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An Experimental Test of the Impact of Overconfidence and Gender on Trading Activity

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Abstract. We perform an asset market experiment in order to investigate whether overconfidence induces trading. We investigate three manifestations of overconfidence: calibration-based overconfidence, the better-than-average effect and illusion of control. Novelly, the measure employed for calibration-based overconfidence is task-specific in that it is designed to influence behavior. We find that calibration-based overconfidence *does* engender additional trade, though the better-than-average also appears to play a role. This is true both at the level of the individual and also at the level of the market. There is little evidence that gender influences trading activity.

JEL Classification: G10, G11, G12, G14

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1. Introduction

We present experimental evidence investigating the link between overconfidence and trading activity in an asset market setting. The calibration-based variant of overconfidence (CBO), namely the overestimation of knowledge precision (e.g., Lichtenstein et al (1982)), is stressed. While a relationship between CBO and trading is an implication of some behavioral models (e.g., Odean (1998)), the intuition behind the relationship is clear: the more certain you are of your view, the less credence you will accord those of others and the more likely you will be to transact at a price perceived favorable to your view.[1] Since there are other manifestations of overconfidence and it is not clear which matter more for financial decision-making, we also investigate the role of the better-than-average effect (BTA), the tendency for most people to see themselves as smarter or more skilled than average (e.g., Taylor and Brown (1988)); and illusion of control (IoC), stemming from the exaggerated belief of control over external events (e.g., Langer (1975)).

Field research has preceded experimental work. Nevertheless, a connection between overconfidence and trading activity in naturally-occurring markets can at best be circumstantial, since it is not obvious who in a group of real-world traders is overconfident and who is not. Barber and Odean (2000), in a study of over 60000 brokerage accounts during 1991–96, document the losses that are *likely* attributable to overconfidence, finding that those trading the most earned the least on a risk-adjusted basis. A survey or experimental setting, however, has the advantage of allowing for a *direct* test of the relationship between overconfidence and trading. This paper builds on previous survey and experimental work in this context (Kirchler and Maciejovsky (2002), Biais et al. (2005) and Glaser and Weber (2007)), but new ground is broken in several respects.

First, the measure of overconfidence employed here is task-specific in the sense that it is designed to influence experimental behavior. Closest to our approach, Camerer and Lovallo (1999) show that excess entry in markets is more likely to occur if payoffs on entry are linked to post-experimental relative performance on skill and trivia tasks. We on the other hand tie signal accuracy to pre-experimental (and unknown to participants) relative performance on general knowledge questions. In both cases, greater overconfidence is likely to lead to aggressive behavior in

[1] Kyle and Wang (1997), Odean (1998), Benos (1998), Wang (1998, 2001), Daniel et al. (1998, 2001), Gervais and Odean (2001), Hirshleifer and Luo (2001), Caballé and Sákovics (2003) and Lin (2003) are some of the principal models of overconfidence in a financial setting. Arguably, miscalibration measures based on stock market predictions and associated confidence intervals (e.g., Deaves et al. (2007)) come closest to the way that overconfidence is modeled in the theoretical literature.

pursuit of higher wealth. We argue that this aspect of our experimental design is a key driver of the results generated.[2]

Second, the experimental design also facilitates investigation of a possible gender effect. Evidence suggests that men are more predisposed to overconfidence (Lundeberg et al. (1994)), perhaps in part due to the fact that self-attribution bias (Miller and Ross (1975)), the tendency to ascribe success to personal effort and failure to external forces, is less pronounced for women (Beyer (1990)). Differences in overconfidence between genders seem to be greater when tasks are perceived to be in the masculine domain (e.g., Beyer and Bowden (1997)). Indeed Barber and Odean (2001) find that men trade 45% more than women, resulting in lower risk-adjusted portfolio returns.[3] In the present experiment gender-based differences in trading activity are tested for, and, to the extent that they exist, it is possible to consider whether overconfidence is the only driving force. We conjecture that other forces may be at play. For example, there is evidence that in mixed groups women are less assertive than men (Carli (2001)). And the finding that men tend to be less risk-averse (e.g., Agnew et al. (2003)) may make them more likely to transact even based on information they know to be incomplete.

Third, we explore the impact of overconfidence both at the level of the individual and at the level of the market. In the latter regard, we investigate whether market-level overconfidence and trading volume are related. Consistent with the dynamics of overconfidence as modeled by Gervais and Odean (2001), Statman et al. (2006) find that, perhaps due to self-attribution bias, market-level volume changes are correlated with market surprises. And past success in prediction leads to greater overconfidence in the future (Deaves et al. (2007)) for groups of market forecasters.

The next section of the paper describes the experimental design. Section 3 provides the key experimental results. The penultimate section discusses relevant issues. Finally, section 5 concludes.

2. Experimental design

This section describes the essentials of the experimental design, with additional details being laid out in Appendix A. Four sessions were conducted at McMaster University in Canada and four more sessions were conducted at the University of Konstanz in Germany using pools of finance and economics students. A series of requested confidence intervals for general knowledge questions with specific

[2] Kogan (2006) also employs task-specific overconfidence in his experiment, in the sense that he infers from market behavior individuals' overconfidence, rather than directly utilizing the artifice of a survey or quiz.

[3] Further, Atkinson et al. (2003) find that male fixed-income portfolio managers trade 36% more than women (a difference which is significant at 10%), but do no better (nor any worse) than their male counterparts.

numerical answers on a pre-experimental questionnaire were designed to elicit individual-specific levels of knowledge and CBO. Additionally, several questions on this same questionnaire and on a post-experimental questionnaire facilitated construction of BTA and IoC proxies. The pre- and post-experimental questionnaires are provided in Appendix C and E (see http://www2.wu-wien.ac.at/rof/supmat.html). Appendix B describes the construction of the overconfidence variables.

In Canada, the sessions differed by gender (holding the average level of CBO fixed), whereas in Germany the sessions differed by average CBO level (low or high) while maintaining a roughly balanced gender mix. After detailed instructions, reproduced in Appendix D (http://www2.wu-wien.ac.at/rof/supmat.html) were read by participants and time was taken to answer questions in a neutral fashion, 12 unrelated single-period markets were conducted, each lasting five minutes. In each market traders were endowed with a given amount of a numeraire currency and four shares of a stock. The stock paid a dividend at market-end and afterwards had no value. Thus, the risk-neutral value was the expected end-of-period dividend.

A computerized double auction market environment allowed students to trade in real time, with participants able to post bids and asks, or act as price-takers in accepting the best bids or asks posted by others. Before trading in a given market began, each trader was provided with a private noisy signal (it appeared on their screens) on the dividend to be paid out at the end of the market. Further, they were informed that the average signal was equal to the true value of the dividend, and, importantly, that those who had exhibited higher levels of general knowledge (based on conference interval midpoints from the pre-experimental questionnaire) would have more informative signals (on average over the entire session). Subjects were compensated based on their performance in one (of the 12 conducted) randomly selected market. One additional opportunity for reward was made available. In each market, after signals were revealed to traders but before trading began, the participants were asked to predict dividends. The individual performing best in this regard received an additional cash supplement. After the completion of all markets, a post-experimental questionnaire was filled out by the subjects, after which subjects were paid their (domestic) cash.

3. Experimental results

We begin by providing sample statistics on the three variants of overconfidence and individual-specific trading activity (number of completed transactions), both for the full sample of participants and for pertinent subsamples. As Appendix B describes, CBO/BTA/IoC is constructed such that 0.10/15.50/0.00 signifies proper calibration, lower values underconfidence and higher values overconfidence. Table I documents that the subject group as a whole was highly overconfident using CBO,

Table I Overconfidence and trading activity sample statistics

This table displays the mean, SD, max and min for CBO, BTA, IoC and Trades, both for the full sample and (in the case of means) for pertinent subsamples. P-values are calculated vs. the maintained hypothesis of no overconfidence for each metric. We also calculate correlations between CBO, BTA, IoC and Trades (with p-values), and p-values of differences between group means for pertinent subsamples.

A. Basic pooled sample statistics

Obs	Statistic	CBO	BTA	IoC	Trades
64	Mean (p-value)	0.781 (0.000)	15.744 (0.367)	0.469 (0.013)	44.594
	SD	0.143	5.722	1.642	26.089
	Max	1.000	31.000	4.000	130.000
	Min	0.450	0.000	−4.000	7.000

B. Correlation matrix

	CBO	BTA	IoC	Trades
CBO	1.00	.119 (0.348)	.091 (0.477)	.278 (0.023)
BTA		1.00	.212 (0.092)	.218 (0.084)
IOC			1.00	−.093 (0.463)
Trades				1.00

C. Group means

Obs	Group	CBO	BTA	IoC	Trades
34	Male	0.766	16.664	0.353	45.088
30	Female	0.798	14.700	0.600	44.033
32	Canadian	0.842	15.863	0.500	55.438
32	German	0.720	15.625	0.438	33.750
16	Canadian male	0.847	17.038	0.313	51.875
16	Canadian female	0.837	14.688	0.688	59.000
18	German male	0.694	16.333	0.389	39.056
14	German female	0.754	14.714	0.500	26.929

D. P-values of group mean differences

		CBO	BTA	IoC	Trades
	Male vs female	0.356	0.168	0.549	0.875
For:	Can. vs Ger.	0.000	0.870	0.880	0.001
Can.	Male vs female	0.641	0.213	0.455	0.522
Ger.	Male vs female	0.328	0.458	0.871	0.009
Male	Can. vs Ger.	0.003	0.737	0.900	0.142
Female	Can. vs Ger.	0.070	0.989	0.751	0.001

less significantly so using IoC, and neither overconfident nor underconfident using BTA. While all correlations between the overconfidence measures are positive, they are quite low, ranging from 0.091 to 0.212, and only one is marginally significant (at 10%). Thus, as will be discussed later, it seems that these measures might be capturing different aspects of overconfidence. On average subjects transacted 44.6 times per session. There were no significant differences in any of the three overconfidence measures between genders; only in Germany was there a trading activity difference by gender, with men transacting more. With respect to country differences, Canadians had both higher levels of CBO and higher trading activity (primarily from female differences) than Germans. Thus, at the broad-brush level, this accords with our expectation. Further evidence comes from pairwise correlations between overconfidence measures and trades. As predicted by overconfidence models, trading activity was (at least at 10%) positively correlated with CBO and BTA; there was however no significant correlation between trading and IoC.

The first three equations in Table 2 provide evidence on the explanatory power of the three overconfidence measures for trading activity. The regressions reported are at the level of the individual (of which there are $8 \times 8 = 64$).[4] Looking at equation 1, when individual trading activity is regressed on all three overconfidence measures, both CBO and BTA have independent explanatory power, while the coefficient on IoC is insignificant. When with equation 2 the latter is dropped from the regression we continue to see that CBO strongly matters, while the better-than-average effect matters more weakly (p-value = 0.062). Equation 3 is a simple regression of trading activity on CBO.

Equations 4–7 of Table II allow for an exploration of additional potential determinants of trading activity beyond overconfidence measures. Initially we leave country of origin and gender out of the mix. Additional regressors that are easily obtained from our pre-experimental questionnaire are age, experience investing in mutual funds, trading experience, financial education (the sum of current and past economics and finance courses) and knowledge (from the calibration test questions). Equation 4 indicates that older subjects (p-value = 0.016) who are more pertinently educated (p-value = 0.003) trade less. On the other hand those who have traded on their own seem to feel more comfortable "pulling the trigger" and hence trade more (p-value = 0.023).[5] Knowledge and experience investing in mutual funds are inconsequential. The inclusion of all these demographic variables degrades the impact of BTA rendering it insignificant (p-value = 0.164). With equation 5 we drop all insignificant variables. Equation 6 investigates whether the

[4] Later (in Table 3) the regressions will be at the level of the market (of which there are $8 \times 12 = 96$)).

[5] This could be related to the finding of Graham et al. (2006) that investors who feel more competent trade more often.

Table II Regressions of trading activity on overconfidence metrics and demographic variables

This table displays the coefficients and p-values from regressions when individual-specific trading activity is regressed on calibration-based overconfidence (CBO), better-than-average effect-based overconfidence (BTA), illusion-of-control (IoC), age (AGE), financial education (EDUC), mutual fund exposure (MUT), trading experience (EXP), calibration session knowledge (KNOW), country (COUNTRY) and gender (GENDER). Note that high values of CBO, BTA and IoC indicate high levels of overconfidence. Further note that COUNTRY = 1 for Canada and GENDER = 1 for males. Results reported use heteroscedasticity-consistent standard errors. Adjusted R^2 is in parentheses below R^2.

Ind. Var.	Eqn 1	Eqn 2	Eqn 3	Eqn 4	Eqn 5	Eqn 6	Eqn 7
Constant	−8.854	−6.085	4.119	43.908	51.748	31.709	38.815
	(0.509)	(0.671)	(0.755)	(0.026)	(0.004)	(0.058)	(0.040)
CBO	49.673	47.650	51.808	40.499	45.489	29.964	28.854
	(0.008)	(0.014)	(0.007)	(0.023)	(0.003)	(0.041)	(0.063)
BTA	1.008	0.854		0.700			
	(0.027)	(0.062)		(0.164)			
IOC	−2.611						
	(0.152)						
AGE				−1.818	−1.923	−0.872	−0.997
				(0.016)	(0.008)	(0.205)	(.1644)
EDUC				−0.794	−0.717	−0.454	−0.525
				(0.003)	(0.004)	(0.048)	(0.040)
MUT				−1.241			
				(0.824)			
EXP				16.454	17.991	17.060	20.818
				(0.023)	(0.010)	(0.014)	(0.003)
KNOW				0.003			
				(0.971)			
COUNTRY						13.756	12.952
						(0.028)	(0.046)
GENDER							−7.004
							(0.244)
R^2	13.8%	11.2%	7.7%	27.5%	25.3%	28.6%	30.0%
	(9.5%)	(8.3%)	(6.3%)	(18.5%)	(20.2%)	(22.5%)	(22.6%)

inclusion of a country indicator variable (COUNTRY = 1 for Canada) captures some of the impact of the other explanatory variables. Since more trade occurred in Canada, it is not surprising to see that COUNTRY has a significantly positive coefficient (p-value = 0.028). The significance level of all other variables declines, with age moving outside the 10% range. Notably though, after consideration of all reasonable explanatory variables, CBO remains significant at better than 5% (p-value = 0.041). To consider whether, controlling for CBO, gender impacts trade, refer to equation 7, which is identical to equation 6 except that a gender indicator variable is included (GENDER = 1 for male). The latter is safely insignificant

Table III Market-level volume regressions

This upper panel of the table displays the coefficients and p-values (in parentheses) when generalized least squares regressions are done with heteroscedastic errors across trading sessions and autocorrelated errors across markets. The first two rows show regression results for the pooled sample where the market trading volume in session i at market t (denoted as VOLUME(i,t)) is regressed on the average calibration-based overconfidence level of the eight traders in each session (denoted as MEANOC(i)) and (potentially) a country dummy (denoted as COUNTRY(i) where COUNTRY(i) = 1 for Canada and zero otherwise). The third row reports the regression results for German data where market trading volume (VOLUME(i,t)) is regressed on an overconfidence level indicator variable (denoted as $H(i)$, where $(H(i)) = 1$ for a low level of overconfidence and zero otherwise). The fourth row displays the regression results for Canadian data where market trading volume (VOLUME(i,t)) is regressed on a gender dummy variable (denoted as $G(i)$, where $G(i) = 1$ for an all-male session and zero otherwise). Analogous to ordinary least squares, for generalized least squares the Buse (1973) R^2 can be interpreted as a measure of the proportion of the generalized sums of squares of the dependent variable which is attributable to the influence of the explanatory variables. The lower panel repeats the above, but now also includes the realized risk premium (RP(i,t) for each market.

Specifically, for trading session i in market t:

$$\text{VOLUME}(i,t) = C(1) + C(2)\text{COUNTRY}(i) + C(3)\text{MEANOC}(i) + C(4)H(i) + C(5)G(i) + C(6)\text{RP}(i,t) + e(i,t)$$

$$\text{where } e(i,t) = \rho(i)e(i,t-1) + v(i,t) \text{ with } E[v(i,t)] = 0;$$
$$\text{and } E[v(i,t)v(j,s)] = \text{variance}\,(i) \text{ for } i = j, t = s; \text{ otherwise } E[v(i,t)v(j,s)] = 0.$$

A. Without realized risk premium

Group	Obs	$C(1)$	$C(2)$	$C(3)$	$C(4)$	$C(5)$	Buse R^2
All sessions	96	5.297		8.486			2.24%
		(0.201)		(0.145)			
All sessions (with COUNTRY)	96	3.762	7.559	9.882			14.96%
		(0.266)	(0.003)	(0.020)			
German sessions	48	12.445			−3.107		10.83%
		(0.000)			(0.022)		
Canadian Sessions	48	15.249				5.329	1.94%
		(0.001)				(0.346)	

B. With realized risk premium

Group	Obs	$C(1)$	$C(2)$	$C(3)$	$C(4)$	$C(5)$	$C(6)$	Buse R^2
All sessions	96	7.663		5.248			1.763	4.49%
		(0.047)		(0.302)			(0.067)	
All sessions (with COUNTRY)	96	5.822	5.627	7.461			0.990	10.10%
		(0.100)	(0.035)	(0.087)			(0.297)	
German sessions	48	12.421			−3.201		0.517	11.74%
		(0.000)			(0.020)		(0.780)	
Canadian Sessions	48	14.956				5.034	1.343	5.17%
		(0.000)				(0.295)	(0.233)	

(p-value = 0.244).[6] Thus, there is no evidence that, after controlling for overconfidence, women trade with different frequency than men.

In the upper panel of Table III market-level regressions are reported.[7] In the first row market volume is regressed on session-average CBO. Note that all values of the latter are clustered at three levels since Canadian sessions all have roughly the same average level of overconfidence (0.84–0.85), while German sessions, designed to be either high or low overconfidence sessions, have two levels (0.87–0.88 vs. 0.56–0.57). We report regressions with and without a country indicator. There is suggestive (though inconclusive) evidence that, when we focus on the market, just as in the case of the individual, high overconfidence encourages trading activity. When a country indicator is included, the coefficient on mean overconfidence is positive and significant at 5%. It is however insignificant without the country indicator.

It is possible to argue that the correlation between volume and mean overconfidence is to a certain extent driven by the stark differences between the German and Canadian groups. For this reason the German-sessions regression is more revealing. Recall that only in Germany do groups differ in overconfidence. For Germany, the coefficient on mean overconfidence level (where an indicator variable has been used) is positive and significant at 5%: higher levels of overconfidence lead to higher levels of trading volume *at the level of the market.* In Canada markets differ by gender, not overconfidence. In the final regression of the upper panel we document that gender does not explain volume differences.

4. Discussion

Several issues, primarily suggested by the experimental results, merit discussion. To preview, these are: 1/ the degree to which subjects are overconfident varies with the measure employed, with pairwise correlations being only weakly positive; 2/ CBO is a more powerful predictor than its competitors in explaining trading activity; 3/ men are *not* more overconfident than women; 4/ men and women trade about the same amount in Canada, while women trade less in Germany; 5/ trades are often at prices at some distance from intrinsic value; 6/ does overconfidence lead to not

[6] In another (unreported) estimation we investigate whether gender and overconfidence interact in some fashion. No such effect is found.

[7] The regression methodology employed controlled for heteroscedasticity across sessions and first-order serial correlation across markets within a session. This was necessary because participants in each trading session are different and markets in each session take place sequentially. As an indicator of heteroscedasticity across sessions, for the all-sessions regression (with country indicator) the error variances (in order, starting with the four Canadian trading sessions) are 345.75, 113.01, 30.97, 39.92, 21.98, 34.28, 39.33 and 15.22. As for autocorrelation, for the regressions corresponding to all-sessions (without country indicator), all-sessions (with country indicator), German-sessions and Canadian-sessions, the Durbin-Watson statistics were 0.849, 0.942, 1.309 and 0.504, respectively.

only trade but also poor portfolio performance? and 7/ does risk-aversion, as well as overconfidence, predict trade?

1. *The degree to which subjects are overconfident varies with the measure employed, with pairwise correlations being only weakly positive*. This is consistent with previous work. Kirchler and Maciejovsky (2002), in investigating overconfidence in a market setting by focusing on two strains of overconfidence, miscalibration and the difference between objective accuracy and subjective certainty, conclude that individuals are not consistently overconfident. They also find that sometimes the proxies designed to measure overconfidence generate inconsistent conclusions, with individuals at times exhibiting overconfidence and at other times underconfidence. And Glaser et al. (2005) find that, while individuals tend to be consistent in their degree of overconfidence using one manifestation, their overconfidence levels across manifestations are often weakly related.

Additionally, the egregious overconfidence detected using the calibration test (CBO) is somewhat troubling. While a properly calibrated individual would have CBO $= 0.10$, amazingly no one comes close to this number. The average value is 0.78, which is consistent with only 22% of intervals being "right." Two possible culprits are the experimental design in particular and calibration tests in general. As for the first, despite the best efforts of experimenters to explain the nature of these intervals, it is of course possible that some participants never really quite understood what they were being asked to come up with. Nevertheless, it seems reasonable to believe that at least some students understood what they were being asked for. Yet, even if we take the (say) half of all students who come closest to being properly calibrated as being in this category, we are still not even close to appropriate calibration. Interestingly, the German cohort is significantly less overconfident than the Canadian cohort (0.72 vs. 0.84–0.85). It is possible that there may be societal factors at work (e.g., Yates et al. (1997) and Kim and Nofsinger (2002)). Another factor may be that the German and Canadian cohorts, despite best efforts, are slightly different. The Canadian contingent is made up of second-year commerce students with an average age of 21. The German contingent is somewhat older (24) and more heterogeneous (with students doing degrees in mathematical finance, economics, public business administration and international economics).[8] A final possibility is that the nature of confidence intervals was (again, despite best intentions) less effectively explained in Canada than in Germany.[9]

[8] There was no pool in Germany of sufficient size that was a perfect match to the Canadian cohort's makeup.

[9] In both countries a roughly 10-minute "lesson" was given to explain what an *x%* confidence interval meant. The two different experimenters doing these sessions compared "notes" in advance to try to make the descriptions as close as possible. Nevertheless the fact that there were more technically-oriented students in Germany than in Canada may have made it easier for the Germans to grasp this concept.

The other possible problem is the nature of calibration tests themselves.[10] Gigerenzer (1991) argues that overconfidence, when calculated on the basis of calibration tests, is vastly overstated, showing that overconfidence can be made to disappear if the testing procedure is reframed. If subjects are asked for certainty levels they are overconfident, but if asked for frequency success they are properly calibrated. Despite these concerns, while *absolute* overconfidence may be overstated using CBO, there is no reason to believe that *relative* overconfidence levels do not reflect true differences between individuals, and of course it is relative levels that regression analysis relies on.

2. CBO is a more powerful predictor than its competitors in explaining trading activity. This result differs from previous results in the literature. Most notably, Biais et al. (2005) in their experiment consider the impact of CBO (measured, as in the present experiment, prior to the participation of students in a series of trading sessions), finding that it does not lead to an increase in trading intensity, though it does serve to significantly reduce profits.[11] Glaser and Weber (2007) combine data from naturally-occurring markets with information elicited from a survey. Using trading data from online brokerage accounts and psychometric data obtained from the same group of investors who responded to an online questionnaire, they correlate various measures of trading activity with a number of metrics of overconfidence. While there is solid evidence that those who are most subject to BTA trade more, there is little such corresponding evidence for those with higher CBO.

One interpretation of the variance in results is that CBO impacts trading *here* due to the nature of the experimental design. Specifically, the design provides a *reason* for overconfident traders to think that their signals are more informative.[12] In previous experimental work where private information is provided, there are either no differences in signal quality (Biais et al. (2005)) or, when differences in quality exist, signals are randomly assigned (Kirchler and Maciejovsky (2002)). Under such circumstances, it is not clear why an overconfident trader should believe that her private information is more informative than the next trader's. Her ability after all had nothing to do with signal quality. We take our cue from naturally-occurring markets where many, through some form of analysis, generate their own information. In the present experiment, even if there is no difference between individuals in terms of knowledge, overconfident people will tend to *think* that their answers were more accurate, implying that their signals are more revealing,

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[10] One problem with calibration tests is that underconfidence can arise in the case of easy tasks (Fischhoff (1982)).

[11] They also investigate the impact of self-monitoring, namely the disposition to attend to social cues and appropriately adjust behavior, finding that high self-monitors earn relatively larger trading profits.

[12] Despite the fact that there is no deception, those thinking that they have more informative signals may or may not be right.

and thus trade accordingly.[13] An alternative interpretation is that BTA is being let in "through the back door," since the driver is people's belief that they have performed better than others. In truth it is impossible to extricate the two, so BTA may be operating both directly through its own question as well as indirectly through the stated signal accuracy component of the experiment.

Related to this issue is the possibility that it is not overconfidence (whatever its manifestation) but rather confidence that is driving the results. If there is little or no variation in knowledge, variations in overconfidence and confidence will coalesce. In line with this view, Bloomfield et al. (1996) present laboratory results relating confidence to trade. To test this possibility, we constructed a metric for confidence, and then proceeded to regress trading activity on both confidence and overconfidence.[14] From this unreported regression it is clear that overconfidence is the key determinant (p-value (0.005) while confidence is far from significant.[15]

3. Men are not *more overconfident than women.* As mentioned earlier, the literature suggests that men are more overconfident than women. For example, Bhandari and Deaves (2006), in a survey of defined contribution pension plan members, which, among other things, tested investment knowledge and confidence in that knowledge, found that men were more overconfident than women in this realm. And yet p-values of gender difference (shown in Table I) indicate there is no evidence supporting a gender gap in our data. We conjecture that the reason for the inconsistency is the nature of the participant pool. Could it be that women who are attracted to "male" disciplines such as economics, finance and business are more overconfident than the overall female population, even as overconfident as is the typical male?

4. Men and women trade about the same amount in Canada, while women trade less in Germany. One possible explanation of the difference between male and female trading behavior across the two countries may have been the experimental design itself. Recall that in Canada females and males were segregated. In Germany, segregation was by overconfidence level. It is perhaps telling that when males and females are segregated (Canada) there is no statistical difference in trading activity (in fact females trade slightly more); whereas, in Germany, where males and females trade together, despite the fact that trading is done anonymously, with no one being able to observe the actions of others, males trade substantially (50%) more. Perhaps

[13] It should be noted in passing that overconfident traders would only in fact tend to have more informative signals if overconfidence and questionnaire skill (i.e., knowledge) are correlated (which turns out to be only weakly true – with a p-value of 0.08).

[14] Our confidence metric is derived as follows. For each calibration question, we calculated for each individual their confidence interval width scaled by the midpoint. Then on each question we ranked individuals from most to least confident (using a zero to one scaling). Finally we summed up for each individual these ranks to get their overall confidence metric.

[15] In a regression of trade on confidence alone, the latter is still insignificant.

the presence of males in the same room somehow inhibits the behavior of women. As mentioned earlier, in mixed groups women tend to be less successful in exerting influence and taking on a leadership role (Carli (2001)). Whether this can be mapped to the level of naturally-occurring markets (where of course women and men must trade side by side), suggesting an alternative determinant of differential trading behavior over and above differences in overconfidence, is an open question. In any case, even beyond such an "inhibition effect," there is the possibility of a cultural/pool factor, as we see that Canadian males trade roughly 25% more than their German counterparts (though the difference is not quite statistically significant at 10%).[16]

5. Trades are often at prices at some distance from intrinsic value. One interpretation is that some traders put a lot of stock in their own private signals. Over all markets, the average *ex post* risk premium ((dividend-mean price)/mean price) was 34%.[17] Nevertheless it is comforting that price convergence typically occurred during a market. In an unreported regression of the change in the median price (from the first 50% of all trades in a market to the last 50% in the same market) on the gap between the dividend and the early (first 50% of trades) median price, the coefficient is positive and statistically significant at close to 1%.

6. Does overconfidence lead to not only trade but also poor portfolio performance? Biais et al. (2005) and Fenton-O'Creevy et al. (2003) have documented that overconfidence has a negative impact on trading performance.[18] In an unreported series of regressions, we corroborate this finding. Average wealth, namely the average (over 12 markets) end-of-market post-dividend cash balance (for each individual), is regressed on CBO *and* prediction error (the sum of absolute differences between dividend predictions and realizations). While the coefficient on CBO is insignificant, by dropping the first or first two market(s) (during which time we conjecture participants were developing a feel for the environment, leading to excessive noise), the coefficient becomes significantly negative (p-value = 0.078 or 0.003).[19] The inference to be drawn is that overconfident traders perform poorly as

[16] Part of the reason for this is differences in demographics between the two pools.

[17] Note that the interquartile range was from −6.4% to 28.9%. In Canada the average risk premium was 46% while in Germany it was 4%. Much of the reason for the very high Canadian risk premium was that in one of the sessions (no. 1) the figure was a whopping 207%, suggesting some degree of misunderstanding of the nature of the dividend process. While obviously not desirable, this did not necessarily detract from our main concern which was the potential tendency for overconfident traders to trade excessively.

[18] The first paper argues that overconfident traders are more subject to winner's curse risk and hence engage in frequent unprofitable trades. The second paper links illusion of control and poor performance among traders at four London investment banks.

[19] The coefficients on CBO (and their significance) are similar if we drop prediction error.

they are too liable to make trades at unprofitable prices (and an inability to forecast dividends contributes to the problem).[20]

7. Does risk-aversion, as well as overconfidence, predict trade? Some of our sessions are stratified by gender. Given that men are less risk-averse than women (e.g., Bhandari and Deaves (2008)), it could be that trading differences are partly due to differences in risk-aversion. Risk-aversion lowers the price that someone is willing to pay for future cashflows: the resultant risk premium is technically reflected by the fact that the pricing kernel shifts the mean of the objective distribution to the left.[21] Overconfidence on the other hand reduces the perceived risk of the distribution while leaving the mean unchanged. The impacts of high overconfidence and low risk-aversion on trading volume are similar in that they both lead to greater trading volume (Hirshleifer and Luo (2001)). While we have not elicited from participants proxies for risk-aversion, we can investigate the impact of a noisy proxy, the realized risk premium, at the level of the market. The lower panel of Table III repeats the regressions of the upper panel, with the inclusion of a market-specific realized risk premium. The first regression indicates that, counter-intuitively, a higher risk premium (greater risk-aversion) is associated with higher volume.[22] Nevertheless, when a country indicator variable is incorporated, the impact of risk-aversion disappears, with country of origin and mean CBO explaining volume (at least at the 10% level) as before. Therefore on balance there is no compelling evidence that risk-aversion matters once overconfidence is accounted for.

5. Concluding remarks

Taken together, the empirics reported here provide solid evidence that greater overconfidence leads to increased trading activity. This is true both at the level of the individual and at the level of the market. While CBO dominates, BTA matters as well, both directly and indirectly through the experimental design.

On the other hand, we are not able conclude much on the impact of gender. Likely because of the nature of the participant pool, there are no differences between genders in overconfidence or trading activity. Nonetheless, there is the hint of an "inhibition effect" reducing trading among the German female participants.

[20] While logically the ability to forecast dividends is related to signal informativeness, which is in turn determined by general knowledge (based on the calibration section of the pre-experimental questionnaire), the latter variable (in an unreported regression) turns out to have no explanatory power.

[21] See Lüders (2004) and Düring and Lüders (2005) for more details.

[22] Our result is counterintuitive in the sense that one would expect the trading volume to be lower with greater risk-aversion after controlling for overconfidence. This point can be seen from Hirshleifer and Luo (2001).

Several avenues for future research present themselves. Overconfidence appears to be a multi-faceted dynamic phenomenon, and it is not clear how to best measure it, to what extent competing measures are related, which manifestations correlate most closely with financial behavior and to what extent overconfidence may change based on experience. While the present exercise has contributed to the debate, additional psychological and financial research to answer these questions is called for. Additionally, while we did provide some preliminary evidence on what factors over and above overconfidence do and do not impact trading behavior, it is clear that much of the cross-sectional variation remains unaccounted for. Success in exploring these additional issues should provide some guidance to financial theorists as they continue to refine some of the behavioral models that have recently been proposed.

Appendix A: Additional Details on Experimental Design

Location: There was good reason for using two locations. The experimental design was based on having experimental subjects first fill out an administered pre-experimental questionnaire from which certain measures were calculated which allowed individuals to be assigned to sessions as well as to ascertain how informative their information signals would be. The reason for the pre-experimental questionnaire only became apparent to subjects when they were present at the experimental sessions. Once such pre-experimental questionnaire sessions were conducted followed by a "tranche" of experimental sessions, to repeat the same procedure in the same location would likely lead to contamination because of information leakage. Nonetheless care was taken to ensure that the exact same procedure was followed in both locations. It should be noted that the same two experimenters were present at the experimental sessions in *both* venues to ensure that this was so. In total, 108 students (47 in Canada and 61 in Germany) were invited to fill out the pre-experimental questionnaire. Of these 41 were females (23 in Canada and 18 in Germany). It was more difficult to recruit females than males in Germany because there are substantially more males than females in economics and finance classes at the University of Konstanz.

Pre-experimental questionnaire: See Appendix C (http://www2.wu-wien.ac.at/rof/supmat.html) for the pre-experimental questionnaire. In addition to obtaining certain information on the students' backgrounds (such as age, educational background and previous experience in financial markets), the main purpose was to see how well calibrated the subjects were. With this in mind, the students present answered 20 general knowledge questions which had objectively known numerical answers. The questions and answers were obtained from a variety of credible sources. The reason for not using investment/market questions was to avoid giving either group of participants a relative advantage because of subject content. In fact an attempt was made to make the general knowledge questions non-culture-specific. Specifically, subjects were asked to supply 90% confidence intervals. Afterwards, they were assessed both on their level of knowledge and on their degree of CBO. Knowledge was measured by summing up absolute differences between midpoints of confidence intervals and correct answers (scaled by correct answers). The lower was the resultant value, the more knowledgeable the individual in question was inferred to be. CBO was assessed by calculating the percentage of times that confidence intervals contained correct answers. The higher was this percentage the *less* overconfident an individual was inferred to be.

Setup of sessions: In Canada, from the group filling out the pre-experimental questionnaire, 32 students – 16 female and 16 male –were chosen to participate in four experimental sessions. The participants were segregated by gender. That is to say, there were two all-female sessions, each consisting of eight female traders, and two all-male sessions, each consisting of eight male traders. The participants were chosen in such a way that each session had (as closely as possible) the same mean level of overconfidence. The fact that we had extra subjects allowed us to do this efficiently. In Germany, stratification was done on the basis of overconfidence, not gender. Individuals were divided into two discrete groups, the most overconfident and the least overconfident. All sessions were designed to have roughly the same number of male and female participants (with five males/three females attending two sessions and four males/four females attending the other two sessions). Those having experience conducting experimental simulations know that it is virtually impossible to ensure that all invited individuals attend. For this reason (roughly similar) "reserves" had to be invited, and that is why it was not possible to precisely keep constant overconfidence in Canada and gender mix in Germany. Each experimental session began with the students reading the detailed instructions and then being given abundant time for questions and answers. The full instructions are provided in Appendix D (http://www2.wu-wien.ac.at/rof/supmat.html) In Canada the instructions were in English, while in Germany the students could choose between German (available on request) and English versions. Some of the German-based students (being foreign students) chose English instructions. In Germany, questions were answered in the language of choice of the student. For numeraire currency we used the term 'baht' supposing there would be few (Thais) for whom the word 'baht' might generate a meaningful connotation. In fact, by coincidence, no Thais participated. Each session consisted of 12 markets (for details see below).

Private signals: The reason for giving task-specific private signals was, as stated earlier, to give overconfident traders a reason to think that their signals were more informative (even if reality often proved otherwise). Traders were informed that dividends were chosen based on a uniform distribution bounded by '1' and '99,' with values rounded to integer values. (More precisely, as will be described below, these two numbers were base values, with actual values being grossed up using session-specific factors.) As for signals, while traders were not given any distributional information in the instructions, our drawing was based on the normal distribution. Looking into our black box in more detail (a possibility not afforded the student subjects), while our dividends and signals were obtained via a random number generator, we repeated our draws (unbeknownst to the students) until several screens had been satisfied: 1/ all (raw) dividends were between 10 and 90; 2/ the average (raw) dividend was between 45 and 55; 3/ the maximum absolute percentage deviation of an individual's mean signal relative to the mean dividend was no more than 5%; and 4/ the most informative set of signals was at least three times more informative than the least informative set of signals (in the sense of the sum of absolute deviations from true dividends). Without the first screen, a situation where all signals were clustered around a very low or very high dividend (thus reducing differences of opinion) could arise. The second and third screens were employed so that traders would not get the sense that the game was rigged in any fashion and that their signals were without information content. Finally, the requirement of the last screen was *guaranteed* to the traders in the instructions.

Dividends: All sessions had the *exact same set of dividends and signals.* To disguise this from participants (since sessions were one or two days apart), we randomly shuffled the market order and multiplied each set of numbers for a session by a random factor. Therefore the only differences were those of sequence and scale. Additionally, a further disguise was deemed necessary. If dividends were revealed to traders at the end of each market, over time it could perhaps have become apparent to traders whether their signals were more or less informative than those of others. (One could never really have been sure though since signal distributional information was not given.) To avoid contamination from this source, *all* dividends were only revealed at the very end of each session (instead of at the end of each market).

Trading and computerized environment: To keep subjects separated so that they could not share information, experimental sessions were conducted in computerized environments using the *Financial Trading System (FTS)* platform. (This program was developed by John O'Brien and Sanjay Srivastava at Carnegie Mellon. The authors particularly thank the latter individual who provided abundant assistance to us as we were setting up the experiment. Note that the latest versions of FTS have been specifically designed to be amenable to asset market experimentation in that a great deal of freedom has been allowed for programming precise experimental designs.) This computerized double auction market program allows students to participate in market simulations in real time. Participants can post bids and asks, or act as price-takers in accepting the best bids or asks posted by others. Traders begin with endowments made up of cash and securities and the program automatically updates portfolios after transactions. Specifically, all traders are endowed with four shares each market. These markets are independent so shares are not carried over from market to market. As for cash, it was scaled at slightly more than twice the level of the maximum dividend. As stated earlier, the base values of the minimum and maximum dividends were 1 and 99. Actual dividends were grossed up by the factors 9, 10, 5 or 8 (depending on the session). This was done so as to disguise the fact that for each session we used the *exact* same set of draws with all nominal magnitudes being multiplied by a common factor and the order of markets scrambled. So, for example, if the maximum dividend was 891 ($99 * 9$) the cash endowment was 1800 baht ($100 * 2$). Once again, there was no carry-over from market to market. For simplicity the order book was set at a depth of one, which means that posted orders were erased by better bids and asks. Traders were permitted to transact only one share at a time, and no short selling or margin purchases were allowed.

Payout: In order to mitigate wealth effects, in advance all subjects were informed that they would be rewarded only based on their performance in *one* of the 12 markets. This *payout* market was determined by the roll of a 12-sided die at the end of the session. A conversion was made from the numeraire currency to either euros (in Germany) or Canadian dollars (in Canada) based on pre-selected values designed to keep aggregate payouts within budget (and roughly equal across markets). Conversion rates were chosen so that average payout was about $50 in Canada and €50 in Germany. Sessions were about two and a half hours, so the sums of money involved were quite salient to students.

Prediction: The prediction of dividends was done by filling out a "ticket" and handing it to the experimenters who recorded the values on a laptop. As an incentive for careful thought, they were told in advance that a $20 (or €20) bonus would go to the trader whose absolute difference between her prediction and the true dividend in the payout market was lowest.

Post-experimental questionnaire: The full post-experimental questionnaire is shown in Appendix E (http://www2.wu-wien.ac.at/rof/supmat.html).

Appendix B: Construction of Overconfidence Measures

CBO: Individuals were asked to construct 90% confidence intervals for the 20 questions appearing on the pre-experimental questionnaire (see Appendix C (http://www2.wu-wien.ac.at/rof/supmat.html)). Note that a well-calibrated individual would have (subject to sampling error) 90% of the correct answers contained inside her intervals. (Note that incentivization at the point of the calibration test would have been injudicious, since a shrewd "gamer," asked to produce 90% confidence intervals, could virtually ensure proper calibration by producing two ridiculously narrow confidence intervals and 18 ridiculously wide intervals.) We convert the percentage of the time that an individual is "right" into a measure of overconfidence by subtracting the former from one, so that higher values correspond to higher levels of overconfidence. For example, if a subject had correct intervals 40% of the time, her overconfidence measure would be 0.6. A properly calibrated individual would have an overconfidence measure of 0.1. To ensure reasonable internal consistency, we calculated the Cronbach alpha, where we divided the questions into the first half and second half to form two testlets. The value of the Cronbach alpha calculated in this way was 0.639, which is considered to be in the acceptable range.

IOC: In the pre-experimental questionnaire two questions were asked which were designed to elicit a metric for IoC. Subjects were asked to assign a number from 1 to 5 (where 5 = totally agree and 1 = totally disagree) to two questions (similar to those used by Glaser and Weber (2007)):

(a) *I never buy securities or funds that will underperform in the future.*
(b) *I am not able to identify securities or funds with above-average performance in the future.*

The value assigned to the first minus the value assigned to the second is the metric that we used for illusion of control. The higher is this metric the more in control the subject appears to feel. Since neutral answers to both questions would generate 3s, a value of 0.00 would reflect no illusion of control.

BTA: To arrive at a measure for BTA, the following question was asked on the post-experimental question (see Appendix E (http://www2.wu-wien.ac.at/rof/supmat.html)):

OF the 32 (yourself included) people doing this experiment (not just those in today's session), how many do you think will end up making more money from it than you?

The metric that we use for BTA was 31 minus the response to this question. If someone thought they did better than half of the other participants (15.5), which would make them neither better nor worse than average, then their BTA would be 15.5.

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