Interaction and Decomposition of Gender Difference in Financial Risk Perception

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Abstract

Previous literature suggests males tend to perceive lower risks than females. We revisit this gender difference by studying the interaction of gender with other observable characteristics in a survey of forecasting future stock prices. We find that some observable characteristics such as culture, age, and uncertainty of stock prices have a different effect on the risk perception between females and males. This additional source ("coefficient effects") of gender difference is distinct from the differences in personal characteristics ("characteristics effects"). We disentangle these two sources of gender differences in risk perception by applying the Blinder–Oaxaca decomposition technique. We find that characteristics effects and coefficient effects are both important, and the latter can be even more important than the former.

Keywords: Gender difference; Risk perception; Interaction; Decomposition analysis.

JEL Classification: C90, G00, G11

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1 Introduction

Numerous studies show that there is a "gender effect" in risk perception, i.e., males tend to perceive lower risk than females.[1] Conditional on gender, other characteristics may have substantial differences in explaining risk perception across males and females. For example, for the same gender, risk taking or risk perception differs when age (Brinig 1995), and culture (Thomas and Mueller 2000, Bonin, Constant, Tatsiramos, and Zimmermann 2009) differ. These findings highlight one source of gender differences in risk perception: males and females may have different characteristics ("characteristics effects"). Another source is that even having the same characteristics, the effects of those characteristics on risk perception can differ across genders ("coefficient effects").

The aim of this paper is to disentangle the characteristics effects and coefficient effects in explaining the difference in risk perception across genders. In a survey of forecasting future stock prices, we measure the risk perception by the length of the 90% prediction interval reported by subjects for their point forecasts of future stock prices. In line with Byrnes et al. (1999), we find females tend to have wider prediction intervals than males. We then estimate the interaction effects of gender with a range of personal characteristics and stock price movement features. Based on these estimates, we employ the Blinder–Oaxaca decomposition technique, developed by Blinder (1973), Oaxaca (1973), and Oaxaca and Ransom (1994), to investigate the different sources behind the gender difference of risk perception. Specifically, we decompose the differences in the prediction interval between males and females into the differences in observable characteristics at given coefficients ("characteristic effect") and differences in the coefficients of these characteristics at given gender ("coefficient effect").

We find observable characteristics, such as culture, age, and uncertainty of stock prices have different impact on the risk perception depending on subjects' gender. Our results further show that not only the characteristics effects but also the coefficient effects can substantially explain gender differences in risk perception. In particular, we find that the coefficient effects are often more important than the characteristics effects.

[1] See, for example, Byrnes, Miller, and Schafer (1999), Weber, Blais, and Betz (2002), Kahan, Braman, Gastil, Slovic, and Mertz (2007), Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2011), and Halko, Kaustia, and Alanko (2011).

Our paper contributes to a large literature on gender heterogeneity in risk perception. Our decomposition results show that both sources explain risk perception. To the best of our knowledge, this is the first paper to decompose the gender effect of risk perception in forecasting future stock prices. Our results have implications for the previous findings that males perceive less risk in forecasting future stock prices, hold more risky assets (Jianakoplos and Bernasek 1998) and trade more frequently (Barber and Odean 2001).

2 Survey Design

To test the relationship between gender and risk perception in forecasting future stock prices, we conduct a in-class survey which ensures simultaneous and equal information available to subjects, so that their difference in risk perception is not due to difference in available information.

2.1 Subjects

The subjects are undergraduate students from a UK university. The allotted class time for completion of the survey was 15 minutes. Out of the 80 students who participated in this survey, 67 students completed and returned the questionnaires, yielding a response rate of 84%.

2.2 Stimuli

Similar to De Bondt (1993), all subjects are shown six charts with 48 monthly prices of some unnamed stocks. They are then asked to predict the price of each stock in 13 months, as well as their interval forecast with 90% confidence.

Different from De Bondt (1993), the six charts are selected from the FTSE 100 index between 1984 and 2011. Two of the six price series are upwardly trended, two series are downward trended, and the rest do not portray any specific trend. Chart (a) in Figure 1 shows an example of an upward trend, Chart (b) is an example of a downward trend, and Chart (c) provides an example of no specific trend.

[Insert Figure 1 about here]

To mitigate against the practice effect,[2] we assign two different sets of six charts randomly among the subjects, with the ordering of the six charts reversed between the two sets. Within each set of six charts, to minimize the possibility of recognition, we employ two factors to rescale the original series, generating two versions of each set with different degrees of volatility. We rescale the stock prices by multiplying the original stock prices by 1/100 in version 1 and 2, and by 3/100 in version 3 and 4. In addition, We then employ t, $t+1$, $t+2$, $\cdots$, $t+48$ to replace the actual dates.

2.3 Procedures

In the survey, each subject receives one questionnaire with six charts. For each chart, subjects are required to provide 13 month forecasts for the following questions:

estimated price ......

estimated price interval (with 90% confidence level)

high price ......

low price ......

We also ask subjects to provide the following personal information: age, gender, nationality, major, GPA in the previous semester, and state whether they have participated at least two finance courses before, and whether they have any previous investment experience.

As discussed above, the survey approach ensures all subjects to have access to the same information, hence, the differences in risk perception cannot be attributed to differences in access to information.

[2] Practice effect means that the subject's forecasting performance may tend to improve over repeated attempts at a forecasting exercise.

3 Empirical Methods

To examine the effect of the interaction of gender with other characteristics on risk perception, we generate interaction variables by multiplying the gender dummy (= 1 for female subjects and 0 otherwise) by each of the other characteristics. We then regress the prediction interval on these interaction terms. If these observable characteristics have a differential impact on risk perception, the coefficient for the interaction term will be significantly different from zero.

We then perform a decomposition analysis by following Blinder (1973), Oaxaca (1973), and Oaxaca and Ransom (1994). Denoting the length of the prediction interval as PIL, we decompose the difference in PIL between male and female subjects as the following:

$$
\begin{aligned}
\widehat{PIL}_m - \widehat{PIL}_f &= \underbrace{(\widehat{PIL}_f - \widehat{PIL}_f^m)}_{\text{coefficients effect}} + \underbrace{(\widehat{PIL}_f^m - \widehat{PIL}_m)}_{\text{characteristics effect}} \qquad (1)\\
&= \underbrace{(\widehat{PIL}_f - \widehat{PIL}_m^f)}_{\text{characteristics effect}} + \underbrace{(\widehat{PIL}_m^f - \widehat{PIL}_m)}_{\text{coefficients effect}}, \qquad (2)
\end{aligned}
$$

where $\widehat{PIL}_i$, $i = m, f$, are estimated using linear regressions. The decompositions (1) and (2) differ with respect to the chosen counterfactual $\widehat{PIL}_i^{\tilde{i}}$. In equation (1), $\widehat{PIL}_f^m$ uses predictions for female individuals based on the coefficients of males, assuming that the coefficients stayed the same as those of females. In equation (2), $\widehat{PIL}_m^f$ denotes the prediction for the sample of males (based on the characteristics of females). We compute both versions (1) and (2) to investigate the sensitivity of the decomposition result.[3] The characteristics effect involves the part of the overall difference between females and males which can be attributed to differences in regressors in the sample at given coefficients. The coefficients effect captures the part which is due to changes in the coefficients at given gender.

To test the significance of the characteristics effect and the coefficients effect, we use a parametric

[3] It is well-known that the decompositions resulting from different counterfactuals do not necessarily yield identical results. Different approaches to the issue of non-uniqueness have been proposed in the literature. Yet, each of the approaches relies on ad-hoc assumptions of some type, therefore we choose to report the two most prominent cases.

bootstrap to estimate standard errors with 1000 times resampling.

4 Empirical Results

4.1 Summary Statistics

Our measure of perceived risk is the length of the 90% prediction interval around the subjects' own point forecast for the 13 month's stock price. It is defined as the following:

$$\textit{Prediction interval} = \quad \textit{Upper bound} - \textit{Lower bound} \tag{3}$$

In our data, the mean value of the prediction interval is 39.2. About 40% of the subjects are males. When we apply the mean comparison test of risk perception by gender, we find that males have a much narrower prediction interval (29.96) than females (45.26). Their difference is -15.30 which is statistically significant at the 1% level.

Table I reports the summary statistics of other personal characteristics conditional on gender. There is a strong difference in investment experience between males and females. 29% males have previous investment experience, whereas only 6% females have it. This corroborates the argument of Lewellen, Lease, and Schlarbaum (1977) who report that male investors "spend more time and money on security analysis, rely less on their brokers, make more transactions, believe that returns are more highly predictable, and anticipate higher possible returns than do females". As such, male investors may be more prone to overconfidence bias.

[Insert Table I about here]

4.2 Baseline Regressions

Table II reports the regression results of the relationship between gender and the prediction interval. The first three regressions are OLS with robust standard errors, but with different model specifications. To control for the unobserved individual effects, the last model is a random effect panel regression .

[Insert Table II about here]

In all model specifications, the coefficients of gender are significantly positive. In line with Byrnes et al. (1999), it suggests that males have narrower prediction intervals than females. Moreover, the coefficients indicate that the length of females' prediction intervals is wider than that of males in a range of 9.60 to 14.67. This shows that the gender effect is economically significant since the average length of the prediction interval across all subjects is 39.2. We also find the coefficients for the East dummy (= 1 if a subject is from a Eastern country and 0 otherwise) is positive, indicating a significant culture effect. Bringing these two findings together, we find the well-documented "white male effect" in the domain of financial forecasting.

We also find that the coefficient for mark is significantly negative across different model specifications. This suggests subjects with previous superior academic performance tend to have narrower prediction intervals. Features of the stock market also affect the prediction interval. The significant and negative coefficients for trend support the argument of De Bondt (1993) that a positive trend in stock prices make subjects more optimistic about the precision of their forecasts, hence they tend to have a narrower prediction interval. On the other hand, high volatility reflects higher uncertainty in the past stock price, resulting in wider prediction intervals.

4.3 Interactions of Gender with Other Regressors

Before we apply the decomposition analysis, we test the interaction effects of gender with other personal characteristics and stock price movement features.

Table III shows the economic and statistical significance of gender effects on the coefficients of some personal and stock price characteristics. For example, the coefficients of the interaction term between the east dummy and the female dummy are positive and statistically significant at the 1% level in both the OLS regression and the panel regression. This suggests that the effect of being from eastern countries on confidence intervals depends on whether subjects are males or females — female subjects amplify that effect. In a related study, Croson and Gneezy (2009) argue that gender differences in risk attitudes are caused by evolution or by socialization.

[Insert Table III about here]

We also find the effects of age and mark depend on gender, although the latter is weaker as the coefficient on the interaction term between mark and female dummy is significant in the OLS regression but insignificant in the panel regression. The volatility of stock price has different impacts on the prediction intervals for males and females. High volatility makes subjects more cautious, therefore they form a wider confidence interval. Being a female makes this effect stronger as the coefficient on the interaction term between volatility and the female dummy is positive and statistically significant at the 0.1 level of lower. This indicates that females perceive much more risk in response to increased uncertainty than males.

4.4 Decomposition Analysis

In this section, we decompose the gender effects into coefficient and characteristics effects as described in Section 3. The decomposition analyses are based on panel random effect regressions in Table III. Although we do not show the results of the decomposition analysis based on OLS regressions in Table III, they are qualitatively similar to the findings below.[4]

Table IV reports the decomposition results of gender difference. In both versions of decomposition, both characteristics effect and coefficient effect contribute significantly to the difference of risk

[4] These results are available from the authors on request.

perception across genders. The directions of these effects are the same (negative) in both decompositions. In decomposition one, characteristic effects are slightly stronger than the coefficient effects with 58% of the gender difference coming from the characteristics effect, and the remaining 42% comes from coefficient effect. In decomposition two, the coefficient effects appear stronger, and explain 71% of the gender difference, while characteristic effects explain only 29%. These results suggest that not only the difference in personal characteristics, but also the coefficient effects help explain the gender difference, and that the coefficient effects can be stronger than the characteristic effects. While there is a discrepancy in the terms of the relative importance of coefficient effects and characteristics effect, this is not surprising since it is well known that the decompositions resulting from different counterfactuals do not necessarily yield identical results.

[Insert Table IV about here]

5 Conclusion

In this paper, we revisit the gender difference in risk perception by conducting a survey of subjects forecasting future stock prices. We measure risk perception by the length of the 90% prediction interval around their point forecast reported by subjects. Consistent with the existing literature, we find that risks tend to be perceived lower among males than females. We then allow for interaction terms of gender with other observable characteristics in our regressions. We find that the observable characteristics, such as culture, age and volatility of stock prices have a differential effect on risk perception between females and males. We further disentangle two sources of differences that may explain the gender effect: differences in observable characteristics ("characteristics effects") and differences in regression coefficients ("coefficient effects"). We show that both characteristics effects and coefficient effects are important for explaining the gender heterogeneity in risk perception.

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Tables and Figures

Figure 1
Examples of Stock Prices Chart

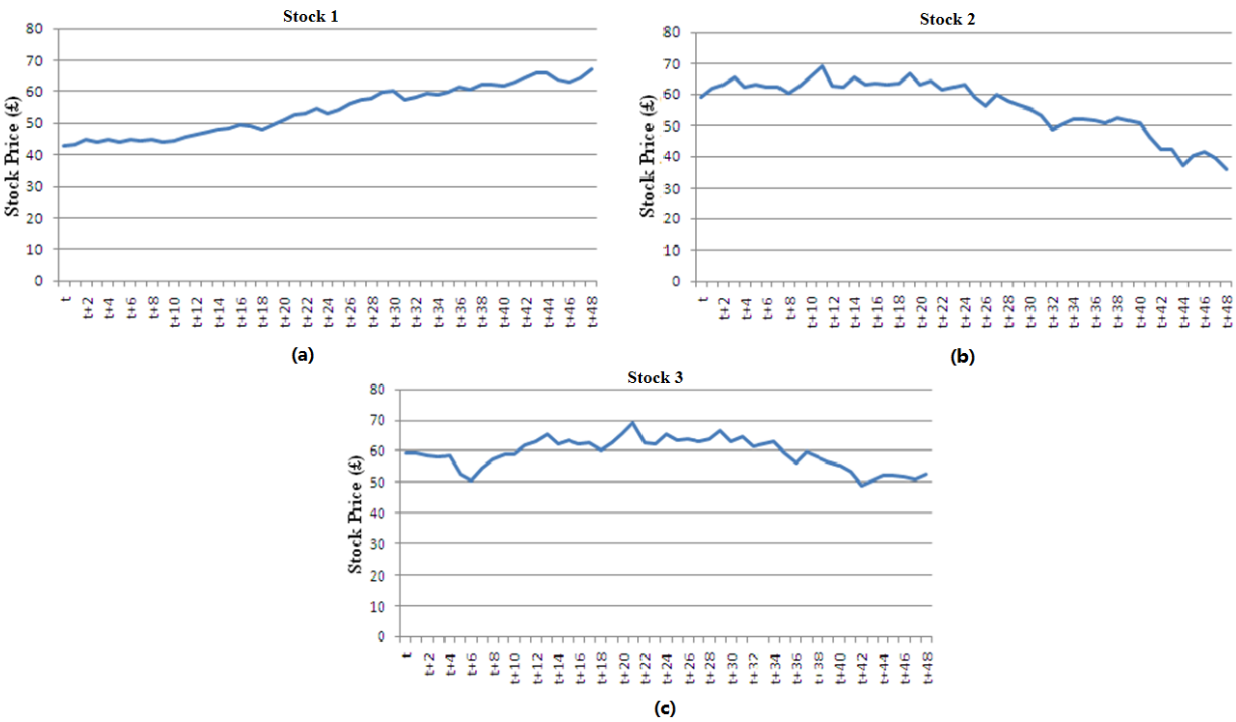

Table I
Summary Statistics: Breakdown by Gender

	Female				Male			
Variable	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
East	0.96	0.19	0	1	0.84	0.37	0	1
Age	21.1	1.39	19	27	20.83	0.77	19	22
Major	0.82	0.38	0	1	0.84	0.37	0	1
Course	0.71	0.45	0	1	0.84	0.37	0	1
Invest	0.06	0.24	0	1	0.29	0.46	0	1
Mark	4.09	1	1	5	3.98	1	2	5
Nob. Obs.	198				130			

This table presents the summary statistics of subjects' other personal characteristics broken down by gender. Gender is the dummy variable with female as one and male as zero. East is the dummy variable with nationality from eastern countries as one and western countries as zero. Age is the subjects' age. Major is a dummy variable indicating whether subjects' major are finance related (1) or not (0). Course is a dummy variable with a value of one if subjects have taken at least two finance course before and zero otherwise. Invest indicates wether subjects have previous investment experience. Mark is the GPA of a subject from last semester.

Table II
Regressions of Prediction Interval on Gender

	OLS Regression			Panel Regression
	model 1	model 2	model 3	model 4
Gender	14.67***	13.71***	11.08***	9.60*
	(3.07)	(3.11)	(3.01)	(5.33)
East		14.30***	14.72***	15.06*
		(4.14)	(5.30)	(8.80)
Age		-1.12	-0.61	-0.77
		(1.37)	(1.34)	(1.58)
Major		13.98***	9.76***	8.83
		(4.26)	(3.58)	(6.68)
Course		8.30**	7.38**	6.06
		(3.43)	(3.31)	(5.95)
Invest		-8.93**	-9.42**	-8.35
		(4.11)	(4.05)	(8.28)
Mark		-7.17***	-4.89***	-4.89*
		(1.84)	(1.74)	(2.77)
Trend			-0.10**	-0.10***
			(0.05)	(0.02)
Volatility			0.05***	0.05***
			(0.01)	(0.01)
Constant	44.63***	67.50***	40.27*	45.63
	(2.23)	(25.63)	(24.34)	(29.60)
N	341	328	328	328

This table presents the regressions of prediction interval on gender with and without control variables. Prediction interval is the difference between upper bound and lower bound reported by subjects. Gender is the dummy variable with female as one and male as zero. East is the dummy variable with nationality from eastern countries as one and western countries as zero. Age is the subjects' age. Major is a dummy variable indicating whether subjects' major are finance related (1) or not (0). Course is a dummy variable with a value of one if subjects have taken at least two finance course before and zero otherwise. Invest indicates wether subjects have previous investment experience. Mark is the GPA of a subject from last semester. Trend is the difference between the ending point minus the starting point of the original indexes of a particular chart. Volatility is the volatility of the original indexes of a particular chart. Significance levels : $*$: 10% $**$: 5% $***$: 1%.

Table III
Regressions of Prediction Interval on Interactions of Gender with Other Regressors

	OLS Regressions	Panel Regressions
Gender	261.79***	255.17**
	(61.08)	(107.14)
East	-0.69	1.36
	(5.18)	(10.54)
Age	11.25***	10.30*
	(2.69)	(5.49)
Major	11.69*	7.68
	(6.85)	(12.99)
Course	0.19	-1.87
	(6.49)	(13.33)
Invest	-5.59	-4.89
	(3.49)	(6.66)
Mark	-0.86	-0.40
	(2.57)	(5.29)
Trend	-0.09	-0.08**
	(0.08)	(0.04)
Volatility	0.02	0.03*
	(0.01)	(0.02)
East × Gender	46.08***	37.87***
	(9.63)	(13.17)
Age × Gender	-13.70***	-12.95**
	(3.09)	(5.65)
Major × Gender	-2.43	1.79
	(7.87)	(14.75)
Course × Gender	11.19	11.81
	(7.53)	(14.60)
Mark × Gender	-5.67*	-6.46
	(3.40)	(6.07)
Trend × Gender	-0.01	-0.03
	(0.09)	(0.05)
Volatility × Gender	0.06***	0.04*
	(0.02)	(0.02)
Constant	49.59	64.07*
	(30.09)	(33.02)
N	328	328

This table presents the various regressions of prediction interval: interactions of gender with other regressors. Prediction interval is the difference between upper bound and lower bound reported by subjects. Gender is the dummy variable with female as one and male as zero. East is the dummy variable with nationality from eastern countries as one and western countries as zero. Age is the subjects' age. Major is a dummy variable indicating whether subjects' major are finance related (1) or not (0). Course is a dummy variable with a value of one if subjects have taken at least two finance course before and zero otherwise. Invest indicates whether subjects have previous investment experience. Mark is the GPA of a subject from last semester. Trend is the difference between the ending point minus the starting point of the original indexes of a particular chart. Volatility is the volatility of the original indexes of a particular chart. Robust standard errors are in parenthesis. Significance levels : $*$: 10% $**$: 5% $***$: 1%

Table IV
Gender Differences in Prediction Interval: Decomposition Analyses

	Predicted Confidence Interval			Char.	Coeff.
	Male	Female	Change	Effect	Effect
Decomposition One	30	45.23	-15.23	-8.84	-6.39
(Equation 1)	(0.12)	(0.08)	(0.15)	(0.06)	(0.15)
Decomposition Two	30	45.23	-15.23	-4.45	-10.78
(Equation 2)	(0.12)	(0.08)	(0.15)	(0.11)	(0.19)

This table reports the decomposition of gender difference in risk perception based on panel regression in Panel A of Table III. Standard errors in parentheses estimated by 1000 bootstrap resamples.