) and Glaser, Langer, Reynders, and Weber (2007), the mean of the asymmetry of JPI measure is negative. We also report the correlation coefficients for several key variables in Panel B of Table I. Consistent with our hypothesis, the correlation between the belief wedge and the asymmetry of JPI is positive. The negative correlation between EPC and the asymmetry of JPI is in line with the predictions of De Bondt (1993). The belief wedge is positively correlated with EPC, while the trend is negatively correlated with the asymmetry of JPI, belief wedge, and EPC. We control for EPC and the trend in the regressions below to account for their linear dependence on the belief wedge.

The relationship between the belief wedge and the asymmetry of JPI was investigated further in a regression analysis that included controls for several factors besides the belief wedge that might have influenced the asymmetry of JPI. The dependent variable is the asymmetry measure defined by equation (1) and applied to the 90% prediction interval specified by the survey respondents. The explanatory variables are the belief wedge measure defined by equation (2) and the EPC defined by equation (3), and the controls include gender, country, mark, trend, and volatility.

We report ordinary least squares (OLS) regressions, median regressions, panel regressions estimated using random effects (RE), and generalized estimating equation (GEE) specifications (Liang and Zeger 1986). The RE specification was based on the standard assumption that the disturbance term contains a component that is constant across all forecasts made by the same subject, and a separate component that is entirely random. The GEE specification describes an equal-correlation model in which the disturbance terms for forecasts made by the same subject are assumed to be correlated. The correlation is assumed to be the same for all pairs of forecasts produced by the same subject, and is the same for all subjects. Each of these methods has its own merits and limitations. OLS is a workhorse regression model that is widely employed in empirical research, the median regression is more robust to outliers and nonlinearity, the panel regression accounts for individual unobserved heterogeneity, and GEE allows the correlated disturbance terms in the forecasts of the same subject. We considered these models to examine the robustness of our results to different econometric models.

[Insert Table II about here]

The estimation results in Table II represent strong evidence of a positive association between the belief wedge and the asymmetry of JPI, consistent with the hedging hypothesis proposed in this study. The estimated coefficients on the belief wedge measure are positive and significantly different from 0 at the 0.01 level in all estimations, and the magnitudes of the coefficients appear to be stable across the various specifications. The coefficients on the belief wedge measured in the GEE estimations, for example, indicate that a one-standard-deviation increase in the belief wedge measure is associated with an increase of 2.46 (= 7.95×0.31) in the asymmetry of the JPI measure.

The estimation results also suggest a negative association between the EPC and the asymmetry of the JPI. The estimated coefficients for the EPC are significant at the 0.1 level or lower in all specifications. The EPC was reported by De Bondt (1993) and O'Connor et al. (2001) as an important determinant of the asymmetry of the JPI. Our results are similar. Since the coefficients for the belief wedge are significant after accounting for the EPC, we infer that the belief wedge is an important determinant, but not the only determinant, of the asymmetry of the JPI in its own right, regardless of any association between the belief wedge and the EPC.

Among the control variables,[13] the coefficients of trend are negative and significant. The negative trend coefficient is consistent with the findings of O'Connor et al. (2001). The price charts displayed to the subjects in Survey 1 included equal numbers of cases where the historical price series were subject to an upward trend, a downward trend, and no trend. When the sample is sub-divided accordingly, the correlation between the belief wedge and the asymmetry of the JPI measure is positive and statistically significant in all three sub-samples. We infer that our results are insensitive to the presence or absence of trends in the historical series. The coefficients of volatility are insignificant for all model specifications. Duxbury and Summers (2018) noted that volatility measures the deviation of prices from their mean, and irregularity in price may be a separate aspect of volatility that affects risk perception. We consider the effect of irregularity in the robustness checks.

3.2 Survey 2

3.2.1 Motivation

As the subjects in Survey 1 were not provided incentives for answering the survey questions, this raises the question of whether the inclusion of incentives in the survey design would affect our results. To answer this question, we conducted Survey 2, in which a small component of the grading of the course was contingent on the completion and accuracy of the forecasts, providing some incentives for subjects to engage in their forecasting tasks.

3.2.2 Subjects

The 42 subjects in Survey 2, 19 male and 23 female, were finance students registered in a postgraduate finance course at the same business school as in Survey 1. Their average age was 25. Subjects were asked to provide the following information: gender, nationality, and whether they had any previous investment experience. None of the subjects had participated in Survey 1 or the experiment.

3.2.3 Stimuli

Survey 2 was conducted over the course of seven non-consecutive weeks from 09/02/2012 to 19/04/2012. On Thursdays, the subjects were asked to forecast the FTSE 100 index one week ahead on the following Thursday. The subjects were not shown any graphs of the FTSE 100 index. To illustrate the movement of the FTSE 100 index around our survey period, we plot its time series from 09/02/2011 to 26/04/2012 (Figure 3).

[Insert Figure 3 about here]

3.2.4 Procedures

The subjects were asked to specify a point forecast and a 90% prediction interval and provide a forecast of the average forecasts of their classmates and the average forecasts of market participants.[14] Subjects were allowed to incorporate any information they chose into their forecasts, including but not limited to news from the media and data on past movements in the index at the time of forecasting. Responses were submitted electronically by 11am each Thursday.

The stimuli and procedures in Survey 2 differed from those in Survey 1 in a few respects. First, it constituted real-time forecasting. The subjects in this survey predicted the FTSE 100 index one week ahead on each Thursday. This obviated the concern that subjects might have remembered the price displayed on the chart, as in Survey 1 (De Bondt 1993). Second, participants could use any information available, including the past FTSE 100 index, to form their forecasts. Third, the forecasting horizon in this survey was much shorter (1 week forecasting horizon) than that of Survey 1 (13 months forecasting horizon). The weekly forecast tasks and the one-week-ahead forecast horizon allowed subjects to observe the realized price and learn from their forecast errors during the course. It also allowed the experimenter to evaluate the subjects' forecast accuracy and award them a component of their grade accordingly. Froot et al. (1992) argued that speculators have stronger incentives to think about the opinions of others in the short term than the long term.

Therefore, subjects might take their FAPFO more seriously when forecasting future stock prices, providing stronger support for the hedging hypothesis in this survey.

3.2.5 Results

[Insert Table III about here]

In this survey, we calculated the asymmetry of the JPI, the belief wedge, and the EPC using Equations 1, 2, and 3, respectively. The trend was computed as the difference between the closing price of the FTSE 100 index on the date of the forecast and the closing price of the previous 25 trading days. Volatility was calculated as the standard deviation of the closing prices for the 25 trading days prior to the date of the forecast.

Table III reports the summary statistics and pairwise correlation coefficients of key variables. Consistent with Survey 1, we find that the asymmetry of the JPI measure is on average negative, suggesting that subjects generally form an asymmetric JPI. In addition, the correlation between the belief wedge and the asymmetry of the JPI is positive. These results support our hypothesis.

We estimate ordinary least squares (OLS), median regressions, random effects panel regressions, and generalized estimating equations (GEE) regressions of the asymmetry of JPI on belief wedge and control variables. Table IV shows that the estimated coefficients on belief wedge are positive and significantly different from 0 at the 0.05 level or below in all of the estimations. Consistent with the results of survey 1, Table IV shows a negative association between EPC and JPI asymmetry. In contrast, the trend loses statistical significance in three out of the four regressions in Table IV. The effects of all other control variables were insignificant. Taken together, these results suggest that our hedging hypothesis is supported despite the differences in survey design between Surveys 1 and 2.

[Insert Table IV about here]

3.3 Survey of Professional Forecasters

3.3.1 Motivation

A common critique of in-class financial surveys/experiments is that students' beliefs/decisions may not represent those of professional participants in financial markets. Therefore, we further tested our hypothesis against the data of a large panel of professional forecasters, the monthly ZEW Financial Market Survey data, obtained from the Centre for European Economic Research (ZEW) in Germany. The forecast horizon was six months, and the sample covered the period from 02/2003 to 02/2011.

3.3.2 Subjects

For each month during our sample period, on average, approximately 210 financial analysts employed by participating banks, insurance companies, and large industrial enterprises participated in this survey. Of the participants, 94% were men and 6% were women. Among them, 76% had a university degree. Their average age was 42.54 and average work experience in the financial industry was 15.40 years.

3.3.3 Stimuli

When forming their forecasts, professional forecasters are free to use any available information. Such information includes, but is not limited to, the past DAX index. We plot the time series of the DAX index from 01/02/2002 to 28/02/2011 in Figure 4.

[Insert Figure 4 about here]

3.3.4 Procedures

For each month during our sample period, participants of the ZEW financial market survey received survey questions that asked their six-month-ahead macroeconomic and financial expectations in several countries and regions. Our focus is on the following questions:

I expect the DAX in 6 months at ... points.
With a probability of 90% the DAX will then lie between points ... and ....

That is, participants were asked to provide their point forecast and 90% prediction interval for DAX in six months. The survey also collected information about participants' characteristics, including gender, age, years of experience in the financial industry, and educational background. Although the participants were not rewarded with monetary incentives, they received timely press releases that contained the survey results of the most recent wave. In total, our sample had 16,186 observations during the 97-month sample period.

3.3.5 Results

The survey did not ask participants' opinions about the forecasting of other financial analysts. Using the same data, Rangvid et al. (2013) suggested a proxy based on the lagged consensus forecast (calculated by averaging the point forecasts of the previous month across responses), and provided empirical support for the validity of the proxy. Alternatively, Rangvid et al. (2013) estimated an expected consensus using the one-month-ahead predicted value generated by an estimated AR(1) model updated monthly as each additional month's historical data became available. Although forecasters do not know what others believe at the time they make their forecasts, they can use the last publicly available consensus as a proxy or employ an autoregressive model to estimate the expected consensus. We used the same two proxies for respondents' FAPFO.

The summary statistics and the correlation matrix in Table V show that the asymmetry of the JPI measure is, on average, negative and is positively correlated with the belief wedge. These results are consistent with those in Surveys 1 and 2 and support our hedging hypothesis. Notably, while the correlations between belief wedges and trends were mixed in signs in Surveys 1 and 2 and the survey of professional forecasters, the correlation was stronger (-0.41) in Table V than in Surveys 1 (-0.22) and 2 (0.09). This might have arisen from the difference in the types of subjects, or from the fact that, unlike in Surveys 1 and 2, the FAPFO was not elicited but proxied using the last available consensus.

[Insert Table V about here]

Table VI reports the regression results where the belief wedge is defined by equation (2), which is the consensus forecast in the previous month, and the point forecast is the individual participant's point forecast in the current month. We also control for the analyst's experience, trends, and volatility in the historical DAX data. Invest_year is the number of years' previous experience in the financial industry. Trend is the difference between DAX at the time of the forecast and the DAX 25 trading days previously. Volatility is the standard deviation of the daily DAX index logarithmic returns during the 25 trading days immediately prior to the date of the forecast.

[Insert Table VI about here]

The association between the belief wedge and the asymmetry of the JPI is positive under all specifications and statistically significant at the 0.01 level under three specifications. These results are remarkable because the subjects in the ZEW survey were not prompted to consider others' estimates. This suggests that the results obtained from our surveys were not driven by the survey design feature, which prompted subjects to consider others' estimates. Furthermore, the evidence obtained from the ZEW survey suggests that our hypothesis holds not only for students but also for professional forecasters.

We also ran regressions with the belief wedge measured using the one-month-ahead predicted value generated by an estimated AR(1) model for the average forecast, which was updated monthly as each additional month's historical data became available. These results (not reported) are consistent with those reported in Table IV.

In addition, consistent with two in-class surveys, the correlation between the EPC and the asymmetry of the JPI measure is negative in Table V, and all coefficients for EPC are negative and statistically significant at the 0.01 level in Table VI. Similar to Survey 1, but not Survey 2, the effect of the trend on the asymmetry of the JPI is comparatively strong. The coefficients of trend are negative and significant at the 0.05 level or less in the four model specifications. Table VI also shows that the number of years of the participants' previous experience in the financial industry, their educational background, and volatility had some (albeit limited) effects on the asymmetry of the JPI.

3.4 Experiment

3.4.1 Motivation

The survey results above indicate a positive correlation between the belief wedge and the asymmetry of JPI measures. However, this finding does not constitute evidence as to whether the relationship is causal. In this section, we present evidence from an experiment designed to shed light on the issue of causality.

According to prior experimental evidence, an individual's perception of his or her own power to influence the opinions, decisions, or actions of others affects the extent to which they take account of others' perspectives in determining their own opinions, decisions, or actions. Galinsky et al. (2006) found that "high power" subjects are less likely to take others' perspectives into account when forming their own opinions, while "low power" subjects are more likely to do so. If the belief wedge exerts a causal effect on the asymmetry of JPI, we would expect the correlation between the belief wedge and the asymmetry of JPI to be greater for low-power subjects than for high-power subjects. Such a pattern in the respective empirical correlations may be interpreted as indirect evidence of a causal relationship between the belief wedge and the asymmetry of JPI.

3.4.2 Subjects

The subjects in the experiment were undergraduate finance students at the same business school as in Surveys 1 and 2. Of the 150 students registered for the course, 134 (61 male, 71 female, and 2 subjects who did not report their gender) completed and returned the survey, yielding a response rate of 89.3%. The average age was 21. Subjects were asked to provide the following information: gender, nationality, major, average GPA in the previous semester, and whether they had any previous investment experience. None of the subjects had participated in Surveys 1 or 2.

3.4.3 Stimuli

Following the procedures described by Galinsky et al. (2006) and Ronay and Von Hippel (2010), the subjects were randomly assigned to be primed as either high-power or low-power.[15] Subjects assigned to the high-power condition were asked to recall a situation in which *"... you had power over another individual or individuals. By power, we mean a situation in which "you controlled the ability of another person or person to get something they wanted or were in a position to evaluate those individuals. Please describe this situation in which you had power-what happened, how you felt, etc."* Subjects assigned to the low-power condition are asked to recall a situation in which *"... someone else had power over you. By power, we mean a situation in which someone had control over your ability to get something you wanted or was in a position to evaluate you. Please describe this situation in which you did not have power-what happened, how you felt, etc."* After the subjects were primed, they were presented with stock price time series charts identical to those used in Survey 1.

3.4.4 Procedures

Following the random assignment of subjects to the high-power and low-power conditions, the rest procedure was the same as that described for Survey 1.

3.4.5 Results

Consistent with our previous results, Table VII shows that the JPI was on average negative, and the correlation between the belief wedge and the asymmetry of the JPI was positive. These results provide further support for the hedging hypothesis.

[Insert Table VII about here]

Table VIII reports the results for the regressions with an additional "power" dummy (1 = high-power subject, 0 = low-power subject), and an interaction between the power dummy and the belief wedge measure. As high-power subjects are less likely to consider what others think, we expected a positive coefficient for the belief wedge measure, which would indicate a positive association between belief wedge and asymmetry of the JPI for low-power subjects, and a negative coefficient of the interaction term with a magnitude such that the implied coefficient of the belief wedge measure for high-power subjects would be close to zero. Across all estimation methods, the coefficients of the belief wedge measure were positive and significant at the 0.01 level, while the coefficients of the interaction term were negative under all specifications, although they were significant at the 0.1 level only in the median regression. These findings, although not all of them statistically strong, provide some causal evidence that belief edges affect the asymmetry of the JPI.

[Insert Table VIII about here]

Finally, Tables VII and VIII show a negative relationship between the EPC and the asymmetry of the JPI, corroborating the findings of our surveys and De Bondt (1993), as well as O'Connor et al. (2001). We also found that the coefficients of the trend were negative and significant at the 0.01 level across all regressions in Table VIII. Additionally, we found gender differences in two regressions are significantly associated with the asymmetry of the JPI measure in this experiment.

3.5 General Discussions

To summarize, the results of two in-class surveys, the survey of professional forecasters, and the experiment all show a positive relationship between the belief wedge and the asymmetry of JPI. Such a result is robust to different estimation methods, the inclusion of controls for the subjects' personal characteristics and the attributes of the observed price movement, the horizon and frequency of forecasting, and whether incentives for forecasting accuracy were provided to the subjects.

In untabulated regressions, we conducted several additional robustness checks.[16] First, we controlled for additional salient attributes of the observed price movement. As mentioned in Section 2, previous research has shown that the salient features of the presented time series affect subjects' forecasts/decisions. Therefore, we added the respective measures of salient features of past price series in our regressions to control for their effects. The salient features we considered included extreme points (Mussweiler and Schneller 2003), crashes (Borsboom and Zeisberger 2020), last trade direction (Duclos 2015, Sobolev and Harvey 2016), run length, local minima and maxima (Raghubir and Das 2010), mean absolute price change and irregularity (Duxbury and Summers 2018). Second, we included the price chart fixed effects in the regressions. By doing so, we controlled for any chart-specific features, including but not limited to all the salient features mentioned above. Third, we used an alternative belief wedge measure, calculated using subjects' assessments of market participants' average forecasting.[17] The hedging hypothesis is supported under all these robustness checks.

It is important to rule out several possible alternative explanations for the observed positive association between the belief wedge and the asymmetry of JPI. One such hypothesis is that the observed correlation between the belief wedge and the asymmetry of JPI measures is non-causal, or that it reflects a reverse causal effect whereby the asymmetry of the JPI affects the belief wedge. The experiment reported in Section 3.4 above was designed to address the issue of causality.

Alternatively, our findings might have arisen from the fact that in our surveys, the subjects were asked to forecast a price or index value in levels. Glaser et al. (2007) showed that forecasts of future stock prices (expressed in levels) are more likely to demonstrate a tendency for mean reversion than forecasts of future returns. Glaser, Iliewa, and Weber (2019) and Hanaki, Cars, Dávid, and Jan (2019) showed that individuals' elicited beliefs depend on whether they are asked about price or returns. We leave it for future work to explicitly examine how our hypothesis would be affected if subjects were asked to elicit returns instead. We acknowledge that if the forecasts in our study were based on returns rather than prices, the asymmetry of the JPI expressed in returns would differ, and the results reported above might not hold. Consider, for example, the case where the current price is 100, and the subject's point forecast for the future price is also 100. The upper bound of the prediction interval is defined by the optimistic projection that the price doubles to 200, and the lower bound is defined by the pessimistic projection that the price halves to 50. The asymmetry of the JPI is positive, but the JPI for the logarithmic return is symmetric around zero. To test this, we recalculated the asymmetry of the JPI, belief wedge, and the EPC using the logarithms of prices and price forecasts, and repeated the estimations of the previous regressions with the log transformations applied. These results also support our hypothesis.

A different explanation for the positive association between the belief wedge and the asymmetry of JPI proceeds as follows: A subject might formulate an asymmetric JPI of 100 to 200 around a point forecast of 120 (for example), and use the midpoint of the JPI as his FAPFO. A JPI that is symmetric around the subject's FAPFO is consistent with anchoring on a prior of ignorance about others' estimates. If the point forecast increases, the belief wedge declines, as does the measured asymmetry, and the belief wedge is positively correlated with JPI asymmetry. This argument implies a negative correlation between the point forecast and the asymmetry measure, as shown in the example. However, we found the correlation between the point forecast and the asymmetry measure to be positive and significant in Survey 2 and positive but insignificant in the experiment, while our hedging hypothesis was supported by both samples. We therefore infer that our results were not driven by this alternative mechanism.

Another hypothesis, also consistent with the observed positive association between the belief wedge and the asymmetry of JPI, is that subjects reported the mean of the subjective probability distribution as their own point forecast, but used the median to form their FAPFO, and formulated a JPI symmetric around the latter estimate. This procedure renders the JPI asymmetric around the subject's point forecast. However, our data do not support the conjecture that the JPI is symmetric around the FAPFO, and there appears to be no rational basis for the conjecture that subjects use the mean for their own forecast and the median as their best FAPFO.

4 Conclusion

This study proposes a new hedging hypothesis that helps explain the asymmetry of JPI. The hypothesis suggests that a forecaster may form a prediction interval by hedging his own forecast with FAPFO. According to our hypothesis, a forecaster formulates a point forecast and a JPI around this forecast. The lower and upper bounds of the JPI are influenced by the forecaster's FAPFO. This procedure leads to a positive association between the belief wedge and asymmetry of the JPI.

We tested the hypothesis using data from two in-class surveys in which students were asked to forecast future stock prices. This empirical evidence was consistent with the hedging hypothesis, and the results were robust to the inclusion of controls for the subjects' personal characteristics and the attributes of the observed stock price movements, the different model specifications, the alternative measure of FAPFO, the logarithmic transformation of the variables, and the adjustments for nonlinearity and outliers.

We provide additional supporting evidence based on an analysis of a data set comprising monthly predictions of a panel of professional financial analysts, compiled over an eight-year period. The evidence helps rule out the conjecture that the positive relationship between the belief wedge and the asymmetry of JPI is a consequence of the feature of our survey design, which required subjects to elicit their FAPFO.

To shed light on the question of whether the observed positive association between the belief wedge and the asymmetry of JPI represents a causal relationship, we conducted an experiment that primed one group of randomly selected subjects to consider themselves influential over the opinions or actions of others (high power), while the rest were primed to consider themselves influenced by the opinions or actions of others (low power). Previous evidence suggests that low-power subjects are more likely than high-power subjects to take others' perspectives into account when forming their own opinions. We report evidence that the positive association between the belief wedge and the asymmetry of the JPI was stronger for the low-power group than for the high-power group.

There are some caveats. This study examined the association between the belief wedge and asymmetry of the JPI. We did not manipulate the belief wedge to directly test the hypothesis of a causal relationship, and our experiment provides only limited evidence that the belief wedge affects the asymmetry of the JPI. Furthermore, this study does not fully address the issue of the impact of incentives on predictive behavior. In Survey 1 and the experiment, we did not provide any incentives, while in Survey 2, we rewarded subjects for the accuracy of their point forecasts only. It remains to be investigated whether the results would differ if the subjects were also rewarded for the accuracy of their FAPFO. We leave this question for future research. Another possible line of investigation would involve manipulation of the importance of "others" by running an experiment in which some subjects are encouraged to believe that they have access to private information. This should reduce the influence of FAPFO on one's own forecast, with possible implications for asymmetry that could be explored in an experimental setting. Finally, the survey and experimental evidence presented in this study referred to forecasting or prediction in financial markets. However, it is conceivable that our hypothesis is relevant for other situations in which people's FAPFO may affect outcomes. For example, it may matter in forecasting election or referendum results if some voters' choices are influenced by their expectations of the outcome of the ballot. The relevance of the hedging hypothesis in contexts other than financial market forecasting requires further research.

Data Availability Statement

The survey of professional forecasts data that supports the findings of this study is from a third party and confidential. We therefore won't be able to share the data.

5 Tables and Figures

Figure 1
Stylized Representation of Principal Hypothesis

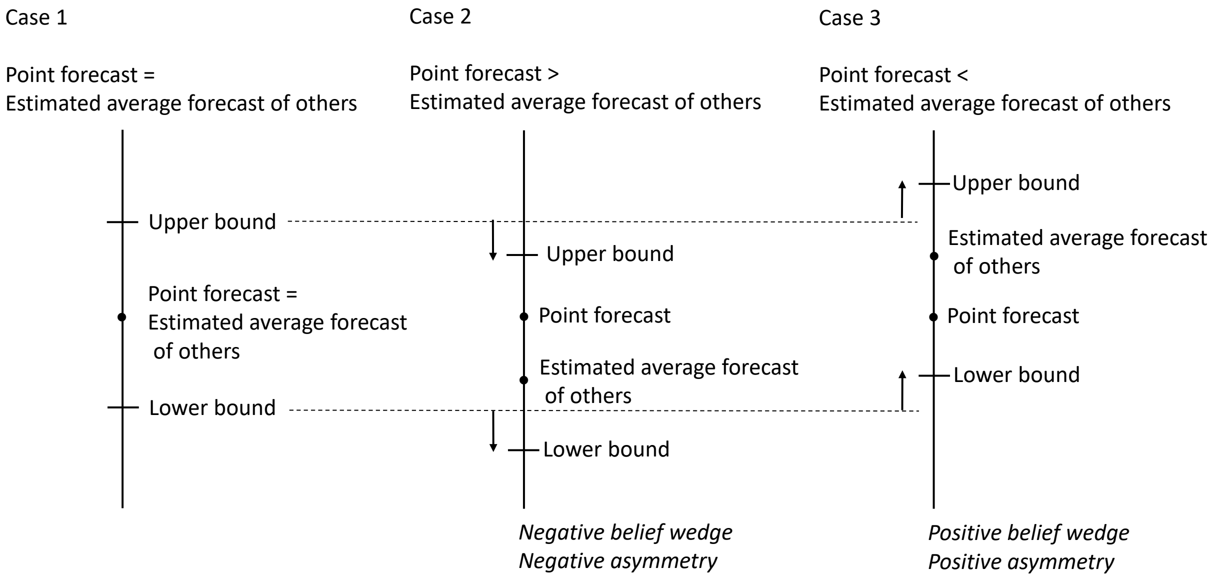
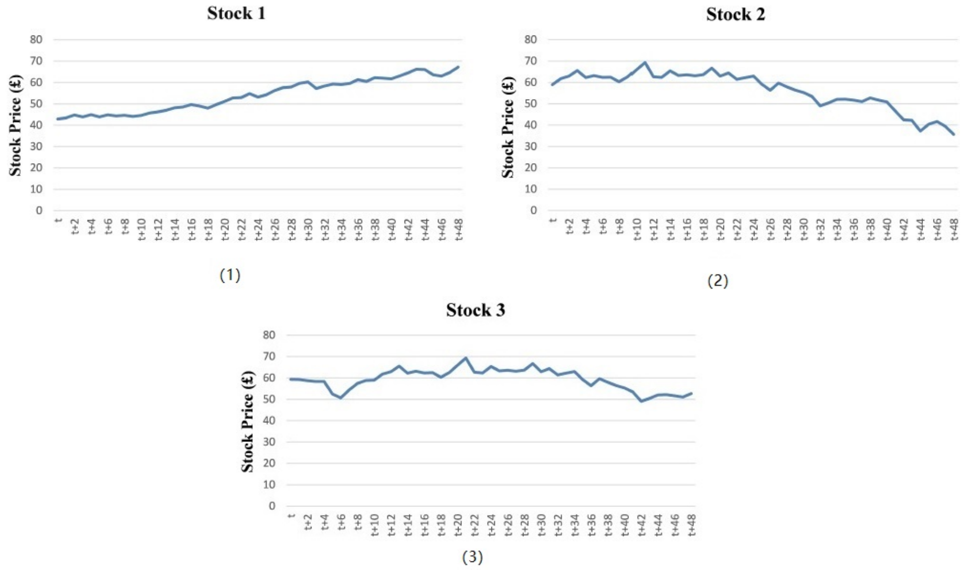
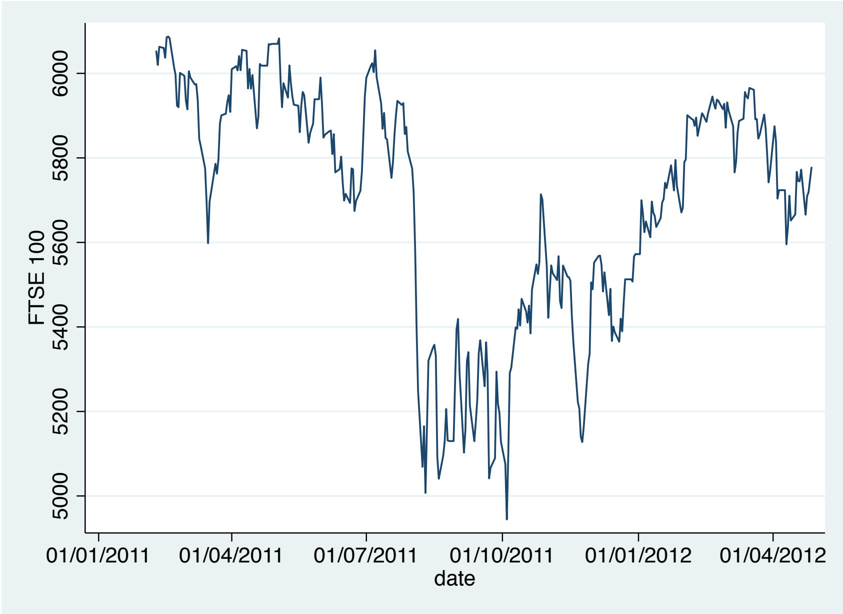


Figure 2
Examples of Stock Prices Used in Survey 1



This figure provides three examples of stock prices presented to subjects in Surveys 1 and the experiment, one with an upward trend (1), one with a downward trend (2), and other without a trend (3).

Figure 3
FTSE 100 index around Survey 2



This figure shows the FTSE 100 index between 09/02/2011 and 26/04/2012. Each Thursday (except holidays) during 09/02/2012 and 19/04/2012, the subjects were asked to forecast the following Thursday's FTSE 100 index.

Figure 4
DAX Index

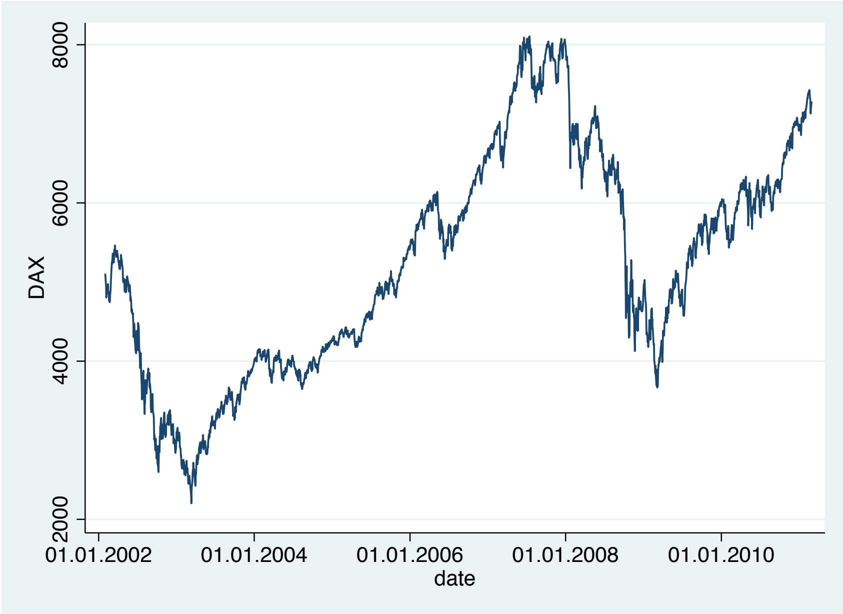


Figure (c) shows the DAX index between 01/02/2002 and 28/02/2011. Our sample of ZEW survey data covers the sample period between 02/2003 and 02/2011.

Table I
Summary Statistics and Variable Correlations in Survey 1

	Panel A: Summary Statistics					Panel B: Correlations		
	Mean	Std. Dev.	Min	Max	N	Asymmetry of JPI	Belief wedge	EPC
Asymmetry of JPI	-1.41	6.34	-13.36	13.36	246			
Belief wedge	0.14	7.95	-20.98	57.09	246	0.37		
EPC	6.04	19.98	-10.44	135.07	246	-0.07	0.19	
Trend	-3.79	33.36	-69.86	73.02	246	-0.17	-0.22	-0.53
Gender	0.39	0.49	0	1	246			
Country	0.94	0.25	0	1	246			
Mark	4.03	1.06	1	5	241			
Volatility	183.40	198.91	9	678.42	246			

This table reports summary statistics for all variables and the correlations between asymmetry of JPI, belief wedge, EPC and trend for survey 1. Asymmetry of JPI is defined by equation (1). Belief wedge is defined by equation (2). EPC is defined by equation (3). Trend is the difference between the last price and the first price shown in the chart. Gender is a 0-1 dummy variable that takes a value of one if the subject is male, zero otherwise. Country is a 0-1 dummy variable that takes a value of one if the subject is from an east or south-east Asian country, and zero otherwise. Mark is the subject's GPA from the previous semester. Volatility is the volatility of the historical stock prices in the chart that is displayed to the subjects. The asymmetry of JPI, Belief wedge, and EPC are winsorized at the 1% and 99% levels.

Table II
Regressions of Measured Asymmetry and Belief Wedge in Survey 1

	OLS Regression	Median Regression	Random Effects	GEE
Belief wedge	0.33***	0.25***	0.30***	0.31***
	(0.05)	(0.06)	(0.05)	(0.05)
EPC	-0.08***	-0.06*	-0.07***	-0.08***
	(0.03)	(0.03)	(0.02)	(0.02)
Gender	-0.76	-0.09	-0.52	-0.60
	(0.76)	(0.89)	(1.12)	(0.97)
Country	0.02	0.59	0.59	0.39
	(1.50)	(1.76)	(1.99)	(1.77)
Mark	0.30	0.07	0.50	0.44
	(0.36)	(0.42)	(0.53)	(0.46)
Trend	-0.04***	-0.03*	-0.04***	-0.04***
	(0.01)	(0.02)	(0.01)	(0.01)
Volatility	0.01	-0.01	0.01	0.01
	(0.02)	(0.03)	(0.02)	(0.02)
Constant	-2.13	-0.97	-3.55	-3.11
	(2.35)	(2.75)	(3.20)	(2.84)
R-squared	0.20	0.08	0.20	
N	241	241	241	241

This table reports OLS, median regression, random effects and generalized estimating equations (GEE) estimation results for survey 1. The dependent variable is the asymmetry of JPI which is defined by equation (1). The independent variable is belief wedge which is measured as equation (2). EPC is defined by equation (3). Gender is a 0-1 dummy variable that takes a value of one if the subject is male, zero otherwise. Country is a 0-1 dummy variable that takes a value of one if the subject is from an east or south-east Asian country, and zero otherwise. Mark is the subject's GPA from the previous semester. Trend is the difference between the last price and the first price shown in the chart. Volatility is the volatility of the historical stock prices in the chart that is displayed to the subjects. The asymmetry of JPI, Belief wedge, and EPC are winsorized at the 1% and 99% levels. Standard errors of estimated coefficients are reported in parentheses. $*$, $**$, and $***$ indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table III
Summary Statistics and Variable Correlations in Survey 2

	Panel A: Summary Statistics					Panel B: Correlations		
	Mean	Std. Dev.	Min	Max	N	Asymmetry of JPI	Belief wedge	EPC
Asymmetry of JPI	-16.31	37.38	-90	100	233			
Belief wedge	-0.04	0.54	-2.17	1.97	233	0.25		
EPC	0.08	0.66	-2.71	2.92	233	-0.40	-0.15	
Trend	14.38	50.55	-71.52	80.99	201	0.03	0.09	-0.27
Gender	0.44	0.50	0	1	233			
Country	0.96	0.20	0	1	233			
Invest	0.21	0.41	0	1	233			
Volatility	6052.05	2976.46	1777.21	10285.14	233			

This table reports summary statistics for all variables and the correlations between asymmetry of JPI, belief wedge, EPC and trend for survey 2. Asymmetry of JPI is defined by equation (1). Belief wedge is defined by equation (2). EPC is defined by equation (3). Trend is the difference between the closing price of the FTSE 100 index on the date of the forecast and the closing price on the date that is 25 trading days prior to the date of the forecast. Gender is a 0-1 dummy variable that takes a value of one if the subject is male, zero otherwise. Country is a 0-1 dummy variable that takes a value of one if the subject is from an east or south-east Asian country, and zero otherwise. Invest is a 0-1 dummy variable for previous investment experience that takes a value of one if the subject has investment experience, and zero otherwise. Volatility is the standard deviation of the closing prices for the 25 trading days prior to the date of the forecast. The asymmetry of JPI, Belief wedge, and EPC are winsorized at the 1% and 99% levels.

Table IV
Regressions of Measured Asymmetry and Belief Wedge in Survey 2

	OLS Regression	Median Regression	Random Effects	GEE
Belief wedge	16.13***	16.42**	14.19***	14.08***
	(5.08)	(7.45)	(5.19)	(5.09)
EPC	-24.52***	-28.16****	-27.07***	-27.22***
	(4.25)	(6.24)	(4.31)	(4.23)
Gender	3.164	2.11	3.04	3.04
	(5.24)	(7.68)	(6.43)	(6.39)
Country	-9.22	-8.84	-9.04	-9.02
	(12.67)	(18.57)	(15.00)	(14.88)
Invest	4.87	5.83	4.41	4.40
	(6.20)	(9.08)	(7.65)	(7.60)
Trend	-0.07	-0.08	-0.08	-0.08*
	(0.05)	(0.07)	(0.05)	(0.05)
Volatility	0.10	0.14	0.12	0.12
	(0.08)	(0.11)	(0.07)	(0.07)
Constant	-12.74	-15.94	-12.52	-12.51
	(14.00)	(20.51)	(16.17)	(16.02)
R-squared	0.22	0.11	0.22	
N	201	201	201	201

This table reports OLS, median regression, random effects and generalized estimating equations (GEE) estimation results for survey 2. The dependent variable is the asymmetry of JPI which is defined by equation (1). The independent variable is belief wedge which is measured as equation (2). EPC is defined by equation (3). Gender is a 0-1 dummy variable that takes a value of one if the subject is male, zero otherwise. Country is a 0-1 dummy variable that takes a value of one if the subject is from an east or south-east Asian country, and zero otherwise. Invest is a 0-1 dummy variable for previous investment experience that takes a value of one if the subject has investment experience, and zero otherwise. Trend is the difference between the closing price of the FTSE 100 index on the date of the forecast and the closing price on the date that is 25 trading days prior to the date of the forecast. Volatility is the standard deviation of the closing prices for the 25 trading days prior to the date of the forecast. The asymmetry of JPI, Belief wedge, and EPC are winsorized at the 1% and 99% levels. For easy presentation, volatility is divided by 100 in this table. Standard errors of estimated coefficients are reported in parentheses. $*$, $**$, and $***$ indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table V
Summary Statistics and Variable Correlations in Survey of Professional Financial Forecasters

	Panel A: Summary Statistics					Panel B: Correlations		
	Mean	Std. Dev.	Min	Max	N	Asymmetry of JPI	Belief wedge	EPC
Asymmetry of JPI	-0.26	0.50	-2.35	1.45	16186			
Belief wedge	-0.24	1.47	-4.22	5.84	16186	0.33		
EPC	0.58	1.38	-4.09	5.48	16186	-0.38	-0.75	
Trend	1.46	6.14	-34.29	21.05	16186	-0.01	-0.41	-0.18
Gender	0.94	0.23	0	1	16186			
Age	42.54	8.69	24	67	16186			
Invest_year	15.40	8.98	0.5	45	16186			
Education_uni	0.76	0.42	0	1	16186			
Volatility	1.98	2.99	0.19	25.20	16186			

This table reports summary statistics for all variables and the correlations between asymmetry of JPI, belief wedge, EPC and trend for survey of professional financial analysts. Asymmetry of JPI is defined by equation (1). Belief wedge is defined by equation (2). EPC is defined by equation (3). Trend is the difference between DAX at the time of the forecast and DAX on the date that is 25 trading days prior to the date of the forecast. Gender is a 0-1 dummy variable that takes a value of one if the subject is male, zero otherwise. Age is the age of the professional forecaster. Invest_year is the number of years of previous experience in the financial industry. Education_uni is a 0-1 dummy variable that takes a value of one if the forecaster has a university degree, zero otherwise. Volatility is the standard deviation (in percentage) of the daily DAX index logarithmic returns during the 25 trading days immediately prior to the date of the forecast. The asymmetry of JPI, Belief wedge, and EPC are winsorized at the 1% and 99% levels.

Table VI
Regressions of Measured Asymmetry and Belief Wedge in Survey of Professional Financial Forecasters

	OLS Regression	Median Regression	Random Effects	GEE
Belief Wedge	3.17***	1.20	3.47***	3.47***
	(0.76)	(0.74)	(0.59)	(1.01)
EPC	-11.71***	-8.87***	-11.72***	-11.72***
	(0.75)	(0.72)	(0.57)	(1.11)
Gender	0.04	-1.11	-5.40	-5.39
	(1.52)	(1.84)	(5.31)	(5.37)
Age	0.14**	0.14	0.04	0.04
	(0.07)	(0.09)	(0.29)	(0.24)
Invest_year	-0.32***	-0.21**	-0.14	-0.14
	(0.07)	(0.09)	(0.28)	(0.25)
Education_uni	-1.82**	1.95*	-1.16	-1.15
	(0.88)	(1.03)	(3.23)	(3.16)
Trend	-0.45***	-0.47***	-0.40***	-0.40**
	(0.13)	(0.13)	(0.10)	(0.17)
Volatility	-23.02	-19.30	-33.45***	-33.42*
	(16.64)	(15.13)	(11.81)	(19.07)
Constant	-16.85***	-13.52***	-10.19	-10.12
	(2.71)	(3.34)	(10.04)	(9.23)
R-squared	0.16	0.06	0.15	
N	16186	16186	16186	16186

This table reports OLS, median regression, random effects and generalized estimating equations (GEE) estimation results for the survey of professional forecasters. The dependent variable is the asymmetry of JPI (see equation (1)), which is multiplied by 100 for ease of presentation. Belief wedge is defined equation (2). EPC is defined by equation (3). Gender is a 0-1 dummy variable that takes a value of one if the forecaster is male, zero otherwise. Age is the age of the professional forecaster. Invest_year is the number of years of previous experience in the financial industry. Education_uni is a 0-1 dummy variable that takes a value of one if the forecaster has a university degree, zero otherwise. Trend is the difference between DAX at the time of the forecast and DAX on the date that is 25 trading days prior to the date of the forecast. Volatility is the standard deviation (in percentage) of the daily DAX index logarithmic returns during the 25 trading days immediately prior to the date of the forecast. The asymmetry of JPI, Belief wedge, and EPC are winsorized at the 1% and 99% levels. Standard errors of estimated coefficients are reported in parentheses. $*$, $**$, and $***$ indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table VII
Summary Statistics and Variable Correlations in the Experiment

	Panel A: Summary Statistics					Panel B: Correlations		
	Mean	Std. Dev.	Min	Max	N	Asymmetry of JPI	Belief wedge	EPC
Asymmetry of JPI	-0.44	5.54	-13.36	13.36	256			
Belief wedge	-0.22	1.92	-8.50	8.88	256	0.22		
EPC	0.42	2.96	-7.07	12.39	256	-0.35	-0.18	
Trend	-1.65	12.24	-23.29	24.34	256	-0.05	-0.02	-0.46
Gender	0.51	0.50	0	1	253			
Country	0.74	0.44	0	1	253			
Major	0.91	0.28	0	1	233			
Invest	0.20	0.40	0	1	256			
Mark	4.35	0.99	1	5	244			
Volatility	5.14	1.64	3	8.68	256			

This table reports summary statistics for all variables and the correlations between asymmetry of JPI, belief wedge, EPC and trend for experiment. Asymmetry of JPI is defined by equation (1). Belief wedge is defined by equation (2). EPC is defined by equation (3). Trend is the difference between the last price and the first price shown in the chart. Gender is a 0-1 dummy variable that takes a value of one if the subject is male, zero otherwise. Country is a 0-1 dummy variable that takes a value of one if the subject is from an east or south-east Asian country, and zero otherwise. Major is a 0-1 dummy variable that takes a value of one if the subject has a finance related major, and zero otherwise. Invest is a 0-1 dummy variable for previous investment experience that takes a value of one if the subject has investment experience, and zero otherwise. Mark is the subject's GPA from the previous semester. Volatility is the volatility of the historical stock prices in the chart that is displayed to the subjects. The asymmetry of JPI, Belief wedge, and EPC are winsorized at the 1% and 99% levels.

Table VIII
Regressions of Measured Asymmetry and Belief Wedge in the Experiment

	OLS	Median Regression	Random Effects	GEE
Belief Wedge	0.68***	0.60***	0.68***	0.69***
	(0.24)	(0.23)	(0.25)	(0.24)
Power	-0.47	-0.17	-0.35	-0.48
	(0.68)	(0.63)	(0.86)	(0.61)
Belief Wedge × Power	-0.52	-0.59*	-0.55	-0.52
	(0.34)	(0.31)	(0.34)	(0.32)
EPC	-0.79***	-0.79***	-0.76***	-0.80***
	(0.13)	(0.12)	(0.13)	(0.12)
Gender	1.15	1.78***	0.95	1.23*
	(0.72)	(0.67)	(0.91)	(0.65)
Country	-0.60	-0.59	-0.53	-0.65
	(0.83)	(0.77)	(1.06)	(0.75)
Invest	-0.60	-0.18	-0.67	-0.57
	(0.84)	(0.78)	(1.06)	(0.76)
Mark	0.11	0.26	0.09	0.11
	(0.37)	(0.34)	(0.46)	(0.33)
Major	0.95	1.20	0.73	1.02
	(1.23)	(1.14)	(1.49)	(1.13)
Trend	-0.14***	-0.17***	-0.13***	-0.14***
	(0.03)	(0.03)	(0.03)	(0.03)
Volatility	0.13	0.11	0.09	0.15
	(0.22)	(0.20)	(0.21)	(0.21)
Constant	-2.10	-3.71*	-1.70	-2.23
	(2.27)	(2.11)	(2.76)	(2.09)
R-square	0.24	0.12	0.24	
N	221	221	221	221

This table reports OLS, median regression, random effects and generalized estimating equations (GEE) regression models of asymmetry of JPI on belief wedge, power, their interaction and other control variables in the experiment. The dependent variable is the asymmetry of JPI which is defined by equation (1). Belief wedge is defined by equation (2). Power is a 0-1 dummy variable which takes a value of one if the subject is assigned to high power group and zero if the subject is assigned to low power group. Belief Wedge × Power is the interaction term between belief wedge and power. EPC is defined by equation (3). Gender is a 0-1 dummy variable that takes a value of one if the subject is male, zero otherwise. Country is a 0-1 dummy variable that takes a value of one if the subject is from an east or south-east Asian country, and zero otherwise. Invest is a 0-1 dummy variable for previous investment experience that takes a value of one if the subject has investment experience, and zero otherwise. Mark is the subject's GPA from the previous semester. Major is a 0-1 dummy variable that takes a value of one if the subject has a finance related major, and zero otherwise. Trend is the difference between the last price and the first price shown in the chart. Volatility is the volatility of the historical stock prices in the chart that is displayed to the subjects. The asymmetry of JPI, Belief wedge, and EPC are winsorized at the 1% and 99% levels. Standard errors of estimated coefficients are reported in parentheses. $*$, $**$, and $***$ indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

REFERENCES

Allen, F., S. Morris, and H.S. Shin, 2006, Beauty contests and iterated expectations in asset markets, *Review of Financial Studies* 19, 719.

Balakrishnan, K., C. Schrand, and R. Vashishtha, 2020, Analyst recommendations and stock price bubbles, *Journal of Financial Reporting* .

Banerjee, S., R. Kaniel, and I. Kremer, 2009, Price drift as an outcome of differences in higher-order beliefs, *Review of Financial Studies* 22, 3707.

Bolger, F., and N. Harvey, 1993, Context-sensitive heuristics in statistical reasoning, *The Quarterly Journal of Experimental Psychology* 46, 779–811.

Bolger, F., and D. Önkal-Atay, 2004, The effects of feedback on judgmental interval predictions, *International Journal of Forecasting* 20, 29–39.

Borgsen, S., and M. Weber, 2008, False consensus and the role of ambiguity in predictions of others' risk preferences, Technical report, Social Science Electronic Publishing.

Borsboom, C., and S. Zeisberger, 2020, What makes an investment risky? an analysis of price path characteristics, *Journal of Economic Behavior & Organization* 169, 92–125.

Budescu, David V, and Eva Chen, 2015, Identifying expertise to extract the wisdom of crowds, *Management Science* 61, 267–280.

Cameron, A., and D. G. Adam, 2006, Power, optimism, and risk-taking, *European Journal of Social Psychology* 36, 511–536.

Cespa, G., and X. Vives, 2015, The Beauty Contest and Short-Term Trading, *Journal of Finance* .

Clemen, Robert T, and Robert L Winkler, 1986, Combining economic forecasts, *Journal of Business & Economic Statistics* 4, 39–46.

De Bondt, W.P.M., 1993, Betting on trends: Intuitive forecasts of financial risk and return, *International Journal of Forecasting* 9, 355–371.

Du, N., and D. V. Budescu, 2007, Does past volatility affect investors' price forecasts and confidence judgements?, *International Journal of Forecasting* 23, 497–511.

Duclos, R., 2015, The psychology of investment behavior: (de) biasing financial decision-making one graph at a time, *Journal of Consumer Psychology* 25(2), 317–325.

Duxbury, D., 2015, Behavioral finance: insights from experiments II: biases, moods and emotions, *Review of Behavioral Finance* .

Duxbury, D., and B. Summers, 2018, On perceptions of financial volatility in price sequences, *The European Journal of Finance* 24(7-8), 521–543.

Egan, D., C. Merkle, and M. Weber, 2014, Second-order beliefs and the individual investor, *Journal of Economic Behavior & Organization* 107, 652–666.

Froot, K. A., D. S. Scharfstein, and J. C. Stein, 1992, Herd on the street: Informational inefficiencies in a market with short-term speculation, *The Journal of Finance* 47, 1461–1484.

Galinsky, A. D, D. H. Gruenfeld, and J. C. Magee, 2003, From power to action., *Journal of Personality and Social Psychology* 85, 453.

Galinsky, A. D, J. C. Magee, D. H. Gruenfeld, J. A. Whitson, and K. A. Liljenquist, 2008, Power reduces the press of the situation: implications for creativity, conformity, and dissonance, *Journal of Personality and Social Psychology* 95, 1450.

Galinsky, A. D., J. C. Magee, M. E. Inesi, and D. H. Gruenfeld, 2006, Power and perspectives not taken, *Psychological Science* 17, 1068–1074.

Gilovich, T., D. Griffin, and D. Kahneman, 2002, *Heuristics and biases: The psychology of intuitive judgment* (Cambridge university press).

Glaser, M., Z. Iliewa, and M. Weber, 2019, Thinking about prices versus thinking about returns in financial markets, *The Journal of Finance* 74, 2997–3039.

Glaser, M., T. Langer, J. Reynders, and M. Weber, 2007, Framing effects in stock market forecasts: The difference between asking for prices and asking for returns, *Review of Finance* 11, 325–357.

Grissey, C., 2008, Higher order beliefs and the comovement of asset prices, *SSRN Electronic Journal* .

Grosshans, D., and S. Zeisberger, 2018, All's well that ends well? on the importance of how returns are achieved, *Journal of Banking and Finance* 87, 397–410.

Hanaki, N., H. Cars, K. Dávid, and T. Jan, 2019, The effect of framing on the emergence of bubbles and crashes in a learning to forecast experiment, *University of Amsterdam Working Paper* .

Himmelstein, M., P. Atanasov, and D.V. Budescu, 2021, Forecasting forecaster accuracy: Contributions of past performance and individual differences., *Judgment & Decision Making* 16.

Huber, C., and J. Huber, 2019, Scale matters: Risk perception, return expectations, and investment propensity under different scalings, *Experimental Economics* 22(1), 76–100.

Keynes, J. M., 1936, The general theory of employment, interest and money, *Macmillan Cambridge University Press* .

Lawrence, M., P. Goodwin, M. O'Connor, and D. Onkal, 2006, Judgemental forecasting: A review of progress over the last 25 years, *International Journal of Forecasting* 22, 493–518.

Lawrence, M., and S. Makridakis, 1989, Factors affecting judgmental forecasts and confidence intervals, *Organizational Behavior and Human Decision Processes* 43, 172–187.

Lawrence, M., and M. O'Connor, 1992, Exploring judgemental forecasting, *International Journal of Forecasting* 8, 15–26.

Lawrence, M., and M. O'Connor, 1993, Scale, variability, and the calibration of judgmental prediction intervals, *Organizational Behavior and Human Decision Processes* 56, 441–458.

Lawrence, M., and M. O'Connor, 1995, The anchor and adjustment heuristic in time-series forecasting, *Journal of Forecasting* 14, 443–451.

Liang, K. Y., and S. L. Zeger, 1986, Longitudinal data analysis using generalized linear models, *Biometrika* 73, 13–22.

Marks, G., and N. Miller, 1987, Ten years of research on the false-consensus effect: an empirical and theoretical review, *Psychological Bulletin* 102, 72.

Monnin, P., 2004, Are stock markets really like beauty contests? empirical evidence of higher order belief's impact on asset prices, *Social Science Electronic Publishing* .

Muradoglu, G., 2002, Portfolio managers' and novices' forecasts of risk and return: are there predictable forecast errors?, *Journal of Forecasting* 21, 395–416.

Mussweiler, T., and K. Schneller, 2003, " What goes up must come down"- How charts influence decisions to buy and sell stocks, *The Journal of Behavioral Finance* 4(3), 121–130.

O'Connor, M., and M. Lawrence, 1992, Time series characteristics and the widths of judgemental confidence intervals, *International Journal of Forecasting* 7, 413–420.

O'Connor, M., W. Remus, and K. Griggs, 2001, The asymmetry of judgemental confidence intervals in time series forecasting, *International Journal of Forecasting* 17, 623–633.

Önkal, D., P. Goodwin, M. Thomson, S. Gönül, and A. Pollock, 2009, The relative influence of advice from human experts and statistical methods on forecast adjustments, *Journal of Behavioral Decision Making* 22, 390–409.

Raghubir, P., and S. R. Das, 2010, The long and short of it: why are stocks with shorter runs preferred?, *Journal of Consumer Research* 36(6), 964–982.

Rangvid, J., M. Schmeling, and A. Schrimpf, 2013, What do professional forecasters' stock market expectations tell us about herding, information extraction and beauty contests?, *Journal of Empirical Finance* 20, 109–129.

Ronay, R., and W. Von Hippel, 2010, Power, testosterone, and risk-taking, *Journal of Behavioral Decision Making* 23, 473–482.

Ross, L., D. Greene, and P. House, 1977, The "false consensus effect": An egocentric bias in social perception and attribution processes, *Journal of Experimental Social Psychology* 13, 279–301.

Sobolev, D., and N. Harvey, 2016, Assessing risk in graphically presented financial series, *Risk Analysis* 36(12), 2216–2232.

Spence, M. T., 1996, Problem–problem solver characteristics affecting the calibration of judgments, *Organizational Behavior and Human Decision Processes* 67, 271–279.

Timmermann, A., 2006, Forecast combinations, *Handbook of Economic Forecasting* 1, 135–196.

Townsend, R.M., 1983, Forecasting the forecasts of others, *The Journal of Political Economy* 91, 546–588.

Tversky, A., and D. Kahneman, 1974, Judgment under uncertainty: Heuristics and biases, *Science* 185, 1124–1131.

Welch, I., 2000, Views of financial economists on the equity premium and on professional controversies, *The Journal of Business* 73, 501–537.

Notes

[1] Forecasters' own point forecast may differ from their FAPFO when the forecasters believe that: 1) They have more information than others; 2) others adopt forecasting models that differ from their own; 3) others have different prior beliefs.

[2] The psychology literature reports a tendency for subjects to overestimate the extent to which other people agree with them, known as the "false-consensus bias" (Ross, Greene, and House 1977, Marks and Miller 1987). Although false-consensus bias may tend to reduce the belief wedge, we argue that it does not eliminate it.

[3] We refer to a prediction interval that is other than symmetric around the point forecast as asymmetric. When the distance between the point forecast and the lower (upper) bound of the prediction interval exceeds the distance between the upper (lower) bound and the point forecast, the measured asymmetry is negative (positive).

[4] The definitions of the asymmetry and belief wedge measures are provided in equations (1) and (2) of Section 3.

[5] Other forms of overconfidence include overestimation of one's own ability or performance, unwarranted faith in the precision of one's beliefs, and an overly optimistic judgement of one's own performance versus others'. Duxbury (2015) provides an excellent review of the literature on overconfidence in financial experiments.

[6] Bolger and Harvey (1993) provide evidence that when the serial correlation of a trended time series is low, people follow a similar anchoring and adjustment heuristic to the first step of De Bondt (1993), and forecast by adding a proportion of the last change in the series. Lawrence and O'Connor (1992) show that such an anchoring and adjustment is equivalent to exponential smoothing.

[7] High-order beliefs in finance typically refer to one's beliefs about others' beliefs, one's beliefs about others' beliefs about others' beliefs, and so on.

[8] The "Pygmalion effect" means the greater the expectation placed upon the subjects, the better they perform. The subject's performance could be influenced by the experimenter's behaviors, such as an encouraging glance.

[9] The questions were worded as follows: 1. Predict the price of each stock after 13 months; 2. State your interval forecast at the 90% level for the price of each stock after 13 months (that is, write down a lower value and an upper value, such that you feel that the probability that the realized value will lie between your lower value and your upper value is 0.9); 3. Predict the average of the predictions made by your classmates for the stock price after 13 months.

[10] Although we elicited subjects' FAPFO after their point forecast and JPI, our conjecture is that subjects considered what the FAPFO was even before it was elicited due to its relevance to the equilibrium price, a fact that is well acknowledged by academic researchers and market participants. Our hedging hypothesis implies that, after the point forecast and the FAPFO are formed (no matter which is formed first), decision-makers form their interval forecasts and adjust them toward the FAPFO.

[11] The standardization (denominators of equations (1) and (2)) made the asymmetry of JPI measure independent of the scaling of the price series for which the forecast is produced. Similarly, the belief wedge measure was made independent of the scaling, and independent of the forecast period (measured in weeks). In the case that the price series follows a random walk, the standard deviation of price increases in proportion to $\sqrt{T}$, where $T = time$. It is plausible to assume that the variation in the (non-standardized) belief wedge is proportional to the standard deviation of price, and therefore proportional to $\sqrt{T}$.

[12] Our results were qualitatively similar if we did not winsorize these variables. We also note that the number of observations in all our regression tables was affected by winsorization, missing values in dependent and independent variables, and the exclusion of observations with point forecasts lying outside of the JPI.

[13] Although we had information on the age of the subjects, as the age variation across subjects was small, age is excluded from the reported estimations. The inclusion of an age covariate did not qualitatively affect our results.

[14] The questions were worded as follows: 1. Predict the value of the FTSE100 index at the close of trade next Thursday; 2. State your interval forecast at the 90% level for the value of the FTSE 100 index at the close of trade next Thursday (that is, write down a lower value and an upper value, such that you feel that the probability that the realized value will lie between your lower value and your upper value is 0.9); 3. Predict the average of the predictions made by your classmates for the value of the FTSE 100 index at the close of trade next Thursday; 4. Predict the average of the predictions made by market participants for the value of the FTSE 100 index at the close of trade next Thursday.

[15] Prior studies have shown the same high- or low-power experiential prime reliably manipulated a sense of power (see, for example, Galinsky, Gruenfeld, and Magee (2003), Cameron and Adam (2006), Galinsky et al. (2006) and Galinsky, Magee, Gruenfeld, Whitson, and Liljenquist (2008))

[16] The results are available from authors upon request.

[17] In Survey 2, the subjects were asked to report their beliefs about the average forecast of market participants. Conceivably, the subjects might have formulated different estimates of the average forecasts of their classmates and market participants, which would produce a different measured belief wedge in each case. As a further robustness check, we repeated the estimations of the regressions reported in Table IV using the data from Survey 2, with the belief wedge recalculated using the subjects' assessments of market participants' average predictions. The results were qualitatively similar to those reported in Table IV.