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DOSPERT's Gambling Risk-Taking Propensity Scale Predicts Excessive Stock Trading

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Using a data set that combines trading records in a financial investment simulation with survey responses, this study provides evidence that a domain-specific variant of risk-taking propensity, namely risk taking in gambling (but not in investing) situations, predicts the volume of trades of financial investors. We find that investors' gambling risk-taking propensity, measured by the Weber, Blais, and Betz [2002], Domain-Specific-Risk-Taking (DOSPERT) gambling subscale, increases the number of trades made and hence transaction costs, as well as the extent of their day trading. The short (four-item) gambling risk-taking propensity DOSPERT subscale thus provides a useful diagnostic addition to risk attitude assessment instruments for private investors.

Keywords: Domain-specific risk taking, DOSPERT scale, risk attitude, trading volume, day trading

> "The high trading volume on organized exchanges is perhaps the single most embarrassing fact to the standard finance paradigm." (De Bondt and Thaler [1995], p. 392)

Rational expectations make it difficult to understand why investors trade so excessively. The turnover on the New York Stock Exchange (NYSE) in 1999 amounted to 78% (Barber and Odean [2001b]) and has been growing systematically over the past decade, hitting approximately 100% in 2004 (Glaser and Weber [2007]). Arguments have been made that such turnover is due to portfolio risk-rebalancing needs, or tax or liquidity reasons, though research shows that almost two-thirds of the realized turnover cannot be justified by such rational motives (Barber and Odean [2002], Dorn and Sengmueller [2009]).

Furthermore, investors seem to be hurt by this intensive trading activity (Odean [1999]). Barber and Odean [2000] investigated portfolios held during 1991–1996 and found that frequent traders paid a huge penalty for active trading, earning 7.1% less than infrequent traders, mostly due to the high commission costs associated with intensive trading. The title of their most recent paper is suggestive, asking not "if" but "how much" individual investors lose by trading (Barber, Lee, Liu, and Odean [2009]).

CAUSES OF EXCESSIVE TRADING

Overconfidence

Some have suggested that the key to understanding frequent trading is investors' overconfidence, that is, their belief that their abilities are above average and that they can outwit the market (De Bondt and Thaler [1995], Odean [1999]). Using gender as a proxy for overconfidence, in an empirical study Barber and Odean [2001a] demonstrated that men, considered to be more confident (especially in the financial domain), were more active traders than women. Accordingly, Gervais and Odean [2001] proposed that overconfidence may increase among successful investors, resulting in more active trading.

Although appealing, this model relating investors' excessive trading activity to overconfidence (Gervais and Odean

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[2001], Odean [1998]) is not consistent with many empirical findings (Biais, Hilton, Mazurier, and Pouget [2005], Glaser and Weber [2007]). The study by Barber and Odean [2000] is the only one which, without any restriction, supports this hypothesis, but does so by using gender as a proxy for overconfidence, which is questionable since gender is correlated to many other variables, including risk taking propensity (Charness and Gneezy [2007]). In studies that directly try to assess the degree of overconfidence of investors, evidence for the effect of overconfidence on trading volume is decidedly mixed. Some studies find that overconfidence (measured as "better than average" beliefs) is related to turnover (Dorn and Huberman [2005], Glaser and Weber [2007]) or trading frequency (Graham, Harvey, and Huang [2009]), whereas other studies fail to find such a relationship (Dorn and Sengmueller [2009]). Even articles that report such a relationship do so only after some post-hoc reasoning and data exclusions. Thus, Glaser and Weber [2007] had to exclude the most aggressive traders from the analysis to find a correlation between overconfidence and trading, suggesting that these traders might be driven by motives other than overconfidence.

Furthermore, there is clear empirical evidence that overconfidence is not a unitary construct (Moore [2007], Moore and Healy [2008]) and the significant gender differences in overconfidence are only observed when overconfidence is defined as a "better-than-average effect" and not when it is defined as "miscalibration," that is, the inability to accurately assess one's own performance (Grinblatt and Keloharju [2009]).When overconfidence is defined as "miscalibration," there is little support for Odean's hypothesis. Glaser and Weber [2007] reported that for their most active investors overconfidence measured as miscalibration had no influence on investors' trading volume. Biais et al. [2005] found that miscalibration reduced trading performance but was not related to trading volume. Other studies that examined real transaction data also find no relationship (Dorn and Huberman [2002, 2005], Oberlechner and Osler [2008]). The bottom line, however, is that overconfidence as a cause (and certainly as the only cause) of excessive trading is far from established and other determinants should be considered.

Gambling Risk-Taking Propensity

Quite recently, a new explanation for the observed excessive trading activity has emerged. Dorn and Sengmueller [2009] reported that "investors who enjoyed investing or gambling turn over their portfolio at twice the rate of their peers. The results are robust to controlling for gender and for proxies for overconfidence constructed from survey response" (601). The authors suggest that there are at least three possible motives for trading: (a) the recreation/leisure motive, which treats active investing as a hobby; (b) the aspiration for reaches motive, which treats investing like a lottery for providing a chance of highly unlikely but possible extreme payoffs; and (c) the sensation seeking motive, which uses acts of trading with its uncertainties as providing the stimulation and novelty some people require to feel alive. Combining investors driven by the last two motives into a category they call "gamblers" and differentiating them from investors driven by the first motive called "hobby investors," Dorn and Sengmueller found some demographic differences as well as differences in investing behavior between these two groups: "Gamblers are motivated by a quest for arousal or an aspiration for riches; relative to hobby investors, they tend to be younger, less wealthy, and hold more concentrated portfolios of more volatile securities to provide the necessary stimuli or to increase the chance of reaching a desired wealth level" (Dorn and Sengmueller [2009], p. 597). Dorn and Sengmueller's sensation-seeking motive received empirical support from Grinblatt and Keloharju [2009], who found a relationship between the number of recent speeding tickets and trading volume of male Finnish investors. Moreover, the gambling motive in investing gets indirect confirmation from a study by Barber et al. [2009], who noticed that the legalization of gambling (in the form of a national lottery) in Taiwan resulted in a sizable drop in the turnover volume on the Taiwanese Stock Exchange, suggesting that investing and gambling were treated by at least some investors as substitutes.

Dorn and Sengmueller suggest that both "groups of investors—hobby investors and gamblers (sensation seekers or those with an aspiration for riches)—derive enjoyment from trading," but that "it is difficult to assess the relative importance of leisure versus gambling-motivated trading with the data at hand" (Dorn and Sengmueller [2009], p. 602). In this article, we take advantage of a psychometric scale, the Domain-Specific Risk-Taking (DOSPERT) scale, that allows us to unpack and measure different motivations for financial risk taking and to examine their influence on the quantity of stock trades. Rather than measuring investors' general attitudes toward gambling or investing (as done by Keller and Siegrist [2006]), the DOSPERT subscales measure investors' willingness to take risks in each of these domains. Whereas Dorn and Sengmueller [2009] and other authors (Jadlow and Mowen [2010]) have established that those who enjoy trading and those who enjoy gambling will trade more, the DOSPERT investing and gambling risk-taking subscales used in our study go beyond measuring the enjoyment of investing or gambling, quantifying the degree of risk individuals are willing to take in both domains and relating those two risk-taking propensities in a parametric fashion to degree of trading.

Our study builds on the growing consensus that risk taking has multiple, qualitatively different determinants (see Weber and Johnson [2008] and Weber [2010] for recent reviews), and that risk propensity is not a unitary construct (Figner and Weber [2011]). Multiple determinants, many of which are situational, make sense of the empirical observation that risk taking often varies by domain and thus needs to be assessed in the domain of decisions in which one attempts to use it as a predictor (Tyszka and Domurat [2002], Weber et al. [2002]). Self-reported risk-taking propensity in survey items about a specific domain has been shown to be far more successful in predicting real-world risk taking than expected utility-model derived risk attitude coefficients from content-free choices such as the Holt-Laury task (Harrison, Young, Butow, Salkeld, and Solomon [2005]). Finding the best way to classify risk-taking tasks into distinct domains that yield consistent risk-taking behavior has been an empirical challenge. The *Do*main-*Spe*cific *R*isk *T*aking (DOSPERT) model by Weber et al. [2002] initially hypothesized risk-taking differences between the five substantive domains for which the authors developed assessment items: social, recreational, health-and-safety, ethical, and financial risks. To assess self-reported risk taking in each of these five domains, respondents answer eight questions from each domain on 5-point Likert scales, indicating how likely from 1 (*very unlikely*) to 5 (*very likely*) they would engage in a specific behavior (e.g., "Betting a day's income at the horse races"). However, a factor analysis of respondents' answers to the 40-item survey revealed that the eight financial domain items actually split into two separate factors, namely investment versus gambling decisions. Table 1(a) lists the four items that make up each of the two subscales. Subsequently other investigators have replicated that self-reported risk taking in the investing and the gambling domains are not highly correlated (Weber et al. [2002] found a correlation of

TABLE 1
Scales used in survey

(a) Gambling and investing risk-taking propensity subscales of DOSPERT scale (Weber et al. [2002]).
For each statement, respondents indicate their likelihood of engaging in each activity or behavior, by providing a rating from 1 (*very unlikely*) to 5 (*very likely*).

Gambling Risktaking Propensity Subscale
– Betting a day's income at the horse races.
– Betting a day's income at a high stake poker game.
– Betting a day's income on the outcome of a sporting event (e.g. baseball, soccer, or football).
– Gambling a week's income at a casino.

Investing Risktaking Propensity Subscale
– Investing 5% of your annual income in a conservative stock.
– Investing 10% of your annual income in government bonds (treasury bills).
– Investing 10% of your annual income in a moderate growth mutual fund.
– Investing 5% of your annual income in a very speculative stock **

(b) Stimulating-Instrumental Risk Inventory (Zaleśkiewicz [2001]).
For each statement respondent state how the statement fits their beliefs or actions, on a scale from 1 (*does not fit me at all*) to 5 (*fits me very well*).

Stimulating/Arousal-Seeking Risk Motive
– If I play a game (e.g., a game of cards) I prefer to play for money than for fun
– I make risky decisions quickly without an unnecessary waste of time
– I take risk only if it is absolutely necessary to achieve an important goal (reverse scored)
– I enjoy risk taking
– While taking risk I have a feeling of a very pleasant flutter
– Gambling seems something very exciting to me
– I avoid activities whose results depend too much on chance (reverse scored)
– I am attracted by different dangerous activities (e.g., wandering through unknown lands)
– I often take risk just for fun
– In business one should take risk only if the situation can be controlled (reverse scored) **

Instrumental Risk Motive
– I willingly take responsibility in my work-place
– The skill of reasonable risk taking is one of the most important managerial skills
– To achieve something in life one has to take risks
– To gain high profits in business one has to take high risks
– If there is a big chance of profit I take even very high risks **
– If there were a big chance to multiply my capital I would invest my money even in the shares of a completely new and uncertain firm **
– At work I would prefer a position with a high salary which could be lost easily to a stable position but with a lower salary **
** – failed to load on scale in this study

(c) Perceived market knowledge scale.
Respondents indicated how each statement applied to them making stock market decisions, on a scale from 1 (*it doesn't fit me at all*) to 5 (*fits me very well*).
– I try to be up-to-date with announcements concerning the company's situation of the stocks I own or consider to buy.
– I have wide knowledge concerning the current situation of stock-trading companies of whom I own shares in my portfolio (going beyond current quotations and its history).
– I try to be up-to-date by consulting internet forums, web pages or/and press and TV programs dedicated to investing.
– Companies' announcements influence my investment decision.
– I have extensive knowledge concerning the stock market as well the rules influencing the market

only .33 in their sample of 357 undergraduate students). Deck et al. [2008] verified that investment risk taking and gambling risk taking as measured by the two DOSPERT scales were not highly correlated in their sample of adult respondents and that they predicted different behaviors: investment risk taking was correlated with decision in the Holt and Laury [2002] task, and gambling risk taking predicted behavior in a variant of the game show "Deal or No Deal."

Zaleśkiewicz [2001] identified two different motives for taking financial risks, one instrumental (i.e., taking risks to achieve financial returns) and the other arousal-seeking (taking risks for the thrill or stimulation it generates), and designed and validated a scale that measures the two constructs (the Stimulation-Instrumental Risk Inventory (SIRI)). Table 1(b) lists the items that make up the two subscales. These two motives for taking financial risks seem to map well on Dorn and Sengmueller's [2009] distinction between hobby investors and gamblers. We hypothesize that SIRI and DOSPERT subscales are related in the following ways, thus validating that different motives underlie gambling and investing risk taking:

> *H1a: Investors'* DOSPERT gambling risk propensity *is positively related to* their SIRI stimulation-seeking risk motive.

> *H1b: Investor's* DOSPERT investment risk propensity *is positively related to* their SIRI instrumental risk motive.

In this article, we test whether the two DOSPERT subscales will allow us to distinguish between the two classes of investors in Dorn and Sengmueller's [2009] model, those who seek sensation and those with aspiration for riches. Investors who are more or mostly driven by Dorn and Sengmueller's aspiration-for-riches motive are predicted to invest in ways that will correlate with Weber et al.'s [2002] DOSPERT investment risk-taking subscale. In contrast, investors who are more or mostly driven by Dorn and Sengmueller's sensation-seeking motive are predicted to invest in ways that will correlate with their score on Weber et al.'s [2002] DOSPERT gambling risk-taking subscale. Since it is the process rather than the outcome of risky decisions that lies at the heart of the sensation- or stimulation-seeking motivate, a greater need for stimulation and hence greater propensity to take gambling risks would predict a greater volume of trading, by virtue of turning stock market investing into a gambling activity that has consumption utility:

> *H2(a): Trading volume is positively related to investors' DOSPERT gambling risk propensity.*

Gambling Risk-Taking Propensity as a Cause of Day Trading

In addition to overall trading volume, this study also examines determinants of the trading pattern of day traders, who are commonly perceived to be risk takers and gamblers ("Day Traders as Gamblers" [1999], Norris [1999]). Day trading refers to the practice of some investors to buy and sell the same company stock within a single day, making it a special case of excessive trading that causes large turnover volumes. Barber et al. [2009] showed that heavy day traders do not earn enough profit to cover transaction cost. Douglas and Diltz [2003] documented that there are two times as many U.S. day traders who lose money than who make a profit. As noted by Andersson [2004], there is little published research on day traders, although they generate a huge part of stock exchange turnovers. At the Taiwan Stock Exchange (investigated period: 1995 to 1999), day trading is responsible for about 22% of the total individuals' trading value, with similar level (15%) for the NASDAQ (Barber, Lee, Liu, and Odean [2005], Barber et al. [2009]). Day trading is almost entirely a behavior shown by individual, not institutional investors.

Existing studies (e.g., Barber et al. [2005]) have focused on day trading profitability and its persistence over a time, not on the psychological determinants of day trading behavior. While overconfidence is again offered as a potential explanation, the authors admit that they are "unable to explicitly test whether day traders are motivated by overconfidence rather than the desire for entertainment." We extend Hypothesis 2 to day trading, predicting that day traders invest in the way they do because they enjoy this activity, and treat it, at least to some degree, as a gambling rather than an investment activity. Therefore, they are probably maximizing thrill and not necessarily profit:

> *H2(b): Extent of day trading is positively related to investors' DOSPERT gambling risk propensity.*

METHODOLOGY

This study examined the records of investment decisions of participants in a virtual investment simulation and survey data collected from a subsample of those participants.

Participants

Participants for the investment simulation were recruited through posters placed on university campuses in major Polish cities that encouraged participation in an investment simulation by providing incentives for doing well, including free tuition for courses related to financial analysis, accounting, and management. To open their virtual brokerage account for the simulation, participants provided their name, affiliation, gender, age, and e-mail address. The sample (N = 3,870) consisted largely of men (81%) and, since the simulation was targeted at university students, the median age was 23 years (M = 22.76, SD = 2.41). Even though this sample of participants differs from the population of real investors (at the very least in terms of age), an analysis of their investment decisions analyzed for a different purpose by a different set of investigators showed several of the same phenomena that have been observed in the investment decisions by representative samples of investors in the United States and elsewhere, including the disposition effect and mean reversion in price trends forecasting (Kubińska and Markiewicz [2008], Kubińska, Markiewicz, and Tyszka [2012]). This suggests that the decisions made by the respondents in our study are at least qualitatively similar to the real decision observed among regular investors. Moreover, the respondents in our sample, while perhaps more risk seeking than typical investors, showed significant heterogeneity in risk attitudes and trading behavior, and the main objective of our study was to predict differences in trading volume from differences in risk attitude.

Investment Simulation Records

The investment simulation was initiated by a Polish business publisher, the PARKIET Company, as a way of raising awareness of their daily business publication in which the game results were posted. The activity was publicized as an "Investment Simulation for Students" and had the educational purpose of increasing familiarity with capital markets.

Participants had to sign up between November 13 and November 30, 2006. Regardless of the starting date, the simulation was known to finish on January 19, 2007. Hence, depending on the sign up date, the simulation lasted between 33 and 47 business days, during which the Warsaw Stock Exchange (WSE) was operating. It is worth of noting that the simulation was conducted before the stock market slump at the turn of 2007 and 2008.

Each participant was given a virtual capital of PLN 100,000 (approx. $34,000) and was asked to invest it in a way that would maximize their portfolio's value on the last day of the game. Participants were allowed to invest their capital only in blue chips, that is, in the 20 biggest companies on the WSE (creating WIG20 index).

A special online transaction platform was designed for the simulation. It allowed participants to track their selected stocks' performance as well as the performance of nonselected stocks, and the total current value of their portfolio in real time, as well as place buying and selling orders. It was possible to place orders at any time, but they were executed only in the time frame of the WSE operations (8:30 am to 4:30 pm), with the price for a particular stock at the time in the stock exchange quotations. In other words, participants' orders had to match an equivalent order placed on the real stock exchange. Thus participants did not interact with each other but, instead, with the Warsaw Stock Exchange. At no point, did they buy and sell stock from and to each other. Like in the real stock exchange environment, both orders with and without price limits (must-be-filled orders) were available to participants. In addition, participants were allowed to set the period of validity for particular orders and use both short and long selling mechanisms (with short selling referring to the selling of borrowed stocks that the seller does not actually own at the time, giving a chance to make a profit on the stock when the price decreases). There were no explanations of these investment options and investing terms provided by the organizer to participants. It was implicitly assumed that participants knew or could find out for themselves what these investment terms meant.

Participants were charged a transaction commission that was .5% of the transaction value for both buying and selling, with no restrictions concerning minimal flat commission per transaction,[1] similar to actual charges on the Polish market at the time of the simulation, where average commissions were .39% to 1% depending on order channel (.5% for internet order placement).[2] In contrast to the real market, our "chip players" did not have to pay taxes for achieved profits. Thus, trading in the month of December was not affected by tax considerations (Odean [1998]).

Participants were motivated in at least two ways: first, by financial incentives, as they could get valuable prizes (e.g., tuition paid for CFA and MBA courses) for their superior performance,[3] and second, by social incentives, as a listing of the top 100 performers (by names and affiliations) was published daily in PARKIET's business newspaper and the full ranking of all participants was updated daily and available on the organizer's website. While it should be noted that investors' motivations in our simulation are somewhat different from those in ordinary investment situations, with the two-stage nature of the competition and only 10 winners advancing to the next stage perhaps introducing a greater incentive for increased trading and risk taking. However, this was true for all participants in our sample, and it was a high fee-adjusted portfolio value at the end of the simulation that enabled other gains, a condition not so very different from ordinary investment situations. To the extent that individual differences on the two DOSPERT risk propensity scales (gambling vs. investing) predict trading volume among the participants in this investment simulation, we would expect to also find such differences in other investment environments.

Survey Data

The survey data were collected between January 10 and 22, 2007, during the final period of the investment game, using an online questionnaire. Personalized e-mail invitations were sent to investment simulation participants, alerting them of the survey and describing its purpose, length, and benefits. The email made it clear that participation was voluntary, confidential, and anonymous. Nine days after the first invitation, an e-mail reminder was sent. Out of $N = 3{,}870$ sent invitation to active game participants, a total of 16.4% ($N = 633$) completed the online survey, a fairly good response rate given that no material incentives were provided for completion.[4]

To check for self-selection biases, the characteristics of traders and their portfolios were analyzed for differences between those who participated in the online survey and those

TABLE 2
Descriptive statistics comparing survey study participants to other investors

	All, N = 3870		Survey respondent, N = 633		Survey nonrespondent, N = 3237		
	M	*SD*	*M*	*SD*	*M*	*SD*	*t*-test value
Investor personal characteristics							
Age	22.765	2.411	22.594	1.863	22.798	2.504	1.946
Gender dummy	0.191	0.393	0.188	0.391	0.192	0.394	0.207
Investor activity							
Total turnover	577 534	596 200	698 952	645 302	553 790	583 275	**−5.255*****
Turnover not generated by day trading	528 541	512 982	638 515	558 736	507 036	500 826	**−5.504*****
Conducted transaction	31.018	38.424	40.319	47.058	29.199	36.229	**−5.628*****
Portfolio diversification							
NV	0.598	0.346	0.592	0.322	0.600	0.351	0.585
SSPW	0.267	0.250	0.225	0.218	0.276	0.255	**5.181*****
Avg. No.	1.863	1.046	1.954	1.008	1.844	1.052	**−2.406****
HHI	0.339	0.261	0.291	0.230	0.348	0.265	**5.605*****
Number of traded stocks	7.158	4.653	8.464	4.845	6.902	4.571	**−7.486*****
Investors performance							
Total paid commissions	2 936	3 008	3 544	3 253	2 818	2 943	**−5.213*****
Final portfolio value after commissions	97 945	13 535	98 966	13 914	97 746	13 452	**−2.076****
Final portfolio value before commissions	100 882	13 845	102 510	14 309	100 563	13 733	**−3.239*****
Ratios							
Proportion of long transaction value among all conducted value (short + long)	0.895	0.197	0.885	0.190	0.897	0.198	1.469
Proportion of day trading transactions value among all conducted value	0.097	0.152	0.105	0.146	0.096	0.153	−1.409
Execution ratio	0.846	0.159	0.849	0.145	0.846	0.162	−0.531

Notes. Short sell dummy is a dummy variable set to one if investor has at least one short sale in his trading record. Gender dummy is one (zero) if the trader is female (male). Working status dummy is one (zero) if the trader is working (not working) professionally.

***/** indicate that the coefficient estimates are significantly different from zero at the 1%/5% level. Portfolio diversification ratios are explained in the text.

Acronyms in the table:

NV: normalized portfolio variance, reflecting the skill of minimizing the average correlation among stocks in one's portfolio. Takes smaller values when choosing noncorrelated stocks, and higher values with choosing stocks whose prices are highly correlated

SSPW: squared portfolio weights ratio, compares the weight of each asset in an investor's portfolio to its weight in the market portfolio. Similar to HHI which is the sum of the squared portfolio weights. Both ratios take a value between 0 and 1, where 0 (*perfectly diversified portfolio*), 1 (*not diversified portfolio*).

Avg. No.: "naïve" diversification skill index, the average number of equities held by an investor at the end of each trading day.

who decided not to respond. The significant differences are summarized in Table 2. In general, survey responders did not differ from nonresponders in terms of demographic variables (age and gender characteristics were the same) but behaved in slightly different way. Survey responders traded more actively (both in terms of transaction numbers and their values) and kept better-diversified portfolios than nonresponders. They also achieved a slightly higher portfolio value at the end of the simulation. These differences suggest that survey responders were more engaged in the investment simulation (and thus more active) than their nonsurveyed counterparts, and perhaps more conscientious. Moreover, it makes our result a conservative estimate of effects in the population, since we found significant relationships even within the subsample of investors skewed toward higher activity, and thus less heterogeneous than the full sample or the general population.

The online survey,[5] which could be completed within thirty minutes, consisted of the following scales: (a) the DOmain-SPEcific Risk-Taking Scale: DOSPERT (Weber et al. [2002]), with the Gambling and Investing Risk Propensity (Sub)scales shown in Table 1(a)[6]; (b) the Stimulation-Instrumental Risk Inventory: SIRI (Zaleśkiewicz [2001]), shown in Table 1(b); and (c) items that measured participants' self-assessment of their knowledge about the stock exchange market as well self-reported characteristics of their stock exchange decisions, shown in Table 1(c). The order of the questions within each block (a-c) was randomized by computer software. Finally some socio-demographic data were collected (i.e., age, gender, university affiliation, university major, working and professional status, income).

RESULTS

Trading Records of Simulation Participants

A transaction record consists of the participant's identification number, the type of transaction placed (short/long), buy/sell indicator, traded stock name, number of shares

TABLE 3
Means and standard deviations of DOSPERT and SIRI scales, across participants and also as a function of gender and age

			Gender			Age median split		
Risk-behavior	*M*	*SD*	Male $N = 513$	Female $N = 119$	*t*-test value	Aged 22 or less $N = 322$	Aged over 22 $N = 310$	*t*-test value
DOSPERT								
Investment	10.55	(2.83)	10.45	10.97	−1.80	10.58	10.50	0.36
Gambling	8.13	(4.30)	8.16	7.99	0.39	8.06	8.20	−0.42
Health/safety	17.29	(4.72)	17.58	16.03	**3.27*****	17.48	17.05	1.14
Recreational	23.98	(7.03)	24.39	22.19	**3.10*****	24.17	23.77	0.72
Ethical	19.98	(6.40)	20.07	19.63	0.67	20.16	19.83	0.65
Social	22.00	(3.86)	21.95	22.24	−0.67	22.19	21.79	1.28
SIRI:								
Stimulation	25.94	(6.57)	26.12	25.17	1.42	26.22	25.65	1.10
Instrumental	17.66	(1.94)	17.74	17.30	**2.23****	17.68	17.63	.32
Perceived market knowledge								
Perceived market knowledge	16.42	(4.64)	16.97	14.06	**6.364*****	15.93	16.95	**−2.76*****

***/** indicate that the coefficient estimates are significantly different from zero at the 1%/5% level.

traded and transaction price, order placement date, period of validity for the order, and transaction date. Using these data, the activity of participants (all buys, sells, and holds) could be summarized on a daily basis.

Generally participants ($N = 3{,}870$) traded quite very actively. On average they made 31.02 transactions ($SD = 38.42$), investing in 7.16 stock companies ($SD = 4.65$) and turning over 5.8 times their provided capital of 100,000 Polish zloty (PLN). While this trading activity is high and probably attributable to the fact that they were not investing real money, their activity seems to be comparable to the activity of real money investors revealed in other studies (75% of annual turnover, 250% for most active group in an American investor sample (Barber and Odean [2000]); mean turnover of 33% per month in a German online investor sample in the period 1997–2001 (Glaser and Weber [2007]); mean turnover of 17% per month in a German online investor sample in the period 1995–2000 (Dorn and Huberman [2005]); average yearly turnover of 113% in a Swedish online investor sample in the period 1991–2002 (Anderson [2008]).

Self Reported Risk-Taking Propensities and Risk-Taking Motives

Traders' risk-taking propensity in different domains was measured with the DOSPERT inventory (Weber et al. [2002]), which assesses degree of risk-taking in six content domains: investing, gambling, health/safety, recreational, ethical, and social decisions. For each particular area, respondents rated the likelihood that they would engage in risky activities typical for the particular domain on a 5-point Likert scale. The sum of the points for the particular domain (and thus subscale) represents respondents' risk-taking propensity in that domain and can serve as a measure of individual differences in domain-specific risk taking.

A factor analysis (PCA with Oblimin rotation) of these data confirmed the six-factor solution: investment, gambling, health/safety, recreational, ethical, and social risk propensity. Means and standard deviations of the six risk propensities are shown in Table 3, as are the results of t-tests examining whether these risk propensities differed by gender or age. Table 3 also reports means and standard deviations of the two SIRI scales, the degree to which investors had an instrumental or a stimulation-seeking motive for their risky decisions.

To confirm the hypothesized relationships between the two sets of scales, we separately regressed investors' gambling and investing risk-propensity scores DOSPERT scores on the two SIRI scales (stimulation and instrumental risk motives). As shown in Table 4 and consistent with Hypothesis 1a, inventors' gambling risk propensity was positively related to their stimulation-seeking motive for risk taking and not related to their instrumental motive for risk taking.

TABLE 4
Results of regression predicting DOSPERT gambling and investment risk propensity scores by SIRI stimulation and instrumental risk taking motive scores.

Column DOSPERT Dependent variable	(1) Gambling risk propensity Estimate	t-statistic	(2) Investment risk propensity Estimate	t-statistic
Intercept		1,282		8,086
SIRI				
Stimulation motive	**0.498**	**13.919*****	−0.021	−1.519
Instrumental motive	−0.054	−1.501	**0.089**	**2.182****
Number of investors		633		633
R square		23.8%		0.8%
Anova		98.429***		2.381

***/** indicate that the coefficient estimates are significantly different from zero at the 1%/5% level.

TABLE 5
Results of regression of investors' turnover volume.

	(1) Ln(turnover)		(2) Ln(turnover)	
Column	Estimate	t-statistic	Estimate	t-statistic
Intercept		35.564***		41.852***
RISK TAKING PROPENSITY				
Investment risk propensity	−0.025	−0.654	x	x
Gambling risk propensity	**0.097**	**2.313****	**0.077**	**2.065****
Health/safety risk propensity	−0.029	−0.651	x	x
Recreational risk propensity	−0.006	−0.139	x	x
Ethical risk propensity	−0.009	−0.211	x	x
Social risk propensity	−0.023	−0.560	x	x
DEMOGRAPHIC				
Age	**−0.127**	**−3.220*****	**−0.120**	**−3.070*****
Gender dummy	**−0.089**	**−2.235****	**−0.090**	**−2.318****
SOPHISTICATION				
Perceived market knowledge	−0.067	−1.703	−0.066	−1,687
Short sell dummy	**0.330**	**8.605*****	**0.327**	**8.644*****
Working status dummy	−0.014	−0.354	−0.022	−0.576
Number of investors		632		632
R square		13.6%		13.2%
Anova		8.856***		15.920***

Note. Short sell dummy is 1 if investor has at least one short sale in trading record. Gender dummy is 1(0) if the trader is female (male). Working status dummy is 1 (0) if working (not working) professionally.
***/** indicate that the coefficient estimates are significantly different from zero at the 1%/5% level.

Consistent with Hypothesis 1b, the opposite was true for inventors' investment risk propensity; that is, it was positively related only to the instrumental motive for risk taking.

Determinants of Trading Volume

To test Hypothesis 2(a) that trading volume is positively related to investors' gambling risk propensity, we regressed investors' turnover volume (defined as the total value of all conducted transactions, both buy and sell) on all six DOSPERT risk propensity subscales. Other independent variables were included as covariates, motivated by previous research results (Dorn and Huberman [2005], Glaser and Weber [2007], Kumar and Lim [2008], Nosic and Weber [2010]): gender, age, perceived knowledge, and three proxies for investors' sophistication (perceived knowledge, short-sell dummy, working-status dummy).[7] We measured investors' perceived knowledge in the stock market using the five items listed in Table 1(c), which provided an internally consistent perceived-knowledge scale, with a Cronbach Alpha coefficient of .79. Perceived knowledge differed significantly as a function to gender and age, as shown in Table 3, with men and older investors reporting greater knowledge, and a significant positive correlation also with the continuous age variable, $r(632) = .121, p < .05$.

The positively skewed "turnover"[8] variable was transformed to be normally distribution by applying a natural logarithm transformation in order to meet the OLS regression requirement of a normal distribution of errors. For this and other regressions reported below, regression coefficients and significance levels were not appreciably affected by this transformation, and thus raw data regressions are not reported.

The results presented in Table 5 support the value of assessing risk propensity in a domain-specific way. Consistent with H2(a), only gambling risk-taking propensity (and none of the other five risk propensity scores) predicts turnover similar to the results reported by Dorn and Sengmueller [2009]. Consistent with previous results, gender and age were also significant predictors of turnover, with men and younger investors showing greater turnover volume. Investor's trading sophistication (measured as short-selling engagement, as proposed by Goetzmann and Kumar [2008]), also increased turnover activity. The percentage of total variance in logarithmically-transformed turnover explained by the full set of predictors was 13.6%, similar to what has been reported in regression analyses concerning turnover in real decisions made in the stock market[9] (e.g., Dorn and Sengmueller [2009], Goetzmann and Kumar [2008], Grinblatt and Keloharju [2009], Kumar and Lim [2008], Menkhoff, Schmidt, and Brozynski [2006]). Regressing turnover volume on only gambling risk propensity (instead of all risk propensities of the DOSPERT scale; second column of Table 5) provides essentially the same results.[10]

TABLE 6
Trading style and portfolio characteristics of day-trading and non-day-trading investors for investors who completed the online survey.

	Daytraders, $N = 347$		Nonday traders, $N = 285$		
	M	*SD*	*M*	*SD*	*t*-test value
Investor personal characteristics					
Age	22.435	1.605	22.782	2.123	**2.340****
Gender dummy	0.176	0.381	0.204	0.403	0.886
Investor activity					
Total turnover	1 004 798	694 537	325 785	291 145	**−16.529*****
Turnover not generated by day trading	894 753	595 083	325 785	291 145	**−15.672*****
Conducted transaction	60.550	54.698	15.758	13.269	**−14.736*****
Portfolio diversification					
NV	0.599	0.320	0.584	0.325	−0.603
SSPW	0.155	0.122	0.310	0.273	**8.893*****
Avg. No.	1.973	0.963	1.933	1.065	−0.492
HHI	0.210	0.132	0.388	0.282	**9.809*****
Number of traded stocks	10.700	4.530	5.747	3.705	**−15.122*****
Investors performance					
Total paid commissions	5 091	3 498	1 656	1 461	**−16.607*****
Final portfolio value after commissions	98 649	12 906	99 340	15 087	0.612
Final portfolio value before commissions	103 739	13 237	100 997	15 426	**−2.370****
Ratios					
proportion of long transaction among all conducted (short + long)	0.845	0.204	0.932	0.161	**6.005*****
Execution ratio	0.866	0.115	0.828	0.174	**−3.158*****
Motives and Traits					
Stimulation motive	26.061	6.578	25.782	6.589	−0.528
Instrumental motive	17.634	2.050	17.698	1.804	0.414
Investment risk propensity	10.331	2.901	10.789	2.725	**2.030****
Gambling risk propensity	8.228	4.351	8.011	4.246	−0.631
Health/safety risk propensity	17.277	4.664	17.267	4.756	−0.027
Recreational risk propensity	24.066	6.791	23.867	7.326	−0.352
Ethical risk propensity	20.222	6.720	19.723	5.979	−0.987
Social risk propensity	28.251	4.565	28.393	4.635	0.387
Perceived market knowledge	16.461	4.466	16.396	4.851	−0.174
Online survey question					
Frequency of logging into transaction platform (1-Few times a day, 6-Once a month and less frequently)	2.99	.996	3.35	.948	**4.626*****
Declared engagement into investment game (1-I am strongly engaged in this investment game 5-I am not engaged in this investment game at all)	2.19	1.291	2.88	1.592	**5.883*****

Note. Gender dummy is set to one (zero) if the trader is female (male).
***/** indicate that the coefficient estimates are significantly different from zero at the 1%/5% level.

Determinants of Day Trading

We calculated the cumulated value of turnover due to day trading, as the sum of the value of all day-trading transactions, day by day and stock by stock. As reported by Barber et al. [2005], the majority (64%) of day-trading involves the purchase and then sale of the same number of shares over the course of one day; however, we decided to include in the day trading value also partially closed position. Thus, in case a position was opened and then closed partially on the same day, the value of the day-traded closed part was added to the day-trading value calculation. The total value of all day-trading transactions of respondents who participated in the questionnaire part of the study ($N = 633$) amounted to 76 million PLN, making the day-trading transactions responsible for almost 17% of the total turnover (more than 441 million PLN), similar to the figures reported for real stock markets earlier in the paper. In fact, almost 50% of participants made one day-trading transaction at least once.

Table 6 summarizes the major differences between day trading investors (with at least one day-trading activity) and the other investors (with no day-trading activity at all) for the investors who also participated in the investment simulation and the questionnaire study and thus provided more variables on which they could be compared. Investors with day-trading activity were more active than others, and their turnover was much higher, even for the remaining part of turnover not generated by day-trading activity. The results of the online survey suggest also that they spend significantly more time for trading related activities: more frequently logging into the virtual

TABLE 7
Results of regression predicting extent of day-trading among those with at least one daytrading transaction

Column Dependent variable:	(1) Fourth root (share of daytrading transactions' value in all conducted value) Estimate	(1) t-statistic	(2) Fourth root (total value of all conducted daytrading transactions) Estimate	(2) t-statistic
PANEL A				
Intercept		1.532		0.842
RISK TAKING PROPENSITY				
Investment risk propensity	−0.057	−1.092	−0.007	−0.127
Gambling risk propensity	**0.241**	**4.068*****	**0.253**	**4.266*****
Health/safety risk propensity	−0.072	−1.164	−0.041	−0.661
Recreational risk propensity	−0.020	−0.329	−0.056	−0.903
Ethical risk propensity	−0.041	−0.654	−0.060	−0.948
Social risk propensity	−0.080	−1.388	−0.062	−1.076
DEMOGRAPHIC				
Age	0.118	**2.108****	0.099	1.777
Gender dummy	**−0.171**	**−3.050*****	**−0.159**	**−2.819*****
SOPHISTICATION				
Perceived market knowledge	0.033	0.592	−0.012	−0.224
Short sell dummy	−0.023	−0.416	0.070	1.245
Working status dummy	−0.074	−1.344	−0.069	−1.253
Number of investors		347		347
R square		10.6%		9.9%
Anova		3.607***		3.334***
PANEL B				
Intercept		,166		−,293
RISK TAKING PROPENSITY				
Gambling risk propensity	**0.180**	**3.420*****	**0.188**	**3.572*****
DEMOGRAPHIC				
Age	**0.131**	**2.374****	**0.113**	**2.037****
Gender dummy	**−0.171**	**−3.143*****	**−.155**	**−2.843*****
SOPHISTICATION				
Perceived market knowledge	0.036	0.657	−0.011	−0.198
Short sell dummy	−0.031	−0.567	0.054	0.992
Working status dummy	−0.098	−1.820	−0.097	−1.797
Number of investors		347		347
R square		8.3%		8.0%
Anova		5.123***		4.935***

Note. Short sell dummy is a dummy variable, set to one if investor has at least one short sale in his trading record. Gender dummy is set to one (zero) if the trader is female (male). Working status dummy is set to one (zero) if the trader is professionally working (not working).

***/** indicate that the coefficient estimates are significantly different from zero at the 1%/5% level.

investment simulation system than their counterparts, as well as higher engagement levels in the game than the nonday-trading investors. In general, they kept more diversified portfolios than their nonday-trading counterparts, in terms of diversification measures related to stocks weights in portfolio, though not in terms of choosing noncorrelated stocks. Due to their greater activity, the day-traders also paid significantly higher transaction costs than the other investors. In fact, commissions consumed almost all their interest: before deducting transaction costs, day-traders performed significantly better than other investors, but after costs their portfolio returns were practically equal to those of nonday-trading investors.

The day traders seemed to seek novelty. They traded with more companies' stock and kept more diversified portfolios. They also were more prone to use the short-sell mechanism than others and had a higher execution ratio, suggesting that they placed orders without price limits or with less demanding price limits. Apparently they do not want to delay transactions but want to have them conducted now or soon, with less regard for price. Day traders reported significantly smaller investment risk propensity than nonday traders, but contrary to our expectations did not report greater gambling risk propensity.

A different result emerges, however, when we analyze the *extent* to which investors were engaged in day trading. Whereas almost half of traders engaged in day trading at least once, some conducted only one day trading transaction (accounting for less than 1% of all their conducted transactions). For others, day trading transactions were up to 77% of their turnover volume. Day-trading related

TABLE 8
Pearson correlations among the explanatory variables

	Investment risk propensity	**Gambling risk propensity**	Health/safety risk propensity	Recreational risk propensity	Ethical risk propensity	Social risk propensity	Stimulation motive	Instrumental motive	Age	Gender	Perceived market knowledge	Short sell dummy	Working status dummy
Investment risk propensity	1.00												
Gambling risk propensity	.05	1.00											
Health / safety risk propensity	.01	.31**	1.00										
Recreational risk propensity	.04	.30**	.36**	1.00									
Ethical risk propensity	.00	.37**	.43**	.31**	1.00								
Social risk propensity	.08**	.19**	.27**	.37**	.19**	1.00							
Stimulation motive	.00	.49**	.34**	.47**	.30**	.22**	1.00						
Instrumental motive	.08*	.06	.12**	.12**	.09*	.23**	.23**	1.00					
Age	−.06	−.04	−.03	.02	−.05	−.07	−.05	−.06	1.00				
Gender	.07	−.02	−.13**	−.12**	−.03	.09*	−.06	−.09*	−0.07	1.00			
Perceived market knowledge	−.02	.04	−.06	.04	−.03	.01	.12**	.18**	.12**	−.25**	1.00		
Short sell dummy	−.03	.00	.00	.08	.09*	−.03	−.01	−.03	.12**	−.11**	.10**	1.00	
Working status dummy	−.03	−.06	.07	.10	.02	.08*	.02	.05	.26**	−.08	.11**	−.01	1.00

**/* indicate that the coefficient estimates are significantly different from zero at the 1%/5% level.

turnover among investors was highly related to nonday-trade related turnover ($r(3870) = .708$; $p < .0001$). To get a day-trading propensity measure, we calculated the ratio of total day-trading transactions' value divided by all transactions' value.

Table 7 summarizes the regression of this day-trading propensity index[11] on the same predictor variables described above (column 1, Panel A), as well as the regression of the (nonstandardized) total value of all day-trading transactions on the same predictors (column 2, Panel A). Consistent with H2(b), we found that gambling risk propensity predicted day-trading propensity, with day-trading activity rising with investors' gambling risk propensity.[12] Market knowledge did not predict day trading activity. More extensive day traders appear to be more devoted to trading activity, as evidenced by spending much more time (frequent logging into transaction system; see Table 6) and financial resources (higher transaction fees; see Table 6) on it, but do not get higher profits than others. Their most valued profit may be the thrill they take from investing, as suggested by the demonstrated relationship between gambling risk propensity and excessive trading and day trading.

CONCLUSIONS

This article contributes to the still small number of empirical studies that combine a psychometric approach with the analysis of economic choices. Our study measured financial risk-taking propensity in two domains (gambling and investing) and showed that they are differentially informed by two motives for taking financial risks: (a) a stimulation- or sensation-seeking motive that has the process of taking a risk as its goal, and (b) an instrumental risk-taking motive that has the outcome of the risky choices, that is, the achievement of material returns as its goal. Our results, in particular the fact that these two (easily assessed) risk propensities are not significantly correlated ($r = .05$, see Table 8), and that it is only gambling risk-taking propensity that predicts trading volume, support the utility of and need for such domain specific assessments of risk taking.

Our results suggest that many private investors may simply enjoy trading and focus more on the thrill and less on the profit. Day traders appear to be prime examples of such investors who spend more time and transaction fees than their nonday-trading counterparts but show slightly smaller profits for their efforts than other investors. For this group of traders, gambling risk propensity was significantly related to their extent of daytrading activity. It was previously suggested that some traders simply enjoy trading (Anderson [2008], Dorn and Sengmueller [2009], Glaser and Weber [2007], Kumar [2009]). Our results allow us to identify who this group is and to document and assess this stimulation-seeking rather than instrumental motive for their behavior.

Our results have implications for both researchers and practitioners, even if the results will still need to be replicated among real stock market investors. They show that gambling risk-taking propensity helps explain investors' trading activity and thus confirm the popular idea of day traders being "gamblers" ("Day Traders as Gamblers" [1999]), for at least part of the trading population.

Young men entering trading in stock markets appear to be vulnerable, at least in part because they are more likely to have a stimulation-seeking motive and suffer from overconfidence, making them more susceptible to financial losses by insufficient diversification and/or by excessive trading and transaction costs. Practitioners and regulators ought to consider some interventions designed to influence investors' gambling and instrumental motive, paying perhaps more attention to socio-demographic groups known to be at risk. Financial advisors could customize investment advice and recommend appropriate products to counteract undesirable investment choices or educate clients in customized ways, as envisioned by the European Parliament and the European Council (2004 and 2006) who issued the Markets in Financial Instruments Directive (MiFID), obligating financial advisors to evaluate customers' preferences regarding risk taking and elicit clients' risk profiles (§35,4).

LIMITATIONS

Like any single study, our study is subject to a number of limitations. The first relates to our sample of investment simulation participants, young (students), mostly male, and thus most likely more risk seeking than the general population of the investors (Kumar [2009]). Another limitation could be the investment objective of investment simulation participants. With the ten participants with the most successful portfolio value in the first round, analyzed in this article, moving on to a second round, participants' objective for the first round may not have been the maximization of their portfolio's expected value but rather the probability of entering the second round, choosing, for example, highly risky stocks that could put them in the top ten. Participants invested virtual money, and thus made hypothetical choices, even though the outcome of those choices had some tangible material consequences for them. However, it is worth repeating that the decisions made by investment simulation participants exhibited many investors tendencies, like the disposition effect and contrarianism during price trends forecasting (Kubińska and Markiewicz [2008], Kubińska et al. [2012]), previously observed among stock market participants investing their own money. It is our hope that the results of our study will provide provocative hypotheses for other researchers who will test them in more diversified samples of real investors and under different incentive conditions.

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NOTES

1. The Polish stock market requires a minimum commission that cannot be lower than 3–8 PLN ($1–3) per executed order. However, given the large virtual capital invested by simulation participants (PLN 100,000, or approx. $34,000), the lack of a minimal commission per transaction does not affect commissions charged.
2. In addition, short selling orders incurred an additional charge of .02% of the transaction value that paid for the raised loan. Short selling almost does not exist on the Polish stock investing market for non-institutional investors, which is probably the reason why a sizeable proportion (33%) of contestants had at least one short-sell transaction in their records; short transactions made up of 13% all transactions in term of their total number and 15% in term of their value. Given that no explanation of "short sell" was provided, the investors who used this mechanism were probably more sophisticated than other or alternatively more interested in the stock exchange market and thus decided try out this new mechanism.
3. The investment simulation was designed as a two-stage game. In the first stage all participants traded Polish blue chips stocks and only this stage is the subject of analysis for this paper. The ten investors with the highest portfolio values on the last day of this simulation were allowed to participate in a second investment simulation involving derivative contract betting during a single day chosen by the organizer. The prizes went to the highest achievers in this simulation.
4. A significantly higher response rate was achieved than in other studies with online recruitment among investors. That is, 6% (Dorn and Sengmueller [2009]) up to 7% (Dorn and Huberman [2005], Glaser and Weber [2007]) among German online investors. The greater response rate in our sample could be due to different sample characteristic (students, not adult working population) or by the fact that the invitation email was sent by an academic researcher (and not a private market research institute).
5. The full questionnaire is available from the authors on request.
6. The other subscales can be found in Weber et al. [2002].
7. Following Goetzmann and Kumar [2008], we assumed that the investors who engage in short selling, and those who work (and thus have higher income) are likely to be more sophisticated.
8. The total value of all transactions conducted by the participant, both sell and buy transactions.
9. If such R^2 ratios do not appear to be high, it should be kept in mind that we are explaining a variable that is highly dependent on random factors, for example, changes in stock prices.
10. We also examined whether gambling risk-taking propensity might affect trading volume differentially for different segments of investors, by adding the interactions between gambling risk-taking propensity and the demographic predictors in Table 5 as predictor variables. However, none of these interactions were significant.
11. The fourth-root transformation has been used to meet OLS requirement of a normal error distribution. Regression result with nontransformed dependent variable did not differ in terms of significance of coefficients and their signs, and thus are not presented here.
12. Using only gambling risk-taking propensity instead of all six domain risk propensities (see Table 7, Panel B) does not change these results significantly. Gambling risk-taking propensity remains as a single most important predictor variable, more important than age and gender. Again, there were no significant interactions between gambling risk taking and any of the demographic variables in their prediction of day-trading propensity. Table 8 provides the correlations between all predictor variables used in our study.

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