Testing a New Hedging Theory of Confidence Interval Formation *

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Abstract

We develop and test a simple hedging theory of confidence interval formation. In the presence of uncertainty, forecasters hedge their forecasts by adjusting the confidence interval for their own (first-order) belief in a way that reflects their (second-order) belief about others' beliefs. Anchoring and adjustment leads to a positive relationship between the skewness of confidence interval and the belief wedge, defined as the difference between the second-order belief and the first-order belief. Using data from three experiments in which subjects are asked to forecast future stock prices, we provide strong empirical support for the theoretical predictions.

Keywords: Confidence intervals; Second-order beliefs; Skewness; Forecasts; Decision under uncertainty.

JEL Classification: C91, G02, G17

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1 Introduction

Prior literature typically assumes decision makers' judgmental confidence interval (hereafter JCI) is symmetric around the point forecast (for example, Taylor and Bunn (1999)). However, several studies report evidence of asymmetric JCI (De Bondt (1993), O'Connor, Remus, and Griggs (2001) and Du and Budescu (2007)). Despite this empirical evidence, the explanation for a skewed JCI remains unresolved.

In this paper, we propose and test a new theory that helps explain the skewness of JCI. Our theory takes the viewpoint of a decision maker who faces the task of forecasting a future event. Before knowing the opinions of other forecasters, the decision maker forms his own opinion about the future event, referred to as a first-order belief, as well as a belief about other people's average opinions, referred to as a second-order belief. When the first-order and second-order beliefs differ, the decision maker may ask "As the future is uncertain, how can I be sure that my belief is always the 'correct' one? Maybe I should move closer to others' beliefs rather than rely solely on my own?" That is, we hypothesize that the decision maker may want to hedge his own beliefs with his belief about others' beliefs.

Similar to De Bondt (1993), decision makers in our theory follow a three-step procedure to reach their final point and interval forecasts. At the first stage, the decision maker forms a point forecast, denoted μ_1. At the second stage, a confidence interval is formed around the point forecast. At the third stage, the upper and lower bounds of the confidence interval are adjusted under the influence of the second order belief μ_2, without changing the point forecasts. For $\mu_2 > \mu_1$ the upper and lower bounds of the confidence interval are increased, the point forecast is nearer to the lower bound than the upper bound, and the confidence interval is right-skewed. Conversely for $\mu_2 < \mu_1$ the upper and lower bounds are reduced, the point forecast is nearer to the upper bound than to the lower bound, and the confidence interval is left-skewed. Defining the belief wedge as the difference between the second-order belief and the first-order belief, we anticipate a positive relationship between the belief wedge and the skewness of the confidence interval.

We test our theoretical prediction in three experimental studies of forecasting future stock prices. The empirical evidence supports the hypothesized positive relationship between the belief wedge and the skewness of confidence interval, after controlling for the personal characteristics of the forecasters and the nature of the observed (historical) stock price movement in several model specifications. Our results are robust to an alternative measure of skewness, logarithmic transformation of variables, nonlinearity and outliers.

The remainder of the paper is organized as follows. Section 2 briefly reviews the literature. Section 3 discusses the experiment design and the data. Section 4 reports the empirical results. Section 5 concludes.

2 Literature

Our new hedging theory of confidence interval is closely related to De Bondt (1993), in which skewness 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). De Bondt (1993) explains his findings using a hedging theory, under which forecasters follow a three-step procedure to arrive at their interval forecasts 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 his point forecast by applying the rate of past price change to the last observed price. At the second step he constructs a symmetric interval forecast around the point forecast. At the third step he adjusts both bounds of the interval forecast towards the average price, while leaving the point forecast unchanged. In general this procedure produces a skewed confidence interval.

O'Connor et al. (2001) report evidence that JCI is typically skewed. Similar to the role of expected price change on the asymmetry of JCI 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. The decision maker follows a "hedge strategy", by targeting their point forecast in one direction and biasing the confidence interval in the opposite direction.

Spence (1996) hypothesize that a subject's best estimate is less likely to be the midpoint of his confidence interval when it is more difficult to forecast. Difficulty in forecasting creates a need to decompose the initial problem into a series of interrelated subproblems. Miscalculation on the part of a "contingency thinker" can result in a skewed subjective density function.

Muradoglu (2002) finds that De Bondt (1993)'s hedging theory is not supported in a controlled experiment involving portfolio managers and novices. Expert forecasters did not hedge, but they speculated on their optimistic forecasts.

Our empirical findings are consistent with De Bondt (1993) and O'Connor et al. (2001). However, our approach differs from these two studies by introducing a new anchor: the forecaster's belief about the average opinions of others. We provide original evidence that the skewness of the confidence interval is associated with the resulting belief wedge.

Studying the opinions of others links our paper to the literature of higher order beliefs in finance. Since Keynes (1936) introduced the famous metaphor of the beauty contest, it has been acknowledged widely by market participants and academic researchers that others' beliefs matter in financial markets. A growing theoretical literature attempts to relate higher-order beliefs to a number of stylized facts, such as price bubbles, short term momentum, trading behaviors, return co-movements and excess volatility. Beliefs about others' beliefs are typically not directly observable, however, and empirical evidence is sparse. Notable exceptions include Monnin (2004), Rangvid, Schmeling, and Schrimpf (2010), Egan, Merkle, and Weber (2010), and Balakrishnan, Schrand, and Vashishtha (2012). If beliefs about others' beliefs matter, they should affect the decision maker's beliefs about future outcomes. Rangvid, Schmeling, and Schrimpf (2012) provide supportive evidence using new data from a large survey of professional forecasters.

3 Experimental Design and Data

The data for Experiments 1 and 2 were obtained from two surveys in which subjects were asked to forecast stock prices, conducted at Bangor University, UK. Subjects in Experiment 1 are undergraduate finance students, registered on a quantitative methods course. 67 out of 80 students registered for the course completed and returned the survey in 15 minutes, producing a response rate of 84%. Subjects in Experiment 2 are postgraduate finance students, registered on a behavioural finance course. All 44 students registered for the course completed and returned the survey in 40 minutes.

The design of Experiments 1 and 2 follows closely De Bondt (1993), who surveyed 27 students at the University of Wiscosin-Madison. In our case the subjects are shown six charts, and told that these represent 48 consecutive monthly prices of unnamed stocks. The subjects are asked to predict the price of each stock after another 13 months, together with an interval forecast in the form of a 90% confidence interval for each stock price after 13 months. In contrast to De Bondt (1993), we ask an additional question on the subjects' second-order beliefs: "predict the average forecasts made by your classmates, for the stock price in 13 months". In Experiment 2 (but not in Experiment 1), subjects are also asked to predict the average value of the forecasts made by market participants.

The six charts are, in fact, taken from FTSE 100 index between 1984 and 2011. The selected series are rescaled to avoid recognition by the subjects. Among the six charts, in two cases the price series are upwardly trended, in two cases the series are downwardly trended, and in two cases the series appear to be untrended. Two different sets of the six charts are assigned randomly among the subjects, with the ordering of the six charts reversed between the two sets. Within each set, two different rescaling factors are applied to the original index series, generating two versions of each set of charts with different degrees of volatility.

We ask the subjects to provide personal information: age, gender, major, nationality, and investment experience. In Experiment 1 (but not in Experiment 2) subjects are asked to report their GPA in the previous semester.

Experiment 3 was conducted over the course of seven consecutive weeks, involving 38 students registered on a postgraduate finance course at Bangor University. Each Thursday, the subjects were asked to forecast the following Thursday's FTSE 100 index. Students were asked to specify a point forecast, a 90% confidence interval, and a forecast of the average forecasts of their classmates, and the market. A small component of the gradings for the course reflected the accuracy of the forecasts.

The dependent variable is a measure of skewness of the confidence interval

$$Skewness = high + low - 2 \times \mu_1 \quad (1)$$

where high and low are the upper and lower bounds of the 90% confidence interval, and μ_1 is the point forecast.

4 Empirical Results

4.1 Regression Analysis

The regression analysis of skewness on belief wedge includes controls for several factors that might be expected to affect the skewness of JCI. The belief wedge is defined as the difference between the subject's point forecast and his belief about the average forecast of his classmates (hereafter "class belief wedge"). Figure 1 shows scatter plots of the relationship between the belief wedge and measured skewness for Experiments 1 and 2. Figure 1 suggests that this relationship is approximately linear in both cases; the results for Experiment 3 (not included in Figure 1) are similar. Figure 1 also shows that the skewness measure is typically non-zero, indicating that subjects commonly form asymmetric confidence intervals. This is in contrast to the usual assumption in the literature (e.g., Taylor and Bunn (1999)), but consistent with the findings of De Bondt (1993), O'Connor et al. (2001) and Du and Budescu (2007).

[Insert Figure 1 about here]

Table I reports OLS, panel (random effects) and median regressions of skewness on belief wedge, using the data from Experiment 1. In each case we consider two model specifications: the first explains skewness using expected price change (the difference between the point forecast and the last observed value of the price series) and the belief wedge only; while the second includes additional controls for the subjects' personal characteristics and attributes of the observed price movement (trend and volatility) shown on the chart. The trend is measured as the difference between the last and the first prices shown on the chart. Volatility is the volatility of the historical stock prices in the chart that is displayed to the subjects. R-square is adjusted R-square for the OLS regressions, overall R-square for the panel (random effects) regressions, and pseudo R-square for the median regressions.

The estimation results present strong evidence of a positive association between the belief wedge and skewness, consistent with the prediction of our new hedging theory of confidence intervals. The estimated coefficients on the belief wedge are positive and significantly different from zero at the 0.01 level, and this finding is robust to the inclusion of controls for personal characteristics and the attributes of the observed price movement. Furthermore, the magnitudes of the coefficients appear to be relatively stable across the various model specifications.[1]

The estimation results also suggest a negative association between the expected price change (EPC) and skewness. The estimated coefficient in the OLS regression with controls is significant at the 0.01 level, but the coefficient in the regression without controls is insignificant. The coefficients in the panel regressions with and without controls are significant at the 0.01 and 0.1 levels, respectively; and the coefficients in the median regressions with and without controls are significant at the 0.01 level. EPC is reported by De Bondt (1993) and O'Connor et al. (2001) as a major determinant of the skewness of confidence interval. Our results are similar, although the statistical significance of the coefficients on EPC is in some cases weaker than the significance of the coefficients on the belief wedge.

Although not reported in Table I, the correlation coefficient between the belief wedge and EPC is -0.2. An OLS regression of skewness on the belief wedge and a constant only produces an adjusted R-square of 0.39; the regression of skewness on EPC only produces an adjusted R-square of 0.06. The coefficients are significant at the 0.01 level in both regressions. We infer that the belief wedge is an important determinant of the skewness of the confidence interval in its own right, regardless of any association between the belief wedge and EPC.

Among the control variables,[2] the coefficients on "trend" are negative and significant at the 0.01 level in all three model specifications. The coefficients on the other controls are all insignificant.

[Insert Table I about here]

Table II reports the results from the estimations of the same model specifications, using the data from Experiments 2 and 3. For both experiments and for all specifications, the estimated coefficients on the belief wedge are significantly different from zero at the 0.05 level, and with two exceptions these coefficients are significant at the 0.01 level. All coefficients on EPC have the expected negative sign, and the majority of these coefficients are significantly different from zero at the 0.05 level.

The coefficients on the belief wedge in the estimations based on the data from Experiment 2 are slightly smaller than, but qualitatively similar in magnitude to the corresponding coefficients obtained using the data from Experiment 1. Our conjecture is that the longer time allocation for the task of forecasting in Experiment 2 (40 minutes) than in Experiment 1 (15 minutes) might explain the smaller coefficients obtained using the data for Experiment 2: when the time allocated to the task of forecasting is longer, the subjects' beliefs about the average forecasts of other subjects become less influential in determining the bounds of their interval forecasts. The coefficients on the belief wedge in the estimations based on the data from Experiment 3 are much smaller than, and qualitatively different from the corresponding coefficients obtained using the data from Experiments 1 and 2. We conjecture that in Experiment 3 the subjects perceive bigger differences between their own beliefs and the second-order beliefs, rendering the belief wedge less stable. In Experiments 1 and 2, the subjects are aware that all forecasts are based on the same information set, in the form of the chart that is displayed to all subjects. In Experiment 3, students are able to incorporate any information they can locate into their forecasts. Therefore subjects may reasonably expect others' beliefs to differ from their own to a greater extent in Experiment 3 than in Experiments 1 and 2. With more time and more diverse information sets available to the subjects in Experiment 3, as well as a grading incentive for forecast accuracy, it seems reasonable to infer that the subjects' beliefs about the average forecasts of other subjects are less influential in determining the bounds of their interval forecasts than is the case in Experiments 1 and 2. Nevertheless all coefficients on the belief wedge in estimations based on the Experiment 3 data are significantly different from zero at the 0.05 level or below. Therefore the difference in experimental design does not alter the role of belief wedge qualitatively.

[Insert Table II about here]

The coefficients on the other control variables are insignificant in all model specifications,[3] with the exceptions of those on “trend” and “country”. The coefficients on “trend” are significant at the 0.01 level in all three model specifications for Experiment 2, but insignificant for Experiment 3. The coefficient on “country” is significant at the 0.10 level only in the OLS regression for Experiment 3.

4.2 Robustness checks

4.2.1 Logarithmic transformation

Glaser, Langer, Reynders, and Weber (2007) show that surveys that ask for forecasts of future stock prices in levels are more likely to produce mean-reverting expectations than surveys that ask for forecasts of future returns. In our experiments, the subjects were asked to forecast a price or index value in levels. However, if they base their forecasts on logarithmic returns instead of prices, the measured asymmetry of the confidence intervals 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 a subject’s point estimate for the future price is also 100. The upper bound of her confidence 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 confidence interval defined in terms of prices is positively skewed, but her beliefs concerning the log returns are symmetric around zero. As a robustness check, we recalculate the skewness, belief wedge and EPC using log prices and the logarithms of the price forecasts, and repeat the estimations of all of the regressions reported above with log transformations applied.

[Insert Table III about here]

Table III reports random effects regressions of skewness on belief wedge for Experiment 1, 2 and 3 without and with control variables. The coefficients on the belief wedge are qualitatively similar to the corresponding coefficients in Table I and II. These coefficients are positive and significantly different from zero at the 0.01 level in all cases, with the exception of the regression for Experiment 3 with control variables excluded (in which case the coefficient on the belief wedge is significant at the 0.05% lelvel). Table III also suggests that a negative association between EPC and skewness holds when the prices and price forecasts are subject to logarithmic transformation. The results of the corresponding OLS and median regressions (not report in Table III) are qualitatively similar.

4.2.2 Alternative normalized skewness measure

All of the results reported in Section 4.1 are based on the skewness measure shown in Equation (1). An alternative normalized skewness measure is

$$Normalized\ Skewness = \frac{high + low - 2 \times \mu_1}{high - low} \tag{2}$$

As a further robustness check, we repeat the estimations of all of the regressions reported in Section 4.1 with the skewness measure (1) replaced by the normalized skewness measure (2).

[Insert Table IV about here]

Table IV reports the results for random effects regressions in (the OLS and median regressions are similar). As before, the belief wedge is positively associated with the normalized skewness, and EPC is negatively associated with the normalized skewness. All coefficients for these two variables are statistically significant at the 0.05 level.

4.2.3 Belief wedge calculated using subjects' assessments of market participants' average beliefs

Experiments 2 and 3 ask the subjects to report their beliefs about the average belief of the market participants. Conceivably, the subjects might have different second-order beliefs with respect to their classmates and market participants, which would result in a different belief wedge measure based on the subjects' assessments of the average beliefs of the latter. As a further robustness check, we repeat the estimations of the regressions reported in Section 2 using data from Experiments 2 and 3, with the belief wedge recalculated using the subjects' assessments of market participants' average beliefs. The results are qualitatively similar to those reported above and are omitted for the sake of space.

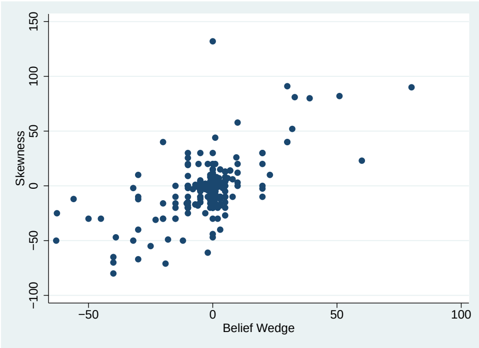
5 Conclusion

This paper has described a new hedging theory of confidence intervals. We argue that a decision maker who faces uncertainty will form a confidence interval by hedging his own beliefs (first-order forecast) with his perception of the average beliefs of others (second-order forecast). According to our theory decision makers initially form a their own point forecast and a confidence interval around the point forecast. They then adjust the upper bound and lower bound of the confidence interval under the influence of the second-order belief, leaving the point forecast unchanged. This leads to a positive association between the belief wedge and the skewness of the confidence interval.

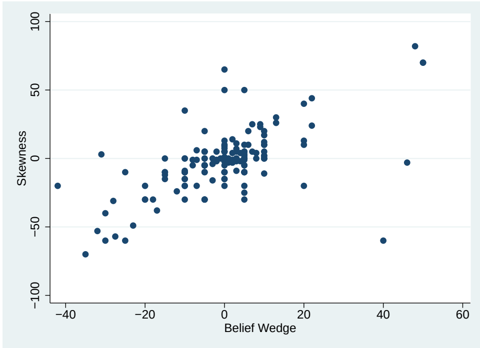
We test the theory using data from three experiments, in which students are asked to forecast future stock prices. The empirical evidence is consistent with the theory. The results are robust to the inclusion of controls for the subjects' personal characteristics and the attributes of the observed stock price movements. Robustness checks yield similar results with estimations based on an alternative skewness measure, with skewness and the belief wedge measured using log prices, and with the belief wedge measured using subjects' perceptions of the average belief of market participants, rather than other class members.

6 Tables and Figures

Figure 1
Skewness and Belief Wedge



(a) Experiment 1



(b) Experiment 2

The figure shows the relationship between skewness of the confidence interval and the belief wedge, which is defined as the second-order beliefs minus first-order beliefs in Experiments 1 and 2.

Table I
Regressions of Skewness and Belief Wedges in Experiment One

	OLS Regression		Panel Regression		Median Regression	
Expected Price Change	-0.094	-0.264***	-0.094*	-0.264***	-0.085***	-0.206***
	(0.061)	(0.088)	(0.051)	(0.069)	(0.031)	(0.046)
Belief Wedge	0.978***	0.889***	0.978***	0.889***	1.115***	1.086***
	(0.116)	(0.131)	(0.082)	(0.091)	(0.047)	(0.058)
gender		-3.318		-3.318		-2.401
		(2.526)		(2.672)		(1.796)
country		-1.789		-1.789		-4.684
		(3.196)		(4.879)		(3.271)
major		0.050		0.050		2.691
		(2.894)		(3.667)		(2.444)
invest		4.180		4.180		2.924
		(2.908)		(3.655)		(2.453)
mark		-0.490		-0.490		-0.078
		(1.297)		(1.180)		(0.794)
trend		-0.190***		-0.190***		-0.090***
		(0.054)		(0.048)		(0.032)
volatility		-0.004		-0.004		-0.005
		(0.006)		(0.006)		(0.004)
Constant	0.213	4.918	0.213	4.918	0.190	3.477
	(1.142)	(6.850)	(1.256)	(7.535)	(0.757)	(5.000)
Adj. R-squared	0.394	0.414	0.399	0.435	0.192	0.203
N	254	249	254	249	254	249

This table reports OLS, random effects and median regressions of skewness on belief wedge for Experiment 1, without and with control variables. Standard errors of estimated coefficients are reported in parentheses. Expected price change is the difference between the point forecast and the last observed value of the price series. Belief wedge is the difference between the subject's second-order belief and the first-order belief. 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. 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. $***$ indicates coefficient significantly different from zero at the 0.01 level; $**$ and $*$ indicate significance at 0.05 and 0.1 levels, respectively.

Table II
Regressions of Skewness and Belief Wedge in Other Samples

	OLS Regression		Panel Regression		Median Regression	
	Panel A: Experiment Two					
Expected Price Change	-0.243**	-0.487***	-0.243***	-0.487***	-0.116**	-0.231***
	(0.116)	(0.140)	(0.065)	(0.079)	(0.045)	(0.078)
Belief Wedge	0.946***	0.837***	0.946***	0.837***	0.977***	1.045***
	(0.192)	(0.172)	(0.094)	(0.092)	(0.065)	(0.092)
gender		1.019		1.019		1.771
		(4.160)		(3.500)		(3.512)
country		1.178		1.178		4.775
		(4.182)		(3.922)		(3.892)
major		2.761		2.761		1.138
		(2.942)		(5.310)		(5.237)
invest		1.049		1.049		-1.424
		(4.820)		(3.931)		(3.814)
trend		-0.236***		-0.236***		-0.115***
		(0.069)		(0.044)		(0.043)
volatility		0.004		0.004		-0.001
		(0.007)		(0.006)		(0.006)
Constant	-0.244	-4.125	-0.244	-4.125	-0.256	-5.256
	(1.328)	(4.496)	(1.341)	(6.443)	(0.922)	(6.321)
R-squared	0.433	0.534	0.440	0.559	0.231	0.280
N	169	149	169	149	169	149
	Panel B: Experiment Three					
Expected Price Change	-0.368**	-0.268*	-0.417***	-0.289**	-0.399***	-0.267***
	(0.170)	(0.147)	(0.120)	(0.135)	(0.045)	(0.050)
Belief Wedge	0.448**	0.692***	0.339**	0.616***	0.269***	0.300***
	(0.181)	(0.220)	(0.168)	(0.204)	(0.063)	(0.096)
gender		-5.794		-6.202		2.032
		(12.917)		(17.150)		(7.465)
country		-36.594*		-34.883		-2.569
		(20.473)		(41.511)		(17.652)
invest		22.110		22.391		6.669
		(21.896)		(20.639)		(8.923)
trend		-0.030		-0.031		0.021
		(0.140)		(0.139)		(0.068)
Constant	-38.367***	-3.707	-37.819***	-4.887	-13.599***	-15.320
	(6.423)	(21.879)	(8.420)	(42.507)	(2.401)	(18.082)
R-squared	0.068	0.060	0.073	0.087	0.065	0.064
N	240	207	240	207	240	207

Note: This table reports OLS, random effects and median regressions of skewness on belief wedge for Experiments 2 and 3, without and with control variables. Standard errors of estimated coefficients are reported in parentheses. Expected price change is the difference between the point forecast and the last observed value of the price series. Belief wedge is the difference between the subject's second-order belief and the first-order belief. 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. 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. $***$ indicates coefficient significantly different from zero at the 0.01 level; $**$ and $*$ indicate significance at 0.05 and 0.1 levels, respectively.

Table III
Regressions of logarithmic transformed variables

	Experiment One		Experiment Two		Experiment Three	
Expected Price Change	-0.131***	-0.161**	-0.158***	-0.164*	-0.381***	-0.253*
	(0.046)	(0.063)	(0.060)	(0.095)	(0.129)	(0.145)
Belief Wedge	0.735***	0.695***	0.965***	0.990***	0.363**	0.650***
	(0.088)	(0.087)	(0.121)	(0.132)	(0.182)	(0.222)
gender		0.091		-0.093		-0.001
		(0.074)		(0.118)		(0.003)
country		-0.166		-0.091		-0.006
		(0.136)		(0.134)		(0.008)
major		-0.102		-0.089		
		(0.101)		(0.175)		
invest		0.147		-0.057		0.003
		(0.102)		(0.137)		(0.004)
mark		0.073**				
		(0.033)				
trend		-0.003***		-0.002*		-0.000
		(0.001)		(0.001)		(0.000)
volatility		-0.001***		-0.001***		
		(0.000)		(0.000)		
Constant	-0.240***	-0.226	-0.222***	0.123	-0.007***	-0.001
	(0.044)	(0.208)	(0.045)	(0.215)	(0.002)	(0.008)
R-squared overall	0.256	0.402	0.324	0.436	0.062	0.074
N	253	248	162	142	240	207

This table reports random effects regressions of skewness on belief wedge for Experiment 1, 2 and 3 without and with control variables. The skewness, belief wedge and EPC are calculated using log prices and the logarithms of the price forecasts. Standard errors of estimated coefficients are reported in parentheses. Expected price change is the log-difference between the point forecast and the last observed value of the price series. Belief wedge is the log-difference between the subject's second-order belief and the first-order belief. 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. 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. $***$ indicates coefficient significantly different from zero at the 0.01 level; $**$ and $*$ indicate significance at 0.05 and 0.1 levels, respectively.

Table IV
Regressions of Normalized Skewness and Belief Wedge

	Experiment One		Experiment Two		Experiment Three	
Expected Price Change	-0.002**	-0.005***	-0.005***	-0.010***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)
Belief Wedge	0.015***	0.013***	0.016***	0.014***	0.001**	0.002***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
gender		-0.110		0.077		0.057
		(0.091)		(0.091)		(0.062)
country		-0.012		0.149		-0.085
		(0.149)		(0.102)		(0.148)
major		0.015		0.037		
		(0.117)		(0.138)		
invest		0.139		0.061		0.056
		(0.122)		(0.102)		(0.075)
mark		0.025				
		(0.040)				
trend		-0.004***		-0.004***		-0.000
		(0.001)		(0.001)		(0.000)
volatility		-0.000		0.000		
		(0.000)		(0.000)		
Constant	-0.054	-0.131	-0.027	-0.219	-0.149***	-0.106
	(0.039)	(0.239)	(0.034)	(0.168)	(0.029)	(0.152)
R-squared overall	0.280	0.343	0.275	0.364	0.120	0.132
N	254	249	169	149	240	207

Note: This table reports random effects regressions of normalized skewness on belief wedge for Experiments 1, 2 and 3, without and with control variables. Standard errors of estimated coefficients are reported in parentheses. The normalized skewness is calculated as in Equation (2). Expected price change is the difference between the point forecast and the last observed value of the price series. Belief wedge is the difference between the subject's second-order belief and the first-order belief. 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. 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. $***$ indicates coefficient significantly different from zero at the 0.01 level; $**$ and $*$ indicate significance at 0.05 and 0.1 levels, respectively.

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Notes

[1] The coefficients in OLS regressions and panel regressions are the same while their standard errors are almost identical. This is due to a high ratio of within to between variation in the data.

[2] Although we have information on the age of the subjects, the age variation across subjects is small, and age is excluded from the reported estimations. The inclusion of age does not affect our results qualitatively.

[3] Volatility in Experiment 2 refers to the volatility of the historical stock prices in the chart that is displayed to the subjects.. We do not include volatility as a control variable in the regressions of Experiment 3. If we use the average of past 5 or 20 days' squared returns as a proxy, our results are similar.