Academic Performance and Financial Forecasting Performance: A Survey Study *

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Abstract

In a survey of forecasting stock prices over 13 months, we find better academic performance is significantly associated with smaller absolute forecasting errors, a lower propensity to be overconfident and narrower prediction intervals. The latter two findings are surprising as one would expect that less overconfident forecasters are more likely to make wider prediction intervals. Such superior forecasting ability of good academic performers may help explain why smart investors perform better in financial markets.

Keywords: Academic Performance; Forecasting Errors; Prediction Intervals; Overconfidence.

JEL Classification: C9, G1

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1 Introduction

It's well documented that smart investors exhibit superior trading performance in the financial markets. For example, they show better market timing, stock-picking skills, trade execution, and less likely to be subject to the deposition effects (Grinblatt, Keloharju, and Linnainmaa 2011b). One plausible, but to our knowledge empirically unexploited, explanation is that smart investors process superior forecasting ability. Yet empirical tests of forecasting performance can easily come across difficulties to distinguish forecasting ability from better information access as forecasters may be differentially informed. We utilise a survey approach in which subjects are equally informed to forecast future stock prices.

Since academic performance is highly correlated with IQ (Gustafsson and Undheim 1996, Brody 1997, Sattler 2001) and reflects individuals' cognitive ability (Rohde and Thompson 2007, Leeson, Ciarrochi, and Heaven 2008, Campbell 2006), we employ it as a measure of brightness[1]. We find that superior academic performers make smaller absolute forecasting errors, are less likely to be overconfident, and form narrower prediction intervals than their peers with worse academic performance. The latter two findings are particularly remarkable since one would expect that less overconfident subjects are more likely to make wider prediction intervals. Yet our findings suggest the opposite. We interpret these results as evidence of superior forecasting capabilities among good academic performers over their peers. Smart forecasters have superior ability of gathering and interpreting public information (Korniotis and Kumar 2013, Grinblatt et al. 2011b); are less likely to be subject to behaviour bias (Grinblatt et al. 2011b); and devote themselves more in a task (Gevins and Smith 2000). Such advantages might help them to make superior forecasting and thus perform better when they trade in the financial markets.

Our findings are robust to the choice of estimation method, the inclusion of controls for the subjects' personal characteristics such as their level of finance education and investment experience, and the attributes of the observed price movements such as trend and volatility.

This paper is the first time to show that investors' brightness is positively related to their financial

[1] Baker and Haslem (1974), Donkers, Melenberg, and Van Soest (2001), and Benjamin, Brown, and Shapiro (2013) also test academic performance relationship with risk perception.

forecasting performance. It also provides a possible explanation as to why smart investors perform better in financial market. If smart investors have prerequisite superior financial forecasting ability, they can pick up right stocks, do better market timing, decisively execute trading, and even avoid some psychology bias since they are confident on their forecasting.

The rest of the paper is structured as follows: Section 2 reviews the literature; Section 3 discusses the survey design; Section 4 reports the empirical findings; and Section 5 concludes.

2 Literature

A large literature show that investors' brightness influences their behaviour in financial market. First, the smart investors exhibit superior trading performance than their peers. For example, Grinblatt et al. (2011b) analyze the influences of IQ on investors' trading behavior and on their trading performance using a large Finnish sample and a database of comprehensive IQ scores recorded from mandatory military service and stock trading data. They find that high IQ investors tend to improve liquidity in markets, are better at stock selection, timing and trade execution, and are less subject to a disposition effect, whereas their sample of low IQ investors tend to hold on to under-performing stocks whilst selling winners. Further, Grinblatt, Keloharju, and Linnainmaa (2011a) illustrate that high IQ investors usually hold well-diversified portfolios and thus bear lower risk and enjoy a better reward-to-variability ratio (Sharp Ratio). Barber and Odean (2001) also suggest that investment biases such as under-diversification, high frequency of trading and taking orders by mistake are highly related to IQ and perhaps present a plausible explanation of why individuals appear less than successful investors.

Second, brightness affects investors' risk perception. In previous literature, the findings of their relationship direction is mixed. Most literature argues that smart investors are more likely to be risk seeking than their peers. For instance, Frederick (2005) show that individuals with the highest scores in his three-item cognitive test are more risk taking. In addition to examine cognitive ability directly, a plenty of researchers employ the academic performance to measure the brightness. For example, Baker and Haslem (1974) report that investors with less education find price stability more important than investors with more education. Donkers et al. (2001) suggest that more educated subjects are more risk seeking in hypothetical gambles: for example, they were more likely to prefer an 80 percent chance of 45 florins (about $23) over a sure 30 florins (about $15). Similarly, Benjamin et al. (2013) found that students who perform better on the math section of the SAT or its Chilean equivalent have more propensity to prefer a 50 percent chance to win $1.05 over a sure 50 cents.

Prior literature also suggests that investors' brightness is associated with their willingness to participate the financial market. For instance, Kézdi and Willis (2003) report financial market participation monotonically increasing with IQ for their sample of 12,000 subjects identified from a National Retirement Survey. Dohmen, Falk, Huffman, and Sunde (2010) also claim that the individuals with higher cognitive ability are significantly more willing to take risk in lottery experiments, and significantly more patient over the year-long time horizon studied in the intertemporal choice experiment. The results of a study by Van Rooij, Lusardi, and Alessie (2011) suggest that respondents with low financial literacy are much less likely to invest in stocks. A number of studies have also highlighted the implications of a positive relationship between cognitive ability and financial market participation for government policy. For example, Grinblatt et al. (2011a) suggest governments who offer privatization to encourage participation could widen the wealth gap between low and high IQ individuals. They further suggest that if lower IQ individuals have a propensity to invest in low return assets, it is likely to increase the gap to a greater extent than wage differences.

Our paper adds to this body of literature by examining whether the brightness affects the investors' forecasting performance of future stock prices. It provides a possible explanation why smart investors exhibit better trading performance in financial markets. We not only study the financial forecasting performance through the forecasting accuracy but also the risk perception. It allows us to solve the debate in literature as mentioned above whether smart investors are more risk seeking.

3 Research and Survey Design

3.1 Research Design

The purpose of our study is to test whether brightness is associated with the financial forecasting performance. We employ academic performance to proxy the brightness and implement a survey to examine the financial forecasting performance through three aspects: absolute forecasting errors, prediction intervals, and overconfidence.

Our hypotheses are shown as the followings where they are stated in the null form:

H_1: There is no relationship between subjects' absolute forecasting errors and academic performance;

H_2: There is no relationship between subjects' prediction intervals and academic performance;

H_3: There is no relationship between subjects' overconfidence and academic performance.

Their alternative hypotheses are that relationships exist between academic performance and absolute forecasting errors, prediction intervals, or overconfidence. Especially, we expect that outstanding academic performers exhibit a superior ability for financial forecasting. That is, the forecasters with superior academic performance make larger absolute forecasting errors, give wider prediction intervals and are more likely to be overconfident than other subjects.

3.2 Experiment Design

To test our hypotheses, we conduct a in-class survey which ensures forecasters' accessible information are equal and subsequently avoid forecasting ability is due to the better information access.

3.2.1 Subjects

The subjects are undergraduate students from a second year quantitative methods course at a UK university. The allotted class time for completion of the survey is 15 minutes. Out of the 80 students who participated in this experiment 67 students (25 male and 42 female) completed and returned the questionnaires, yielding a response rate of 84%. The average age of the respondents is 21.

3.2.2 Stimuli

We follow the methods used by De Bondt (1993) to generate the stimulus series. The subjects are shown six charts, and are told that 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. Two of the six price series are upwardly trended, two series are downwardly trended, and two series appear to be untrended.

To mitigate concerns that respondents might complete the questions for the first few charts and leave the rest blank, we assign 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 helps mitigate against practice effects, whereby a subject's forecasting performance may tend to improve over repeated attempts at a forecasting exercise. Empirically, neither the response rate nor forecasting performance appears to be influenced by the order in which the charts are shown. Within each set of six charts, two different rescaling factors are applied to the original series to minimize the possibility of recognition, generating two versions of each set with different degrees of volatility. We use "t", "t+1", "t+2", $\cdots$, "t+48" to replace the actual time. In addition, we rescale the stock prices by multiplying the original prices with 1/100 in version 1 and 2, and 3/100 in version 3 and 4. Therefore, we have four versions of questionnaires in total.

3.2.3 Procedures

In the survey, each subject only receives one questionnaire by the order from version 1 to version 4, and accordingly, to prevent subjects from copying the answers from their neighbors. The subjects are asked to forecast the price of each stock after 13 months. The following questions are shown after each chart:

estimated price ......

estimated price interval (with 90% confidence level)

high price ......

low price ......

We also ask them to provide their personal information: age, gender, nationality, major, GPA in previous semester, the extent of their participation in finance courses, and state whether they have any previous investment experience. To avoid the experiment biases such as the Hawthorne Effect[2] and/or the Pygmalion Effect[3], all subjects take the experiment in the same place at the same time with the same experimenters. In addition, all experimenters have been trained and have run a pre-test before the survey.

A survey approach enables us to evaluate the forecasters' financial forecasting performance directly, and link it to their academic performance. More importantly, it ensures that forecasters base their forecasts on the provided public information and no one has an informational advantage over others. Therefore the differences in forecasting performance may be attributed to their ability in interpreting public information.

4 Data and Summary Statistics

To test our hypotheses, we have three dependent variables to measure the financial forecasting performance: absolute forecasting errors, length of prediction intervals and overconfidence. They are defined as the following equations:

[2]The term of Hawthorne Effect is suggested by HA (1958). It elicits a phenomenon that the subjects improve or modify an aspect of their behavior in response to the fact of change in their environment, rather than in response to the nature of the change itself. For instance, the different experiment place, time or enjoinment could alter the subject's performance.

[3]Pygmalion Effect is named after the Greek myth of Pygmalion. It indicates that the greater the expectation placed upon the subjects, the better they perform. The experimenter's behaviours, for example, an encouraging glance, could affect the subject's performance.

$$\textit{Absolute forecasting error} = |\textit{Actual stock price} - \textit{Point forecast}| \tag{1}$$

$$\textit{Prediction interval} = \textit{Upper bound} - \textit{Lower bound} \tag{2}$$

$$\textit{Overconfidence} = \begin{cases} 1, & \textit{if actual stock price lies outside the prediction interval} \\ 0, & \textit{if actual stock price falls in the prediction interval} \end{cases} \tag{3}$$

The regressor of particular interest is academic performance which is measured as subjects' GPA of previous semester. We also consider whether personal characteristics including age, gender, origin; previous finance education; and investment experience moderate the relationship between the dependent variables and academic performance. In addition, we consider whether two salient features of stock prices, namely trend and volatility also affect the relationship.

Rather than use a continuous variable for academic performance we divide subjects into quintile with category 1 comprising subjects with the lowest average marks, and category 5 with the highest and assign a score of 1 and 5, respectively. We report a preliminary analysis of the relationship between the academic performance and the performance of forecasting future stock prices, in the form of a cross tabulation as shown in Table I.

[Insert Table I about here]

In Table I, absolute forecasting error, prediction interval and overconfidence almost monotonically increase when GPA decreases. Supporting our hypothesis, we find that better academic performing forecasters make more accurate forecasts, are more confident about their forecasts and less likely to be overconfident than their peers with worse academic performance.

5 Empirical Results

In this section, the relationship between the academic performance and the financial forecasting performance is investigated further in regression analyses. For each hypothesis, we consider t-wo model specifications: the first is a univariate regression of financial forecasting performance (absolute forecast error, prediction interval or overconfidence) on academic performance (and a constant) only; while the second regression model includes additional controls for the forecasters' personal characteristics and attributes of the observed price movement (trend and volatility) shown on the chart. The following OLS regression model with control variables is shown as an example for our regression analyses.

$$\begin{gathered} Financial\ Forecasting\ Performance_{i,j} = \alpha + \beta_1 GPA_{i,j} + \beta_2 age_i + \beta_3 gender_i \\ + \beta_4 country_i + \beta_5 major_i + \beta_6 course_i + \beta_7 invest_i + \beta_8 trend_i + \beta_9 volatility_i + \varepsilon_{i,t} \end{gathered} \tag{4}$$

where i is the subject and j is the chart.

We firstly use OLS analysis to examine what affect the absolute forecast error in H_1 and the prediction interval in H_2, and employ probit analysis to identify the determinants of overconfidence in H_3. To account for unobserved individual effects, we further apply panel random effect regression analysis (panel regression for absolute forecast errors and prediction intervals, and panel probit regression for overconfidence) and gerneralized estimating equations (hereafter, GEE). The random effects specification is 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. We also test the relationship between academic performance and financial forecasting performance by employing median regressions. Their results (not reported) are consistent with those reported in the following three tables.

5.0.1 GPA as a Determinant of Absolute Forecasting Error

Table II reports the regression results where the absolute forecasting error on GPA and other control variables.[4] The coefficient for "GPA" is significantly negative in all the six models at a 1% significance level in the first model and at a 5% significance level in other models.[5] The absolute forecasting errors increase by 2 to 3 pounds if GPA declines by 1. This result suggests that better academic performers make less forecasting errors of future stock prices than worse academic performers. Studies repeatedly show that academic performance is a reflection of cognitive ability. Forecasters with superior cognitive abilities possess stronger memory, superior analytical and numerical abilities (Kézdi and Willis 2003); exhibit greater skills of information gathering and interpreting (Korniotis and Kumar 2013, Grinblatt et al. 2011b); have lower propensity to suffer from psychological bias (Grinblatt et al. 2011b) and tend to be more attentive on a task (Gevins and Smith 2000). Consequently, such characteristics might help them to reduce the forecast errors when they predict the future stock prices.

[Insert Table II about here]

5.0.2 GPA as a Determinant of Prediction Intervals

Table III shows regression results of the model where the prediction interval is the dependent variable on GPA and other control variables. In all model specifications, "GPA" is negatively

[4]The predictability of stock return is a highly debated issue in empirical asset pricing. Early theory considers asset prices as a random walk, later theory shows that return can be predicted if the risk premium is time varying. Cochrane (2005) pointed out that low prices relative to dividends forecast higher subsequent returns. Technical trading is based solely on the trends of the past price as well. Even if the price is a random walk, behavior biases, such as hot hand fallacy and gambler's fallacy may also lead to systematic forecast errors. When the lower GPA subjects are more affected by these behavioral biases, they could still make larger absolute forecast errors than others who are less affected.

[5]The results of OLS regression in model 2 and panel regression in model 4 are identical. This is due to very small within variation (R-squared within, 3%) relative to between variation (R-squared between, 75%)

and significantly related to the lengths of prediction intervals at different significance level (1% in model 1 and model 2, 5% in model 3, model 5 and model 6, and 10% in model 4). That is, forecasters with better academic performance form narrower prediction intervals than their peers with worse academic performance. Gevins and Smith (2000) suggest that superior academic performers are generally more engaged in a task which helps them to built up the confidence on their forecasting and thus make narrower prediction intervals. As the length of prediction the interval is also related to risk aversion, our results are in line with the predictions in Baker and Haslem (1974), Sung and Hanna (1996), Zhong and Xiao (1995). They illustrate that superior academic performers perceive less risk than the inferior academic performing forecasters.

[Insert Table III about here]

5.0.3 GPA and Overconfidence

We next question whether subjects with narrower prediction interval are more likely to be overconfident and we show below that it might depend on the characteristics of subjects.

Table IV reports the results of probit regressions (model 1 and model 2), panel probit regressions (model 3 and model 4) and GEE (model 5 and model 6). "GPA" is significantly negative related to "overconfidence" in all model specifications. It indicates that better academic performance is strongly associated with a less propensity to be overconfident. This result is remarkable. Subjects with better academic performance not only form a narrow prediction interval as indicated before, but also are less likely to be overconfident. If a forecaster elicits a narrower prediction interval, then the outcome is more likely to fall outside the prediction interval. In contrast, the results of Table VI shows that forecasters with higher GPA tend to specify narrower confidence intervals, but the outcome is still more likely to fall inside the narrower prediction intervals. This suggests that those subjects must have superior ability to anticipate a smaller range that future outcome might occur. Putting these results together, we conclude that forecasters who perform better in their studies have an superior ability in financial forecasting. They tend to be more confident (but not more overconfident) about their forecasts, but are making less errors in their forecast of risk.

[Insert Table IV about here]

In addition to GPA, we find that trend is significantly associated with three measurements of financial forecasting performance. When the trend is upward, forecasters make larger absolute forecasting errors; narrower perdition intervals; and are more likely to be overconfident. For forecasters, upward trend could be a positive sign (De Bondt 1993). Thereby, they become more risk seeking, are more prone to be overconfident and thus make larger forecasting errors. In line with the predictions of De Bondt (1993), we also find a significant and positive association between volatility and the length of the prediction interval which suggests that increased risk in the form of volatility lead forecasters to widen their prediction intervals.

6 Conclusion

This paper suggests that forecasters with better academic performance make smaller absolute forecasting errors, narrower prediction intervals, and are less likely to be overconfident than their peers.

These results can be explained by existing evidence that smart forecasters have a superior ability to learn (Grinblatt et al. 2011b, Korniotis and Kumar 2013) and are more focused on forecasting tasks (Gevins and Smith 2000). This paper is the first time to show that brightness is positively associated with the financial forecasting performance. It also provides a possible explanation of smart investors' superior trading performance in financial markets. As smart investors appear to forecast more accurately and are more confident of their predictions, they might choose better stocks, achieve superior market timing, have outstanding trade executions and avoid some irrational trading behaviours such as the disposition effect.

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Tables and Figures

Figure 1
Examples of stock prices chart

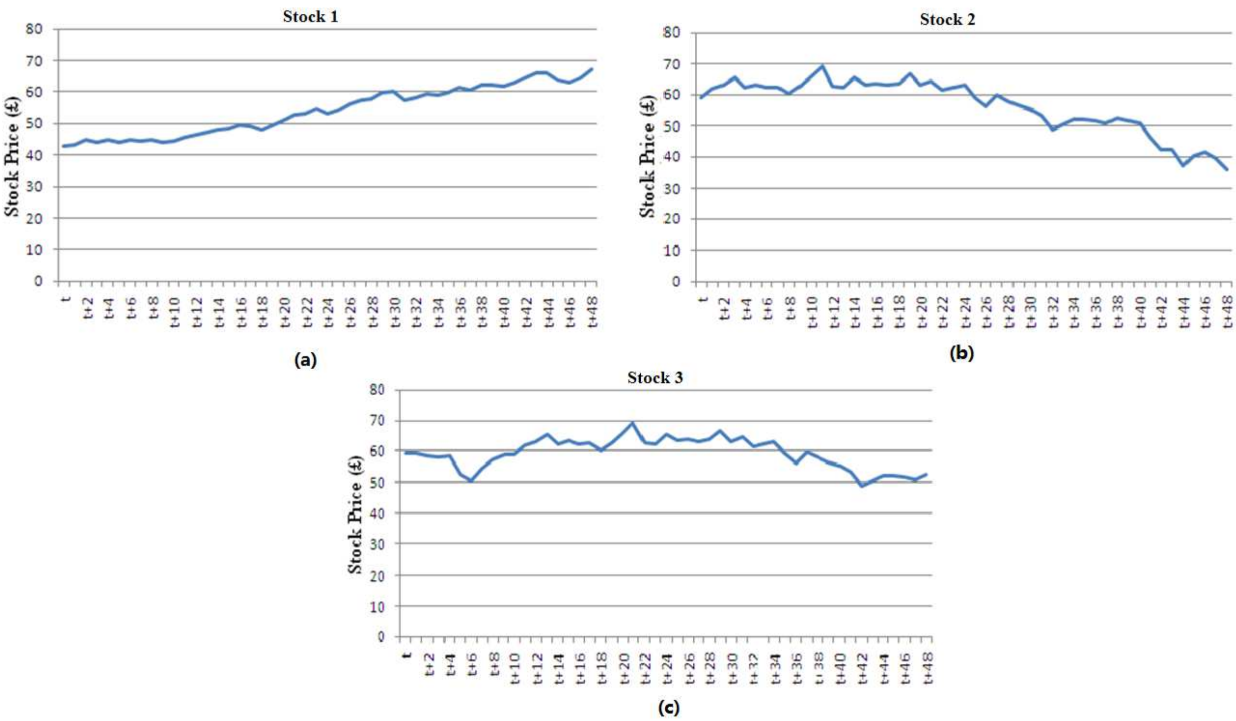

Table I
Dependent Variables Breakdown by GPA

	Absolute Forecast Error		Prediction Interval		Overconfidence	
GPA	mean	sd	mean	sd	mean	sd
1	50.00	30.80	61.25	20.56	1.00	0.00
2	38.56	21.97	53.15	40.30	0.79	0.42
3	29.92	20.31	45.22	39.24	0.76	0.43
4	22.71	23.57	37.93	26.96	0.57	0.50
5	26.63	20.26	34.10	24.15	0.67	0.47

This table presents the summary statistics conditional on the value of GPA. GPA is the GPA of a forecaster from previous semester, which takes a value from 1 to 5. 1 is the worst and 5 is the best. Absolute Forecasting Error is the absolute value of actual stock price minus point forecast. Prediction interval is the difference between high and low bounds of interval forecast with 90% confidence reported by subjects. Overconfidence is defined as a dummy variable, it is 1 if the realization falls outside of the 90% prediction interval and otherwise, 0.

Table II
Regressions of Absolute Forecast Errors on GPA

	OLS Regression		Random Effects		GEE	
	model 1	model 2	m3	m4	model 5	model 6
GPA	-3.020***	-2.160**	-3.438**	-2.160**	-3.432**	-2.161**
	(1.124)	(1.056)	(1.719)	(1.056)	(1.702)	(1.041)
age		-0.610		-0.610		-0.611
		(0.874)		(0.874)		(0.862)
gender		0.549		0.549		0.548
		(2.220)		(2.220)		(2.188)
east		-3.323		-3.323		-3.324
		(3.816)		(3.816)		(3.760)
major		1.930		1.930		1.932
		(2.712)		(2.712)		(2.672)
course		4.074*		4.074*		4.075*
		(2.364)		(2.364)		(2.330)
invest		-5.195*		-5.195*		-5.195*
		(2.978)		(2.978)		(2.935)
trend		0.131***		0.131***		0.131***
		(0.030)		(0.030)		(0.030)
volatility		0.048***		0.048***		0.048***
		(0.005)		(0.005)		(0.005)
Constant	39.461***	39.548**	41.189***	39.548**	41.165***	39.564**
	(4.679)	(18.679)	(7.148)	(18.679)	(7.076)	(18.408)
R-squared	0.019	0.261	0.022	0.281		
N	329	328	329	328	329	328

This table reports OLS, random effects and generalized estimating equations (GEE) estimation results for the relationship between academic performance and absolute forecasting error. Absolute forecasting error is the absolute value of actual stock price minus point forecast. GPA is the GPA of a forecaster from previous semester, which takes a value from 1 to 5. 1 is the worst and 5 is the best. Age is forecasters' age. Gender is 1 if a forecaster is male and 0, otherwise. Country is a 0-1 dummy variable which takes a value of one if the forecaster is from an east or south-east Asian country, and zero otherwise. Major is a 0-1 dummy variable. It takes a value of one if the forecaster has a finance related major, and zero otherwise. Course defines whether forecasters have at least two finance courses. If they do, course is 1 and 0, otherwise. Invest is a 0-1 dummy variable for previous investment experience which takes a value of one if the forecaster has investment experience, 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. Significance levels : *: 10% **: 5% ***: 1%

Table III
Regressions of Prediction Intervals on GPA

	OLS Regression		Panel Regression		GEE	
	model 1	model 2	m3	m4	model 5	model 6
GPA	-6.002***	-4.858***	-6.201**	-4.889*	-6.194**	-4.887**
	(1.648)	(1.513)	(2.892)	(2.666)	(2.969)	(2.490)
age		-0.612		-0.772		-0.765
		(1.253)		(2.258)		(2.108)
gender		-11.081***		-9.595*		-9.647*
		(3.181)		(5.664)		(5.291)
east		14.720***		15.056*		15.011*
		(5.468)		(9.169)		(8.588)
major		9.763**		8.832		8.866
		(3.885)		(6.658)		(6.226)
course		7.382**		6.064		6.107
		(3.387)		(6.127)		(5.718)
invest		-9.417**		-8.346		-8.396
		(4.266)		(7.756)		(7.237)
trend		-0.098**		-0.101***		-0.101***
		(0.043)		(0.033)		(0.032)
volatility		0.054***		0.050***		0.050***
		(0.007)		(0.007)		(0.007)
Constant	63.421***	40.266	63.848***	45.627	63.802***	45.435
	(6.860)	(26.763)	(12.010)	(47.412)	(12.330)	(44.295)
R-squared	0.036	0.311	0.039	0.329		
N	329	328	329	328	329	328

This table reports OLS, random effects and generalized estimating equations (GEE) estimation results for the relationship between academic performance and prediction interval. Prediction interval is the difference between high and low bounds of interval forecast with 90% confidence reported by subjects. GPA is the GPA of a forecaster from previous semester, which takes a value from 1 to 5. 1 is the worst and 5 is the best. Age is forecasters' age. Gender is 1 if a forecaster is male and 0, otherwise. Country is a 0-1 dummy variable which takes a value of one if the forecaster is from an east or south-east Asian country, and zero otherwise. Major is a 0-1 dummy variable. It takes a value of one if the forecaster has a finance related major, and zero otherwise. Course defines whether forecasters have at least two finance courses. If they do, course is 1 and 0, otherwise. Invest is a 0-1 dummy variable for previous investment experience which takes a value of one if the forecaster has investment experience, 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. Significance levels : *: 10% **: 5% ***: 1%

Table IV
Regressions of Overconfidence on GPA

	Probit Regression		Panel Probit Regression		GEE	
	model 1	model 2	m3	m4	model 5	model 6
GPA	-0.130*	-0.202**	-0.137*	-0.276**	-0.045*	-0.075**
	(0.074)	(0.086)	(0.082)	(0.123)	(0.027)	(0.031)
age		-0.033		-0.046		-0.010
		(0.065)		(0.087)		(0.026)
gender		-0.126		-0.181		-0.055
		(0.172)		(0.230)		(0.066)
east		-0.825**		-0.923**		-0.247**
		(0.333)		(0.423)		(0.111)
major		-0.202		-0.148		-0.043
		(0.221)		(0.283)		(0.080)
course		0.186		0.260		0.061
		(0.182)		(0.245)		(0.071)
invest		0.167		0.180		0.057
		(0.238)		(0.310)		(0.090)
trend		0.017***		0.017***		0.004***
		(0.003)		(0.003)		(0.001)
volatility		0.001		-0.000		-0.000
		(0.000)		(0.001)		(0.000)
Constant	0.974***	2.807**	1.014***	3.582*	0.854***	1.478***
	(0.312)	(1.429)	(0.345)	(1.945)	(0.114)	(0.556)
Log likelihood	-206.683	-181.827	-206.345	-180.255		
N	329	328	329	328	329	328

This table reports probit, panel probit and generalized estimating equations (GEE) estimation results for the relationship between academic performance and overconfidence. Overconfidence is a 0-1 dummy variable. It takes a value of 1 if point forecast lays out prediction interval and 0 otherwise. GPA is the GPA of a forecaster from previous semester, which takes a value from 1 to 5. 1 is the worst and 5 is the best. Age is forecasters' age. Gender is 1 if a forecaster is male and 0, otherwise. Country is a 0-1 dummy variable which takes a value of one if the forecaster is from an east or south-east Asian country, and zero otherwise. Major is a 0-1 dummy variable. It takes a value of one if the forecaster has a finance related major, and zero otherwise. Course defines whether forecasters have at least two finance courses. If they do, course is 1 and 0, otherwise. Invest is a 0-1 dummy variable for previous investment experience which takes a value of one if the forecaster has investment experience, 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. Significance levels : *: 10% **: 5% ***: 1%