Academic Performance and Risk Perception: an Experimental Study*

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Abstract

In an experimental study of forecasting stock prices over 13 months, we find higher academic performance is significantly associated with smaller absolute forecasting errors, narrower confidence intervals and a lower propensity to be overconfident. The superior performance of financial forecasting among better academic performers provides a possible explanation for the market participation puzzle. The results are robust to inclusion of controls for personal characteristics, finance education background, investment experience, stock price features, and unobserved individual effect.

Keywords: Academic Performance, Financial Forecasting, Forecasting Error, Risk Perception, Overconfidence.

JEL Classification: C90, G00, G11, G17

*We thank John Goddard for helpful comments. Errors and omissions remain the responsibility of the authors.

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1 Introduction

Traditional asset pricing models prescribe universal participation in financial markets, yet, according to Campbell (2006), for example, many households do not invest in financial markets. Grinblatt, Keloharju, and Linnainmaa (2011a) recently report that only around 50% of US households invest either directly or indirectly via mutual funds in stocks. Explanations for this lack of investment include a lack of stock market awareness (Hong, Kubik, and Stein (2004) and Van Rooij, Lusardi, and Alessie (2011) for example), lower cognitive ability (Benjamin, Brown, and Shapiro (2006) and Grinblatt, Keloharju, and Linnainmaa (2011b)) and risk aversion (Halko, Kaustia, and Alanko (2012)). The cognitive ability explanation suggests that many households have limited ability in processing information and is supported by a number of papers including Dwyer et al (2002) and Grinblatt et al. (2011a) who report a significant negative relationship between cognitive ability and participation. We adopt an experimental approach to question whether a relationship exists between cognitive ability and (1) risk aversion and (2) overconfidence. Utilising prior academic performance as a proxy for information processing ability we examine its impact on subjects'forecasting performances.

We find better academic performance is significantly associated with smaller forecasting errors, narrower confidence intervals and a lower propensity to be overconfident. The latter two findings are particularly interesting since one would expect those who have narrower confidence intervals are more likely to be more overconfident. Yet our findings suggest good academic performers perceive less risk while being less likely to be overconfident. We interpret the results as evidence of superior risk perception capabilities among better academic performers over their peers. The findings are robust to inclusion of personal characteristics such as their level of finance education and investment experience. Our results are also robust to stock return features such as trend and volatility. Whilst our results are not necessarily generalisable they do provide an additional explanation as to why households with lower information processing abilities might be reluctant to invest in financial markets. If such households tend to over-estimate risk they may consider equity premiums insufficient compensation.

Our findings relate most closely to Grinblatt et al. (2011a) who examine how heterogeneity in IQ can help the stock market participation puzzle.

Using Finnish stock market participation and IQ measured early in adult life, they show stock market participation is monotonically related to IQ. Taking academic performance as a proxy for IQ, this study provides complementary evidence which supports the results of the Grinblatt et al. (2011a) study. Utilising an experimental approach we are able to evaluate the forecasting performance of subjects directly, and link it to their academic performance. More importantly, the experimental approach ensures subjects base their forecasts on the information provided and thus no-one has an informational advantage over any other. Thus any differences in forecasting performance may be attributed to their ability in interpreting public information. The rest of the paper is structured as follows: Section 2 reviews the relevant literature; Section 3 discusses the methodology issues of this study; Section 4 reports the empirical findings; Section 5 concludes.

2 Literature

The low participation of households in stock markets has inspired a large and growing literature. A number of plausible reasons have been proposed. Haliassos and Bertaut (2006) and Vissing-Jorgensen (2002) suggest fixed participation costs prevent some households from investing in financial markets whereas Guiso, Sapienza, and Zingales (2008) propose a lack of trust inhibits investment.

One alternative explanation is the heterogeneous ability in information processing, forecasting asset price and associated risk among investors. Studies byKézdi and Willis (2003) and Grinblatt et al. (2011a), for example, have linked Intelligence quotient (IQ), a proxy for information processing ability, to stock selection, market timing and trade execution, as well as the propensity to participate in the stock market. 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.Grinblatt et al. (2011a) report that high IQ investors usually hold well-diversified portfolios and thus bear lower risk and enjoy a better reward-to-variability ratio (Sharp Index). The results of a study byVan Rooij et al. (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 negative relationship between cognitive ability and financial market participation for government policy. For example,Grinblatt et al. (2011a), for example, 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 compounding is likely to increase the gap to a greater extent than wage differences.

Grinblatt et al. (2011b) analyze the influences of IQ on investors'trading behavior and on their trading performance using a large Finnish sample utilising a database of comprehensive IQ scores record?ed from mandatory military service and stock trading data. They find that high IQ investors are less subject to a disposition effect. Grinblatt et al. (2011b) find that their sample of high IQ investors tend to improve liquidity in markets, are better at stock selection, timing and trade execution whereas their sample of low IQ investors tend to hold on to underperforming stocks whilst selling winners.

Barber and Odean (2001) also suggest that investment biases such as under-diversification, high frequency of trading and taking orders by mistake are also highly related to IQ and perhaps present a plausible explanation of why individuals appear less than successful investors.

Our study adds to this body of literature by examining whether the ability to forecast future trends in stock prices and the confidence the predictor places in the forecasts is related to IQ, in particular the paper examines the impact of cognitive ability on risk perception and confidence. Risk perception is defined by Sitkin and Weingart (1995) as *"an individual's assessment of how risky a situation is terms of probabilistic estimates of the degree of situational uncertainty"* (p.1995).

Previous studies have related individuals'risk perceptions to accuracy of information (Ricciardi (2004), to academic knowledge (Lee and Smith (1999),Sung and Hanna (1996) and Zhong and Xiao (1995). and to individuals'knowledge of personal finance and economic expectations (Grable and Joo (1997); Grable and Joo (1999) and Sung and Hanna (1996). Other factors have also been linked to differences in risk perception. Grable and Joo (1997) and Harris, Jenkins, and Glaser (2006), for example, have emphasized the role of gender whereas Traenkle, Gelau, and Metker (1990) suggest age impacts on risk perception and Bontempo, Bottom, and Weber (1997) and

Weber and Hsee (1999) suggest culture affects individuals'risk perceptions. Whilst the main aim of our study concerns the relationship between cognitive ability and risk perception we consider the moderating effect of these personal characteristics.

3 Experiment Design

3.1 Experimental Design

The data were collected from a survey of forecasting stock prices conducted at Bangor University, UK. Subjects from this survey are undergraduate students from a second year quantitative methods course at Bangor Business School (subsequently referred to as subjects). 67 out of 80 undergraduates completed and returned the surveys in 15 minutes, with a response rate of 84%.

The design of the surveys follows closely to De Bondt (1993) which was carried out among 27 students at the University of Wiscosin-Madison. Similar to De Bondt (1993), subjects are shown six graphs with 48 monthly price trends of unnamed stocks. They are then asked to (1) predict the price of each stock 13 months hence; and (2), provide 90% confidence interval for their forecast[1].

The six charts are monthly trends from the FTSE 100 index between 1984 and 2011 and the selected series is rescaled to avoid potential recognition by the subjects. The six charts comprise two with an upward trend, two with a downward trend, and the two series which appear to be stationary. Two versions of the six charts were randomly distributed to the subjects. For each version, we apply two different rescaling factors to the original index series, which generates two versions of charts with different volatilities. Hence, for each subject four different versions of survey questionnaire with twelve different charts are administered. Table I presents the information of each chart in a sample questionnaire.

We collect demographic data for each subject including age, gender, and their major, the extent

[1]We run a pre-test with a few home and international students, and incorporate their comments on final versions of questionnaire. In order to avoid the experiment bias, e.g. Hawthorne Effect and Pygmalion Effect, all subjects answered the survey at the same time and in the same place. The purpose of the survey and the nature of the questions were briefly explained to the subjects at the beginning of the survey period and an example was provided before the main survey

Table I
The information of each chart in Qestionnaire 1

Chart	Ending time	Designation	Trend	Last stock price
Stock 1	1995.2	Bull	Stationary	30.1
Stock 2	2002.7	Bear	Down	42.5
Stock 3	2005.11	Bull	Up	54.2
Stock 4	2003.2	Bull	Down	36.6
Stock 5	2007.10	Bear	Up	67.2
Stock 6	2002.3	Bear	Stationary	52.7

of their participation in finance courses, their nationality, their previous investment experience and the extent of their experience working in the financial industry [2]. We proxy IQ by academic performance which is measured by the subject's average marks from the previous semester. One requirement of the study is that the subjects'forecasts lie within their reported confidence interval. In the empirical analysis, we exclude subjects whose point forecasts fall outside their reported confidence interval which reduces the number of subjects by 5. As not all subjects answered every question our final sample comprises 62 subjects and 328 observations [3].

3.2 Hypotheses

We examine three aspects of forecasting ability as indicated below where our hypotheses are stated in their null form:

H_{OA}: There is no relationship between subjects'forecasting errors and academic performance

H_{OB}: There is no relationship between the length of subjects'confidence intervals and academic performance

H_{OC}: There is no relationship between subjects'overconfidence and academic performance

[2] The working experience dummy variable is subsequently omitted from the analysis as only a few of the subjects had such experience

[3] Not all subjects answered questions relating to all six charts hence the number of observations is less than 372

4 Empirical Results

4.1 Summary Statistics

To test our hypotheses we have three dependent variables are which are

1. absolute forecasting error which is the absolute difference between the actual return and the subject's forecasted return;

2. the length of the confidence interval which is the length of the confidence interval provided by the subjects;

3. overconfidence which is a dummy variable which is defined as the realization of stock price higher than 90% of the subject's confidence interval.

Table II
Description of Variables

Dummy Variables	= 1 if true
Overconfidence	Actual stock return lies out the confidence interval
Gender	being male
East	being from Eastern Countries
Major	having a finance related major
Course	having taken at least two finance courses
Invest	having finance investment experience
Other Variables	
Absolute Forecasting Error	Absolute value of actual return minus point forecast
Confidence Interval	length of the 90% confidence interval reported by subjects
Age	age of subjects
GPA	subjects' GPA from last semester 1 (Worst) to 5 (Excellent)
Trend	difference between the ending point minus the starting point of the indexes shown on a particular chart
Volatility	volatility of the indexes shown on a particular chart

Our hypotheses mainly question the relationship between the dependent variables and academic performance which is proxied by the subject's average marks from the previous semester, and we refer to this as GPA. We also consider whether personal characteristics including age, gender, origin and previous finance education moderate the relationship between the dependent variables and academic performance. In addition, we consider whether two salient features of stock returns, namely trend and volatility also affect the relationship.

Table III reports the summary statistics. The mean value of the absolute forecasting errors is 27.016 and the standard deviation is 20.836. Furthermore, the minimum value of absolute forecasting error is as small as 0.003, although this does not necessarily indicate superior forecasting ability as the accuracy might well be due to luck. We interpret narrower confidence intervals as an indication of a subject's confidence in their forecasts. The mean value of the confidence intervals is 39.038 and the standard deviation is 30.316. The minimum (2) and maximum (268) show that the lengths of confidence intervals vary dramatically.

Table III
Summary Statistics for All Variables

Risk Perception	Mean	s.d.	Min	Max	No. of Obs.
Absolute Forecasting Error	27.016	20.836	0.003	96.36	341
Confidence Interval	39.038	30.316	2	268	341
Overconfidence	0.672	0.47	0	1	341
GPA	4.040	1.004	1	5	329
Age	20.974	1.178	19	27	340
Gender	0.381	0.486	0	1	341
East	0.918	0.275	0	1	341
Major	0.836	0.371	0	1	341
Course	0.768	0.423	0	1	341
Invest	0.164	0.371	0	1	341
Trend	-4.026	33.211	-69.858	73.02	341
Volatility	179.029	203.551	8.999	678.421	341

As mentioned above, overconfidence is defined as the realization of a stock price falling above a subject's 90% confidence interval. This is not necessarily an indication of overconfidence as it could be due to bad luck. Nevertheless, a subject's forecasts should be within their confidence interval, on average, 9 out of 10 times if they are not overconfident. We use a dummy variable for overconfidence with the variable taking a value of 1 if the forecast is above the 90% interval. We find a mean value of 0.672 for overconfidence and a standard deviation is 0.470 suggesting that just under 7 out of 10 times the realization falls above the subjects'90% confidence interval. We interpret this as evidence of overconfidence.

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 refer to this classification as GPA which has a mean of 4.040 and a standard deviation of 1.004.

Other characteristics of our sample are as follows:

a) The average age of the sample is 20.974;

b) 61.9% of the subjects are female;

c) 91.8% of the subjects are from the Far East with less than 10% from the West;

d) Most subjects'majors are Finance or related subjects (83.6% of the sample) and 76.8% of subjects take at least two finance modules;

e) Only 16.4% of the subjects have previous financial investment experience.

Table IV shows the relationship between the GPA classification and the three dependent variables: absolute forecasting error, the length of the confidence interval and overconfidence. All three variables appear to decrease when GPA increases suggesting, higher performing subjects make more accurate forecasts, are more confident about their forecasts and are less likely to be overconfident. Our initial results appear to be in line with Grinblatt et al. (2011b) who report superior investment performance for higher IQ individuals.

Table IV
Dependent Variables Breakdown by GPA

	Absolute Forecast Bias		Length of CI		Overconfidence		
GPA	mean	sd	mean	sd	mean	sd	Percentage
1	50.00	30.80	61.25	20.56	1.00	0.00	1.59%
2	38.56	21.97	53.15	40.30	0.79	0.42	6.35%
3	29.92	20.31	45.22	39.24	0.76	0.43	22.22%
4	22.71	23.57	37.93	26.96	0.57	0.50	28.57%
5	26.63	20.26	34.10	24.15	0.67	0.47	41.27%

This table presents the summary statistics conditional on the value of GPA. "GPA" is the GPA of a subject from last semester, which takes a value from 1 to 5. "Absolute Forecasting Error" is the absolute value of actual price minus point forecast. "Length of CI" refers to the length of the 90% confidence interval reported by subjects. Overconfidence is defined as the realization falls outside of the 90% confidence interval.

4.2 Regression Results

In this section we report our regression results. We use OLS regression analysis to examine the determinants of the absolute forecast error and the length of the confidence interval and Probit analysis to identify the determinants of overconfidence. We test four models by sequentially adding additional explanatory variables and test whether they improve the fit of the regression model by nest model test. In order to account for unobserved individual effects, the results of a panel regression model (random effects) are presented in the fifth column.

4.2.1 GPA as a Determinant of Absolute Forecasting Error

Table V reports the regression results where the absolute forecasting error on GPA and other control variables. The coefficient of "GPA" is negative in all the five models. It is significant at 1% sig?nificance level in the first 3 models and at 5% significance level in m4 and m5.[4] The absolute forecasting errors declines by 2 to 3 if GPA increase by 1. This result supports the findings of Grinblatt et al. (2011b) that the higher IQ of the individuals, the better trading performance they have. Intuitively, subjects with higher GPA have better ability in solving problems than others. For instance, they have better cognitive skills and faster feedback, which will help them deal with problems more correctly and quickly. Moreover, subjects with higher GPA possess stronger self-efficacy, and thus they believe that they are capable of performing in a specific task. "Course" represent subjects¡¯ participation of finance courses. It is significantly and positively related to absolute forecasting errors across different models. This reveals that subjects with financial knowledge have larger absolute forecasting errors than other subjects. This may because that finance educated subjects believe that they have better forecasting ability than other subjects as they have related finance knowledge. This belief will make them overconfident and thus they suffer bigger forecasting errors than other subjects.

The direction of coefficients of "invest" is negative and significant in m4 and m5, showing that subjects with investment experience have smaller absolute forecasting errors. This can be explained

[4]The results of OLS regression in m4 and panel regression are identical. This is due to very small within variation (R-squared within, 3%) relative to between variation (R-squared between, 75%)

Table V
Regressions of Absolute Forecast Error on GPA

	OLS Regression				Panel Regression
	m1	m2	m3	m4	m5
GPA	-3.020***	-3.075***	-3.841***	-2.160**	-2.160**
	(1.124)	(1.161)	(1.185)	(1.056)	(1.056)
age		-1.466	-1.117	-0.610	-0.610
		(0.981)	(0.997)	(0.874)	(0.874)
gender		-1.695	-1.400	0.549	0.549
		(2.379)	(2.522)	(2.220)	(2.220)
East		-1.927	-3.075	-3.323	-3.323
		(4.367)	(4.356)	(3.816)	(3.816)
major			5.766*	1.930	1.930
			(3.062)	(2.712)	(2.712)
course			4.865*	4.074*	4.074*
			(2.697)	(2.364)	(2.364)
invest			-4.862	-5.195*	-5.195*
			(3.399)	(2.978)	(2.978)
trend				0.131***	0.131***
				(0.030)	(0.030)
volatility				0.048***	0.048***
				(0.005)	(0.005)
Constant	39.461***	72.828***	61.773***	39.548**	39.548**
	(4.679)	(20.843)	(21.148)	(18.679)	(18.679)
Adj. R-squared	0.019	0.017	0.036	0.261	0.281
N	329	328	328	328	328

"Absolute forecasting error" indicates the accuracy of the first order belief. "GPA" is the GPA of a subject from last semester. "East"=1, if a subject's nationality belongs to eastern country. "Major" depicts wether subject's major is Finance or related majors with Finance."Course" shows wether subject has at least two finance courses."Invest" means wether subject has previous investment experience. "Volatility" is the volatility of the original indexes of a particular chart. "Trend" is the difference between the ending point minus the starting point of the original indexes of a particular chart.Significance levels : *: 10% **: 5% ***: 1%

as these subjects have more practical experience on forecasting stock returns, and hence they have better their forecasting ability.

Subjects may respond differently to different pattern of stock return movement. It is therefore important to include the characteristics of stock return movement in the model. When these variables are added, the absolute value of the GPA coefficient become less than that in m1, m2 and m3, as much of variations in forecasting bias can be contributed to "trend" and "volatility". Both of these positively affect absolute forecasting errors and are significant at 1% significance level. The absolute forecasting errors increase by 0.131, as the trend is increased by 1, and decreases by 0.048 when the volatility decline by 1. Intuitively, subjects are more prone to be overconfident as they confront with a positive event. Higher volatility makes stock return forecasting to be more difficult, and thus it is not surprising to see bigger forecasting errors with upward with more volatile stock prices.

4.2.2 GPA as a Determinant of Confidence Interval

Table VI shows regression results of confidence interval length on GPA and other control variables. Except "age", all other explanatory variables seem to be determinants of the lengths of confidence intervals in OLS regressions ("GPA", "gender", "invest" and "trend" are significant and negative influence factors, and "East", "major", "course" and "volatility" are significant and posi-tive influence factors of confidence intervals). Only some of them remain significant in the panel regression.

In all model specifications except for model 5, "GPA" is negatively and significantly related to the lengths of confidence intervals at 1% significance level. That is, subjects with better academic performance perceive narrower confidence intervals, indicating they perceive less risk than their worse-performing peers. Taking individual effect into account, the significance is reduced to 10%, though the size of coefficient is about the same as in the other model specifications. "Gender" also has negative and significant influence on confidence intervals. It means that females are more risk aversion than males, which is consistent with the findings of gender difference in risk perception in a vast literature on gender difference in risk perception.[5] Eastern subjects¡¯ confidence intervals are significantly wider than western subjects¡¯ confidence intervals, consistent with the literature on culture difference in risk perception. The gender and culture difference in risk perception is often coined as "white male effect", a phenomena that white males tend to perceive less risk than females and people of color. Both "major" and "course" have significant and positive relationship with the length of confidence intervals in OLS regressions. Controlling for panel random effect,

[5] In a companion, we study in detail the gender difference in risk perception (Lynn Hodgkinson and Zhu (2011)).

Table VI
Regressions of Confidence Interval Length on GPA

	OLS Regression				Panel Regression
	m1	m2	m3	m4	m5
GPA	-6.002***	-5.555***	-7.166***	-4.858***	-4.889*
	(1.764)	(1.782)	(1.843)	(1.735)	(2.770)
age		-1.817	-1.120	-0.612	-0.772
		(1.318)	(1.369)	(1.335)	(1.583)
gender		-14.200***	-13.712***	-11.081***	-9.595*
		(3.219)	(3.107)	(3.010)	(5.329)
East		17.000***	14.302***	14.720***	15.056*
		(3.763)	(4.138)	(5.304)	(8.797)
major			13.977***	9.763***	8.832
			(4.264)	(3.578)	(6.682)
course			8.302**	7.382**	6.064
			(3.427)	(3.314)	(5.953)
invest			-8.928**	-9.417**	-8.346
			(4.107)	(4.052)	(8.257)
trend				-0.098**	-0.101***
				(0.046)	(0.021)
volatility				0.054***	0.050***
				(0.008)	(0.011)
Constant	63.421***	89.897***	67.495***	40.266*	45.627
	(7.861)	(24.093)	(25.633)	(24.342)	(29.601)
Adj. R-squared	0.036	0.116	0.164	0.311	0.329
N	329	328	328	328	328

"Confidence interval" indicates the length between high point and low point of interval forecast. "GPA" is the GPA of a subject from last semester. "East"=1, if a subject's nationality belongs to eastern country. "Major" depicts wether subject's major is Finance or related majors with Finance."Course" shows wether subject has at least two finance courses."Invest" means wether subject has previous investment experience. "Volatility" is the volatility of the original indexes of a particular chart. "Trend" is the difference between the ending point minus the starting point of the original indexes of a particular chart.Significance levels : *: 10% **: 5% ***: 1%

they are not significant at 10% significance level, albeit the sign is still positive, which shows that subjects with finance education background have wider confidence intervals than other subjects. Subjects with investment experience tend to have narrower confidence intervals than those without it, although it is significant in OLS regression, but not in panel regression. As the trend is upward (downward), subjects¡¯ confidence intervals will become narrower (wider). Intuitively, upward trend is a positive sign for subjects, and individuals will perceive future stock price less risky when they are in a comparatively positive situation. "Volatility" is deemed as a sign of risk in the research by De Bondt (1993): the larger the volatility is, the more risky the stock is. Therefore, subjects tend to be more (less) cautious in forecasting stock returns, as the volatility of the stock return series increases (decreases).

4.2.3 GPA and Overconfidence

Do the subjects with wider confidence interval are less likely to be overconfident? Though this sounds intuitively appealing, we show below that it might depend on the characteristics of subjects.

Table VII reports both results of Probit regression (model 1 to 4) and panel Probit regression (model 5). It shows negative and significant coefficients of "GPA" in all model specifications. It indicates that higher academic performance is strongly associated with less propensity to be overconfident. This result is striking, since we find better academic performance is associated with narrower confidence interval, one would expect them to be more likely overconfident. Yet we find the opposite holds. We interpret this result as subjects who perform better in their studies have superior ability in risk perception. They are more confident about their forecasts, and they are making less errors in their forecast of risk.

In summary, we find subjects with better academic performance forecast more accurately the future stock price and associated risk. The heterogeneity in forecasting performance provide possible explanation of stock market participation puzzle: larger forecasting errors in the stock price and its risk incur both psychological pain and monetary loss if one invests in risky assets. Such people will tend to invest less or stay out of stock markets. Our findings of the association between IQ (proxied by academic performance) and forecasting performance provide one possible channel to explain the under-participation of households in stock markets. Our results corroborate the findings in Grinblatt et al. (2011a)

Table VII
Regressions of Overconfidence on GPA

	OLS Regression				Panel Regression
	m1	m2	m3	m4	m5
GPA	-0.130*	-0.168**	-0.169**	-0.202**	-0.276**
	(0.074)	(0.077)	(0.080)	(0.086)	(0.123)
Age		-0.012	-0.026	-0.033	-0.046
		(0.062)	(0.064)	(0.065)	(0.087)
gender		-0.046	-0.091	-0.126	-0.181
		(0.153)	(0.165)	(0.172)	(0.230)
East		-0.805**	-0.786**	-0.825**	-0.923**
		(0.324)	(0.330)	(0.333)	(0.423)
Major			-0.172	-0.202	-0.148
			(0.209)	(0.221)	(0.283)
Course			0.164	0.186	0.260
			(0.174)	(0.182)	(0.245)
Invest			0.137	0.167	0.180
			(0.229)	(0.238)	(0.310)
Trend				0.017***	0.017***
				(0.003)	(0.003)
Volatility				0.001	-0.000
				(0.000)	(0.001)
Constant	0.974***	2.144	2.450*	2.807**	3.582*
	(0.312)	(1.328)	(1.372)	(1.429)	(1.945)
Log likelihood	-206.683	-202.614	-201.507	-181.827	-180.255
N	329	328	328	328	328

"Overconfidence" indicates whether the subject's point forecast lays out her or his confidence interval. "GPA" is the GPA of a subject from last semester. "East"=1, if a subject's nationality belongs to eastern country. "Major" depicts wether subject's major is Finance or related majors with Finance."Course" shows wether subject has at least two finance courses."Invest" indicates wether subject has previous investment experience. "Volatility" is the volatility of the original indexes of a particular chart. "Trend" is the difference between the ending point minus the starting point of the original indexes of a particular chart.Significance levels : *: 10% **: 5% ***: 1%

5 Conclusion

We examine the effect of IQ (proxied by GPA) in an experimental study of forecasting stock prices over 13 months. We find higher academic performance is significantly associated with more accurate forecasts of stock price and its associated risk. The superior performance of financial forecasting among better academic performers provides a possible explanation for the market participation puzzle. Our results are robust to inclusion of controls for personal characteristics, finance education background, investment experience, stock return features, and unobserved individual effect.

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