

House Money Effect:
Evidence from Market Makers at Taiwan Futures Exchange¹

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ABSTRACT

We document empirical support for the ‘house money’ effect proposed by Thaler and Johnson (1990). Market makers for Taiwan’ TAIEX index options take above-average risks in afternoon trading after morning gains. The fraction of market makers with morning gains influences market-level liquidity and volatility in the afternoon trading. Our findings confirm that prior outcomes influence subsequent risk-taking and emphasize that the way in which investors frame previous outcomes alters their subsequent attitude toward risks.

The canonical standard expected utility function in economic theory assumes that all outcomes are integrated into terminal wealth, which singularly influences economic agent behavior (Mas-Coell et al. 1995). Behavioral economics, on the other hand, contends that prior outcomes can change economic agents' prospects and their subsequent risk-taking. In particular, the prospect theory argues that "the value function is normally concave for gains, commonly convex for losses, and is generally steeper for losses than for gains" (Kahneman and Tversky 1979). As a result, prior gains and losses should influence subsequent risk-taking in a different fashion.

One very important implication from prospect theory is loss aversion, which suggests that equal-magnitude gains and losses do *not* have symmetric impacts on decision-making. Losses hurt more than gains satisfy. Instead of pursuing the maximum expected utility, people may rather try to avoid losses (Barberis et al. 2001, Shleifer 2000). Consistent with loss aversion, several studies document the disposition effect that investors are more likely to realize winners than losers in various financial markets.² More recently, Coval and Shumway (2005) report more direct findings that treasury traders at the CBOE significantly increase their afternoon risk-taking after morning losses.

In contrast, little has been understood about how people behave after previous successes. Because the attitude toward risk is quite different facing prior gains vs. losses, it should not be taken for granted that people reduce risk-taking after prior gains. As a matter of fact, some recent research indeed finds that investors take more risks after prior successes, similar to their behavior after prior losses. Malmendier and Tate (2005) find that 'super-star' CEOs, who have garnered recent successes recognitions, are more likely to engage in risky transactions such as aggressive merger and acquisition activities. In addition, Nicolosi et al. (2005) find that individual investors, those who are usually assumed to be the least sophisticated among all, increase subsequent trading intensity and take on greater risks after making profitable trades.

² Odean 1999, Dhar and Zhu 2005, Genesove and Mayer 2001, Heath et al. 1999, among others.

Daniel et al. (2001) and Gervais and Odean (2001) attribute such a relationship to over-confidence and self-attribution, and contend that investors may change beliefs about their own abilities following prior successes. At the same time, it is also likely that prior gains can alter individuals' subsequent attitude toward risks. One specific example is the house money effect proposed by Thaler and Johnson (1990), which claims that people may indeed *increase* their risk-taking after prior gains under some circumstances. The authors argue that, "after a gain, subsequent losses that are smaller than the original gain can be integrated with the prior gain, mitigating the influence of loss aversion and facilitating risk-seeking" (p657, Thaler and Johnson 1990).

Clearly, the house money effect is generally consistent with prospect theory in that the framing of prior outcomes heavily influences individual behavior. What distinguishes the house money effect is that it focuses primarily on dynamic decision-making in which people have to choose how to frame prior losses vs. gains and how such choices influence future risk-taking. It is important to note how behavior shifts when researchers extend the one-stage experiments into multiple-stage versions, which arguably provide a better depiction of many real-life applications. Following laboratory experiments (Ackert et al. 2003, Battalio et al. 1990, Keasey and Moon, 1996) provided strong support for the house money effect. However, there has been little empirical support from the field so far.

The current study intends to bridge the gap by providing empirical support for the house money effect and evidence on how prior outcomes influence subsequent decision making in a dynamic context. We use the complete trading record for all TAIEX option market makers at the Taiwan Futures Exchange (TAIFEX) between 2001 and 2004, and find strong evidence that prior trading successes induce greater subsequent risk-taking. Market makers increase/decrease the number of orders and trades, the size of their orders and trades, and aggressiveness in getting orders filled in the afternoon trading, after obtaining morning profits/losses. Controlling for other factors, market makers with morning profits are 14 percent more likely to take above-average risks in afternoon trading. One standard deviation increase in abnormal morning profits can lead to a 0.08

standard deviation increase in market makers' afternoon risks. Additional analyses reveal that competing hypotheses such as over-confidence, career concerns, and advantageous information cannot explain the findings.

Consistent with a previous study claiming that behavioral biases influence asset prices (Coval and Shumway 2005), market makers' response to previous trading outcomes exerts significant impact on how the market evolves. An increase of one standard deviation in the fraction of market makers with above-average morning performance leads to a 0.23 to 0.35 standard deviation increase in the afternoon market-level volatility. The aggressive trades that market makers engage in after above-average-profit morning trading also improve market level liquidity. An increase of one standard deviation increase in the fraction of market makers who are above their average performance leads to a decrease of 0.14 to 0.23 standard deviation in market level spread. Hence, our findings confirm previous studies that indicate behavioral biases affect asset prices.

Finally, we discuss several factors that may explain why existing studies generate various results on the relationship between prior outcomes and subsequent risk-taking. Although differences in investor type, security type, market development and culture are potentially responsible for the differences in the results, we believe that none of them drives the house money effect.

Our findings that prior outcomes influence future decision-making provide additional support for the prospect theory, in that the prospect of gains and losses changes investors' attitude toward risks. More importantly, the results highlight that risk-taking behavior can be different from loss aversion in a multiple-period context, depending on how subjects frame previous outcomes. The current study calls for future research on how people frame a series of events and under what circumstances investors integrate or separate prior outcomes. The fact that market makers' responses to prior outcomes vary across countries and securities markets highlights the complexity of human behavior and calls for further studies on a broader range of financial markets.

The rest of the study proceeds as follows: Section 2 reviews related literature on behavioral biases that may influence consequent risk-taking; Section 3 presents the data from TAIEX; Section 4 discusses methodology and presents empirical findings; Section 5 discusses the results, while conclusions are offered in Section 6.

2. Prior Outcomes and Risk Taking

In contrast with standard expected utility function, Kahneman and Tversky's (1979, 1981) seminal on prospect theory propose that people derive values from gains and losses in a different fashion, rather than from the absolute level of their wealth. Value function is concave in the domain of gains (implying risk aversion) and convex in the domain of losses (implying risk seeking). Hence, people are expected to take more risks in order to break even after initial losses.

Several studies on the disposition effect, investors' tendency to realize winners but hold onto losers, confirm such an asymmetric response to gains versus losses. Genesove et al (2001), Heath et al.(1999), Odean (1999), and Dhar and Zhu (2005) find that investors in housing, option and common stock markets are more likely to realize winner than loser stocks, primarily because realizing a loss (as opposed to keeping the possibility of breaking-even) incurs greater utility loss.

A more direct test of loss aversion by Coval and Shumway (2005) documents loss-aversion by professional traders in the Treasury bond futures market at CBOT during 1998. The traders with morning gains/losses were more likely to assume above/below-average risks in afternoon trading. Because the initial utility incurs the most utility loss, traders are found to increase risks to break even after morning losses.

Relatively little is known about how prior outcomes influence subsequent risk-taking in dynamic environments. Kahneman and Tversky (1981) acknowledge that the loss aversion implication of prospect theory is most appropriate in interpreting a one-shot game. The outcomes in multiple-period decision making, a more realistic reflection of

decision-making in the financial market, require identification of reference points and assumptions about how people frame decisions under different circumstances. Therefore, it is possible that people behave in ways that deviate from or even contradict with loss-aversion. For example, when looking at the weekly horizon, Locke and Mann (2003) find little change in active traders' risk-taking after abnormal gains³ at the Chicago Mercantile Exchange in 1995.

Thaler (1980), as well as Johnson and Thaler (1990), point out that individuals' sequential decision-making can be heavily influenced by how they frame previous gains and losses. If they follow 'hedonic editing' or 'quasi-hedonic editing,' a rule that decision makers use to maximize their own satisfaction, they may tend to integrate small losses into prior gains. By doing so, individuals can indeed 'eliminate' the losses in their mental accounts and obtain better satisfaction. If this were to hold, prior gains could induce people to take on more risks.⁴ The authors refer to such a phenomenon as the 'house money' effect, from the gambling parlance of "playing with the house money" when gamblers are ahead.

Several other experimental studies (Ackert et al. 2003, Battalio et al. 1990, Keasey and Moon, 1996) provide additional support for the house money effect but there is a lack empirical support on real-life observations. One exception is the work by O'Connell and Teo (2004), which reports an inverted relationship between prior outcomes and risk-taking for institutional investors in the United States: mutual fund managers increase risk-taking after both net gains and net losses. They also find that experience can attenuate such a relationship, consistent with Dhar and Zhu's (2005) finding that experience helps alleviate behavioral biases.

Different from our study that investigates intra-day trading behavior, O'Connell and Teo (2004) focus mostly on longer horizons such as a weekly basis. A longer time horizon clearly provides a richer environment to study how a wider range of factors, such

³ Such trades trade foreign currency and agricultural contracts. Foreign currency included the Deutsche Mark and Swiss Franc, and agricultural contracts include live cattle and pork bellies.

⁴ The opposite holds for prior losses.

as trading strategy and incentives, can influence risk-taking. In contrast, our focus on a very short horizon provides a sharper focus and more detailed depiction on market maker behavior. Hence, our study concentrates squarely on the behavioral patterns of market makers, which differs from O’Connell and Teo’s (2004) emphasis on institutional background and risk-control.

Because the house money effect is built upon the general framework of the prospect theory, with an additional assumption for some forms of mental accounting, our findings on the house money effect lend direct support to the mental accounting of Thaler (1985, 1999), and enrich the extant literature of its impact on financial markets. For example, Barberis et al. (2001) argue that investors treat separate investments differently, and such mental accounting can explain the equity premium and other puzzles in the financial market. Arguments of similar nature received empirical support from Lim (2005) and Kumar and Lim (2005), which document evidence that individuals frame gains and losses separately for trades further apart in time, and that behavior in this vein causes certain portfolio performance implications. Our findings emphasize that framing and mental accounting are not limited to individuals (who are commonly assumed to be susceptible to behavioral biases) but are also prevalent among professional investors who have a potentially greater impact on asset prices.

Further, our paper provides new evidence on how behavioral biases, as shown through market maker behavior, may exert influence on the financial market. Because market makers are integral in maintaining market liquidity and helping set prices, our study relates to the broader literature on how market micro-structure influences asset pricing⁵. Our study complements Coval and Shumway (2005) that documents behavioral biases affect asset price, yet through a different behavioral mechanism. Such findings offer additional support to the developing literature on behavioral finance and emphasize the complexity of investor behavior: investors in different markets may display different behavioral patterns, which ultimately lead to similar impact on asset prices.

⁵ Grossman (1976), Klock and McCormick (1999), Kyle (1985), and Manaster and Mann (1996)

3. Data Description

We obtained complete order and trading data on TAIEX options for 753 trading days between December 24, 2001, and December 31, 2004⁶. The Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) options have been listed in the Taiwan Futures Exchange (TAIFEX), the only futures exchange market in Taiwan, since December 24, 2001 (Appendix A discusses the operational details of the TAIFEX). From 2003 on, the TAIFEX options have become very popular financial products. In 2003, with an annual trading volume of 21,720,083 lots and a growth of 1,286.58% over 2002, the products were ranked No. 4 among all the index options in the world and No. 2 in Asia, in terms of number of traded lots.⁷ The data can identify all transactions, orders and quotations. The transaction data include transaction price, time, and counterparty order for all transactions. By combining the transaction file with the order and quotation file, we can identify the originating party and associated orders and quotes for all trades.⁸

There are both call and put TAIEX options traded at TAIFEX, which expire in five different expiration-months: the spot month, the next two calendar months followed by another couple of months from the March quarterly cycle (March, June, September, and December). The last trading day and the expiration day are the third Wednesday and Thursday of the respective months, respectively. The final settlement price for each contract is computed as the volume-weighted average of each index component stock price in the first 15-minute trading on the final settlement day. For those component stocks whose prices are not available during the beginning fifteen-minute interval on the final settlement day, their last closing prices from the previous trading day would be applied instead. All contracts are settled with cash and in-the-money options will be exercised automatically upon expiration. (For greater details, please see www.taifex.com.tw.)

⁶ There were 6, 248, 249, 250 trading days, respectively, in 2001, 2002, 2003, and 2004.

⁷ See <http://www.futuresindustry.org/sitesear2251.asp?sOperator=AND&sStr=Record+Levels+of+Trading+Activity+&sFunc=Search>

⁸ Unlike the Taiwan Stock Exchange, which changed its regulation on market transparency (the number of best bid and ask quotes available to investors) during the sample period, the Taiwan Futures Exchange maintained the same reporting and disclosure regulation throughout our sample.

According to TAIFEX, three major categories of investors—market makers, institutional traders, and individual traders—participate in the TAIEX options market. Market makers are responsible for providing liquidity for the market by trading through their own accounts. Institutional investors can trade with their own accounts or on behalf of their clients. Both institutional and individual traders include local and foreign investors.

In this study, we focus on the 21 market makers⁹ that actively make market at the exchange.¹⁰ All market makers are employees at different securities companies that obtain permission to serve as market makers in the index option market. The same securities firms also have other branches (i.e. proprietary trading and brokerage services) that trade index options. Market makers execute trades in the following three accounts: quotation, responding to request-for-quote (RFQ), and order account for principal trading. The data enable us to distinguish between the three types of accounts for market makers who perform the three operations at the same time. Among all trades executed on the TAIEX option during the sample period, 58.43, 37.84, and 3.73 percent of the contracts were executed through order, quote, and RFQ accounts.¹¹ Table 1 provides some key summary statistics of the data.

It is worth mentioning that the exchange provides trading commission concessions for market makers for volumes over a certain limit in order to encourage market makers to actively make market and insure market liquidity. Hence, it is common for securities companies to use their market maker arm to execute trades for propriety trading (we provide more details about trading commission concessions in Appendix B).¹² Consequently, market makers represent the majority of trades for the securities

⁹ Not all 21 market makers make market during the entire sample period. A few market makers exit the market-making business because they fail to meet the TAIFEX requirement for liquidity provision.

¹⁰ There are several motivations. First, although there is increasing evidence on individual and institutional investor behavior, evidence on market maker's trading behavior is still limited. Second, market makers make up the majority of the trading volume during the majority of our sample period and trade constantly in the market, which enables us to observe continuous trading patterns over the entire sample period.

¹¹ Order, quote, and RFQ account makes up 53.96, 41.91, and 4.12 percent of total dollar trading volume.

¹² According to supplementary TAIFEX data, major players in the index option market are also major participants in the remaining financial market in Taiwan.

firms. Not surprisingly, there is a great deal of heterogeneity in market makers' profiles. The daily number of trades is 526.14 for the average market maker and the standard deviation is similarly large at 525.14.

We further verified with the employers of market makers that it is common practice for only one person at a time to serve as the market maker at the TAIFEX option market for each company. Market makers are typically evaluated through their performance (including primarily trading profits) on a monthly basis by their employers, who are required to file such information with regulators at the Taiwan Futures Exchange. Such monthly evaluations look at much longer periods than the intra-day observations that we focus on in this study. Therefore, we believe our data provide an unbiased view of market makers' behavior, with little complication from career considerations. In addition, our conversations with brokerage managers, market regulators, and market makers themselves depict the same picture that trading profits from order accounts far outweigh the profits that market makers obtain from the other two accounts, and therefore have the biggest impact on market makers' decisions.¹³ Consequently, we focus primarily on the order accounts in the following analyses.

4. Morning Trading Outcomes and Market Makers' Afternoon Risk-Taking

4.1. Methodology

Similar to Coval and Shumway (2005), we study whether morning trading outcomes influence market makers' risk-taking in the afternoon. This very short period offers the 'cleanest' context for studying how prior outcomes influence subsequent behavior. Market makers actively manage their inventory during trading hours, and doing so requires them to pay close attention to intra-day order flow and trading outcomes. As one extends the period, defining prior outcomes becomes complicated (i.e. whether to use

¹³ We provide additional discussion about the three types of accounts and the compensation scheme and how they might influence market makers' decisions in Sections 4 and 5.

outcomes of the prior day, week, or month) and raises the question of whether more recent prior outcomes exert a greater influence on subsequent decisions (Mullainathan, 2002). Other behavioral biases, such as over-confidence and self-attribution, also tend to develop over time. Studying behavioral change within the same trading day, therefore, provides an ideal setting in which to study shifts in risk-taking in response to prior outcomes.

We take the following steps to calculate market maker profitability and the level of risks that they subsequently take. First, we identify all trades on different TAIEX option contracts made by each market maker on every trading day. Similar to existing studies (Coval and Shumway 2005, Locke and Mann 2003), we assume that market makers start each trading day with zero inventory from previous trading. This assumption is consistent with the literature on market makers' inventory management in the United States.¹⁴ Such a choice makes it straightforward to compute trading profits of each morning. Within each trading day, we divide all trades into morning versus afternoon trades using the time of the trade. Trading sessions begin at 8:45 a.m. and close at 1:45 p.m. at TAIEX. Therefore, we classify trades before the mid-point of 11:15 a.m. as morning trades and those afterwards as afternoon trades.¹⁵

To determine whether a market maker makes a profit or incurs a loss in a morning, we calculate both the realized gains/losses and paper gains/losses for the morning sessions.¹⁶ If a trade was executed on a contract where there is no existing position, it is considered an initiation trade and we record the position after the trade. If a trade was executed on a contract where there is an existing position, the trade is identified as

¹⁴ Alternatively, we utilize the entire trading history of each market maker to trace the market maker's portfolio over time and use the change in the value of market maker holders to compute profits and losses. One shortcoming of such approach is that market makers may engage themselves in some synthetic trading strategies that last more than a single trading day, which may add noise to inferences on the calculation of morning profits. Nonetheless, this alternative approach generates very similar results.

¹⁵ We also perform robustness check in which we profits at 11 a.m. and 12 a.m. as morning profits and obtain very similar results.

¹⁶ Naturally, we have to make certain assumptions about how market makers trade. In the rest of the study, we assume that market makers follow a first-in-first-out rule in trading the same contracts. We believe this is reasonable given that market makers actively trade on the contracts. We also replicate our analyses by using first-in-last-out assumption and the results remain qualitatively the same.

another initiation trade if it is in the same direction as the position (i.e. the market maker currently holds 100 contracts long position and the trade is to purchase another 100 contracts), and a liquidation trade if it is in the opposite direction as the position (i.e., the market maker currently holds 100 contracts long position and the trade is to sell 100 contracts, thereby reducing the current position) and the position is updated after each trade.

Realized gains and losses are calculated whenever there is a liquidation trade. For each liquidation trade, a gain or a loss is determined by comparing the price of the liquidation trade with that of the corresponding initiation trade. The corresponding initiation trade is determined on a first-in-first-out basis.¹⁷ For example, if the liquidation is a sale, a gain/loss is calculated as $(P_s - P_b) * Quantity$, where P_s is the selling price; P_b is the purchase price; and $Quantity$ is the number of shares for the liquidation trade. We sum the realized gains/losses across all contracts held by the same market maker within a morning session, as the realized gains/losses for the morning session.

Paper gain/loss is determined as follows. We first summarize the outstanding position in each contract for each market maker at 11:15 a.m. and estimate the cost of accumulating such positions on a first-in-first-out basis. We then locate the prevailing price for each contract at the end of the morning trading session. Because trading may be sparse on some trading days, we look for the prevailing price within the half-hour window around 11:15 a.m. and use the price that is closest to 11:15 a.m. If no price is available during the window, we exclude the contract from calculating paper gains/losses. Total morning net gains/losses are defined as the sum of the realized and the paper gains/losses for each morning.¹⁸

As to risk taking in the afternoon trading session, the following proxies are used: the number of orders, the number of trades, order size, and trade size. These measures reflect how actively market makers engage themselves in trading and serve as noisy

¹⁷ For details, please refer to the example in Appendix C.

¹⁸ We also perform robustness checks by using only realized gains/losses and paper gains/losses as ways to determine morning gains/losses and obtain consistent results.

proxies for risk-taking.¹⁹ We also use the ratio of trades to orders to reflect the market makers' willingness to trade. A market maker is believed to be more aggressive when a higher fraction of his orders got executed.

Because of trader heterogeneity and high market volatility, absolute value of morning profit and afternoon risk level can introduce significant noise to our analyses. Following Coval and Shumway (2005), we control for this by normalizing the morning profit and risk measures. We calculate the standard deviation of morning profits for each trader and then divide each trader's daily morning profits by the standard deviation to obtain the trader's normalized morning profit. Consequently, normalized morning profit measure has a standard deviation of one for each trader.

The normalized afternoon risk measures are defined in a similar fashion. We calculate the mean and standard deviation of the afternoon risks for each trader. We then demean each trader's afternoon risk by the trader-specific average of afternoon risk and divide the difference by the trader-specific standard deviation of afternoon risk. We demean all measures with the average measure for the market maker in order to trace any 'abnormal' afternoon trading behavior. We denote trader i 's normalized measure of afternoon risk on date t as $Risk_{i,t}^A$, which may be used to reflect trader i 's various risk measures on date t . By construction, our risk measures have means of zero and standard deviations of one for each trader. In short, the above procedures are very similar to those used in Coval and Shumway (2005).

4. 2. Empirical Evidence

We first relate afternoon risk measures to the outcome of morning trading sessions in the summary statistics. Table 2 reports different afternoon risk measures for trading days with morning gains and losses. The most striking result across Panel A and B is that the afternoon risk measures are all above average and considerably greater for

¹⁹ Coval and Shumway (2005) also use the number of trades, trade sizes and total dollar risk. Locke and Mann (2005) and O'Connell and Teo (2004) use VaR approach for positions in foreign currencies futures and foreign currencies.

days with morning gains than those with morning losses. Market makers with morning profits place more orders (0.096 vs. -0.084), execute more trades (0.127 vs. -0.111), and place significantly larger orders and trades after above-average morning profits. All of the above differences are significant at the 1-percent significance level.

(Insert Table 2 about here)

In addition, we plot market makers' afternoon risk-taking in response to morning profits in Figures 1 through 4. For each market maker, we compute the average of various risk measures for trading days with morning gains and with morning losses, respectively. Twenty out of the 21 market makers make more orders and trades than their average during afternoon sessions following morning gains. Fourteen and seventeen of the 21 market makers make larger-than-average orders and trades, respectively, during the afternoon sessions after morning gains. These figures further support that how market makers frame morning trading outcomes as gains and losses matters considerably to their subsequent risk-taking.

Consistent with Coval and Shumway (2005), an investor's preference for risk is highly correlated between morning and afternoon sessions. We next perform the following regression analyses to directly control for the difference²⁰:

$$RISK_a = a + b_1 * PROFIT_m + b_2 * |INV_m| + b_3 * PROFIT_m * |INV_m| + b_4 * RISK_m + e \quad (1)$$

where $RISK_a$ is one of the measures of risk-taking in the afternoon. $PROFIT_m$ is the total morning profit for each market maker, calculated as the sum of the realized gains/losses and paper gains/losses, as defined in Section 4.1. $|INV_m|$ captures the absolute value of the position, which influences the market makers' position and risk exposure after morning trading. We also include the morning risk-taking to control for the findings in

²⁰ We also perform alternative specifications where we include the daily return and intra-day volatility of the TAIEX index. Neither the index return nor the intra-day volatility displays significant impact on market makers' afternoon risk-taking.

Table 2 that market makers take greater morning risks when they make profits during morning sessions.

Because prior outcomes may influence not only the magnitude of the subsequent risk-taking, but also whether market makers take above-average risks in subsequent trading, we also perform the following logistic regression:

$$\Pr(Risk_{i,t}^A > 0) = \frac{\exp(X' B)}{1 + \exp(X' B)}, \quad (2)$$

$$\text{where } X' B = a + b_1 * PROFIT_m + b_2 * |INV_m| + b_3 * PROFIT_m * |INV_m| + b_4 * RISK_m + e. \quad (3)$$

The dependent variable takes the value of 1 if a market maker takes above-average risks in the afternoon trading and 0 otherwise. Independent variables are similarly defined as in Equation (1).

(Insert Table 3 about here)

For Table 3 and Table 4, we use the trading activities in the order account to calculate the dependent variables.²¹ The order account makes up the majority of market makers' trading activities: it on average makes up 58.43 percent of market makers' total number of trades and 53.96 percent of their trading volume. More importantly, we believe that the order account can best reflect market makers' discretionary trading. Regulations on market makers' responsibility to make continuous quotations and ensure bid-ask spreads within reasonable range institute constraints on market maker's decisions in the quote and RFQ account.

Although it is common practice for market makers to execute a proportion of their principal trades through the quote accounts to take advantage of the rebate in

²¹ We also calculate the risk-measure using market makers' trading activity in all three accounts, and the results are similar to the ones presented in Table 3 and 4. Such results are available upon request.

commissions, market makers are far more passive in their RFQ accounts. Therefore, we expect weaker, if any, evidence of the house money effect from these two accounts. We indeed obtain similar, yet weaker, results using quote account and an insignificant relationship between morning profits and afternoon risk-taking for the RFQ account.^{22 23}

For the OLS results in Table 3, an increase of one standard deviation in morning profits can lead to approximately 7, 5, and 3 percent of a one standard deviation change in the afternoon number of trades, orders, and the trade to order ratio. The increases in order size and trade size are not statistically significant. The results using panel-corrected standard deviation in Panel B are similar and indeed stronger. In the panel specification, an increase of one standard deviation results in 8, 6, and 3 percent of one standard deviation in the afternoon number of trades, orders, and trade to order ratio. Finally, the coefficients for all five proxies are significantly positive in the logistic regression. The above findings provide clear support that market makers increase their risk-taking after successful trading during morning sessions. As expected, the coefficients for morning risk levels are highly positive, consistent with the summary statistics in Table 2 showing a strong positive correlation between afternoon and morning profits within the same trading day. Inventory and signed inventory do not have consistent impact on afternoon risk-taking.

Two issues merit further discussion. First, the house money effect predicts that whether a prior outcome is a gain or a loss can influence subsequent risk-taking and does not stipulate a linear relationship between morning profit and afternoon risk-taking. Therefore, we replicate the above regressions by replacing the morning profit variable with a dummy variable that equals to 1 if a market maker recorded morning profit. Findings in Table 4 confirm that the dummy variable for above-average morning profit is indeed associated with greater risk-taking in the afternoon. A market maker with above-

²² We do not include the results on quote and RFQ accounts to conserve space. Results are available upon request.

²³ Different from the order account data that include 753 trading days, the data on quote and RFQ accounts are available on 703 days. Data on quote and RFQ accounts are missing for 52 trading days (6 days in 2001, 42 days in 2002, 1 day in 2003, and 1 day in 2004) during the sample period.

average morning profit executes 0.08 standard deviation more trades than she would otherwise make.

(Insert Table 4 about here)

In addition, we split the whole sample by observations that have morning profits against those that have morning losses, and then compare to market maker averages. If our findings in Table 3 are largely driven by market makers' morning trading outcomes relative to their average profit levels, as opposed to their absolute magnitudes, we expect the relationship between afternoon risk-taking and morning outcome to be weaker within the sub-sample where all morning profits are above or below the average, respectively. The coefficients for morning profits are mostly positive yet insignificant for the sub-sample of observations with morning profits. Most of the coefficients are insignificantly negative for days with morning losses. The fact that market makers with heavy morning losses take on greater afternoon risks than those who suffer less losses is consistent with the prospect theory that the value function is fairly flat for deep losses, which may indeed induce greater risk-taking.

(Insert Table 5 about here)

Now that we have found that market makers adjust their propensity for risk depending on previous trading outcomes, it is interesting to explore whether a market maker's change in risk-taking influences return properties at the market level. Market makers are such an integral component of virtually all financial markets that their behavior is most likely to influence market liquidity and how other market participants interpret the market (for example, De Fontnouvelle et al. 2003, Demsetz 1968). In addition, Coval and Shumway (2005) find that traders' increased risk-taking in afternoon trading increases afternoon return volatilities. Although market makers at TAIFEX increase their risk-taking due to a different reason, we expect them to exert similar impact on the market.

(Insert Table 6 about here)

This is exactly what we found. First, we document higher market volatility when a larger fraction of market makers obtain better-than-average morning trading outcomes. We employ the following regression:

$$\sigma_{h,t}^A = \alpha + \beta_{\sigma} \sigma_{h,t}^M + \beta_{\lambda} \lambda_t^M + \varepsilon_t, \quad (4)$$

where $\sigma_{h,t}^A$ measures market-level afternoon volatility calculated as the equal-weighted average of afternoon volatility of all option contracts on date t at frequency h ; $\sigma_{h,t}^M$ measures the market-level volatility of morning price changes on date t at frequency h ; ²⁴and λ_t^M measures the aggregate fraction of market makers with above-average gains at 11:15 a.m. ²⁵

The coefficients for λ_t^M are positive and significant at the 5 percent level for all specifications using 1-, 5-, 10-, and 30-minute horizons, suggesting that market makers' morning performances collectively have considerable impact on market liquidity. If a larger number of market makers make profits in morning sessions, they tend to trade more aggressively, move prices more and generate more volatile return series. In contrast to the findings of Coval and Shumway (2005), there is only weak evidence that liquidity improvement is smaller when evaluated on a longer horizon. It is possible that market makers can fairly easily reverse average traders' impact on the market in a highly competitive market, as is the case in Coval and Shumway (2005), but it is fairly difficult for ordinary investors to reverse the course set by market makers. ²⁶

²⁴ Because many option contracts are not traded frequently and stay illiquid months before expiration, we only focus on near-the-money ($0.95 < \text{moneyness} < 1.05$) option contracts within one month of expiration.

²⁵ In unreported analyses of regression (4) and (5), we also include the daily index return and trading volume as independent variables and neither variable has significant impact on the relationship between market maker behavior and liquidity and volatility at the market level.

²⁶ We replicate the study by calculating λ_t^M as the fraction of market makers exhibiting the house money effect during the whole sample period that obtain higher-than-average morning profits. A market maker is defined as exhibiting the house money effect if the time series regression specified in Equation (1)

In addition, we find that market makers' aggressive trading also leads to a narrower bid-ask spread at the market level. Table 7 reports the results of a few time series regressions relating afternoon market-level bid-ask spread to aggregate morning gains. All regressions have the basic form,

$$Spread_t^A = \alpha + \beta_s Spread_t^M + \beta_\lambda \lambda_t^M + \varepsilon_t, \quad (5)$$

where $Spread_t^A$ and $Spread_t^M$ are the afternoon and morning market-wide spreads calculated as the equal weighted average of spreads for each individual option contract.²⁷ In particular, we use four different forms of spread measures: quoted bid-ask spread, percentage spread, normalized quoted bid-ask spread, and normalized percentage of spread, on date t. Quoted bid-ask spread is calculated as the difference between the best ask and bid quotes. Percentage spread is calculated as the quoted spread divided by the mid-quote. Normalized quoted and percentage spread are normalized in a similar fashion to the normalized profit and risk measures. λ_t^M measures the aggregate fraction of market makers with gains at 11:15 a.m.

All four measures of liquidity point toward the same direction: bid-ask spread shrinks if a higher fraction of the market makers obtain morning profits. A one percentage increase in the fraction of profitable market makers decreases the normalized afternoon percentage spread by a 0.14 standard deviation. It seems that market makers' response to their prior performance not only influences the volatility of asset price levels, but also directly determines the liquidity of the market. Although not the focus of our paper, these findings provide strong support for Coval and Shumway's (2005) assertion that behavioral biases influence asset prices.

generates a positive coefficient of b_j for a market maker. The results in Panel B of Table 6 generate similar results to those in Panel A of Table 6.

²⁷ Similar to the calculation of market-level volatility, we only focus on near-the-money ($0.95 < \text{moneyness} < 1.05$) option contracts within one month of expiration.

(Insert Table 7 about here)

4.3 Alternative Explanations

Behavioral explanations

Our analyses so far provide evidence that there is a significantly positive relationship between risk-taking and previous trading profits. It is worth noting that self-attribution (Daniel et al. 1998) and related over-confidence (Gervais and Odean, 2001) also predict that investors infer their investment abilities from previous outcomes and are prone to attributing successes to their own abilities while blaming previous failures to bad luck. As a result, investors become over-confident and trade more aggressively after prior gains. Although such patterns seem consistent with our findings at first sight, several features distinguish the house money effect from self-attribution or over-confidence.

First, self-attribution and over-confidence both predict that the absolute level of gains matter, while the house money effect focuses more on whether investors treat prior outcomes as gains or losses, relative to the reference. Our findings in Section 4 suggest that the morning profit/loss indicator, rather than the absolute level of gains or losses, matters significantly to afternoon risk-taking and support the house money effect, but not the competing explanations.

Secondly, self-attribution or over-confidence implies asymmetric response to previous trading outcomes: investors respond positively after positive feedback while ignoring the disappointing feedback. Results in Section 4 indicate that risk-taking is not sensitive to the magnitude of the gains or the losses, within respective territories, which is again at odds with the prediction from self-attribution and over-confidence.

Finally, we attempt to separate the self-attribution and over-confidence explanation by shifting the time horizon of our tests. While the house money effect predicts responses to the presence of gains and losses in the short run, self-attribution and

over-confidence usually take a longer time to develop. It is unlikely that people infer their ability completely from the consequence of one morning's trading. Instead, it seems reasonable to assume that they should also incorporate information from the near past. Therefore, we perform the same analyses as in Table 3 on a daily, rather than intra-day basis²⁸. We ask whether or not yesterday's trading outcome influences today's risk taking. Similar findings to our baseline regression on a daily basis lend support to self-attribution and over-confidence, and a lack of relationship over the longer horizon confirms that the house money effect is at work.

(Insert Table 8 about there)

Results in Table 8 provide little support that market makers change risk-taking behavior in response to trading outcomes from even the previous day²⁹. Most of the coefficients for morning profits are indeed negative, although insignificant.³⁰ When splitting the sample by whether there was a gain in the previous week's trading, we find that market makers indeed tend to reduce their risk-taking after a high return in the previous day's trading, the opposite to what alternative explanations may predict.³¹

Career concerns

In addition to the above behavioral biases, agency problems can also significantly shift the willingness of professional investors to take risks. For example, Chevalier and Ellison (1999) find that mutual fund managers take greater risks toward the end of an evaluation period if they lag behind the benchmark, due to compensation and career

²⁸ We also experiment with the longer weekly horizon and there is little relationship between risk-taking and the previous-week performance.

²⁹ We also replicate the same analyses with weekly horizon and there is little (negative) relationship between the previous week's trading profits and the current week's risk-taking.

³⁰ Because market makers may forget their performance after weekends or holidays, we rerun the regressions by excluding trading days immediately after a weekend or a holiday at the exchange. Our results remain virtually the same.

³¹ A related phenomenon is the representativeness heuristics which prescribes that people put more emphasis on recent outcomes (small sample) than the complete trading history (large sample). Hence, they may over-weigh the recent success/losses and get an overly optimistic/pessimistic view about their own abilities and increase risk-taking. However, representativeness heuristics faces the same challenge in explaining why market makers only focus on intra-day outcomes while ignoring the outcomes of the previous day and the previous week.

concerns. We contend that the agency problem should not be at work in such short horizon studied in the current paper. Market makers are evaluated for their performance (trading profits and satisfaction of liquidity provision) on a monthly basis. Therefore, it is not clear to what extent market makers' morning performances, relative to their own historical benchmarks, correlate with their overall monthly performances.

Nevertheless, we perform the following sub-sample analyses to rule out the possible impact of career consideration. We divide our data into three sub-periods: the first ten days, the second ten days, and the rest of the month. If career concerns induce market makers to display the house money effect, we expect market makers to exhibit different levels of the house money effect, if any, towards the end of every month.³² We replicate the regressions as in Equation (2) and (3), and examine the difference in coefficients for morning profit. Although the coefficient is indeed slightly bigger during the end of the month, hinting of a stronger house money effect, the difference between the three-sub-periods is insignificant. Hence, we conclude that our findings are not due to market makers' career concerns.

Informational advantage

Above-average morning profits may indicate that market makers possess information advantage, and it is therefore possible that market makers may trade more aggressively in the afternoon to exploit the information. However, it is important to bear in mind that in the index option market, information about one or few individual stocks will have marginal impact on the performance of the index³³. Besides, all market makers share the same access to limit order book and investor sentiment, and therefore, no particular market maker enjoys an informational advantage from that source.

³² It is hard to predict whether the house money effect should be stronger or weaker during the end of each month. On one hand, it seems that prior profits may discourage future risk-taking due to loss aversion. On the other hand, market makers may indeed increase their risk taking so as not to lag behind peer market makers.

³³ There were a total number of 697, 669, 638 and 584 stocks, respectively, at the end of 2004, 2003, 2002 and 2001. The stock with the largest weight on TAIFEX is TSMC; one percent movement in TSMC led to 0.0845 percent movement in TAIFEX on 2004/12/31.

In addition, we performed unreported regressions of afternoon profits on afternoon risk-taking and the relationship between the two is statistically insignificant. If market makers take greater risks in the afternoon trading to take advantage of their advantageous information, we expect market makers to make greater trading profits in such afternoons. However, our regression results suggest that greater risks in the afternoon trading cannot help market makers achieve more profits, which is inconsistent with the information advantage explanation.

Other explanations

Finally, institutional background, such as wealth effect and capital constraint (margin requirement) may also influence market makers' attitudes towards the risks. Such constraints, however, should take effect only after initial losses, which ought not to affect our findings following prior gains.

5. Discussions

In agreement with the extant studies on this topic (Coval and Shumway 2005, Haigh and List, 2005, O'Connell and Teo 2005, and Locke and Mann 2005), the current study finds strong support that prior outcomes plays an important role on professional investors' subsequent decisions, which is inconsistent with the standard expected utility assumption. Moreover, it is interesting to learn how the results differ in the direction of the relationship. Specifically, both Coval and Shumway (2005) and Haigh and List (2005) document that futures traders reduce risk-taking after prior gains, while the current study finds that market makers at Taiwan's option market display the house money effect: they take on greater risks after prior gains. Standing in between, O'Connell and Teo (2005) report that institutions take on more risks following an increase in both net profits and net losses and Locke and Mann (2005) argue that the relationship depends heavily on investor experience.

It should not be surprising to find differences among the aforementioned extant research. This is because these studies avail data on various different types of investors, securities, and markets, and adopt different methodologies in measuring prior outcome

and subsequent risk-taking, which can generate different results. Next, we discuss several potential reasons that may explain the discrepancies in the literature.

Different types of market players and investment horizons

Unlike Coval and Shumway (2005) and Locke and Mann (2005), the current study examines the behavior of designated market makers, who probably have a longer investment horizon and evaluation period than the day traders studied in prior research. Benartzi and Thaler (1995) point out with simulations that the length of evaluation periods plays an important role in investor risk aversion. Gneezy et al. (2003) confirmed the phenomenon of myopic loss-aversion with a market experiment and show that shorter evaluation periods are associated with less risk-taking.

While floor traders are believed to be sensitive to daily trading performance, designated market makers probably look at the longer monthly horizon on which they are evaluated. As a consequence, market makers may not be eager to lock in morning profits to avoid losses for each entire trading day, as day traders are. Instead, they may treat the outcome of each morning session as part of a series of events; analogous to gamblers playing multiple hands at the casino. Although day traders treat morning profits as a one-shot game every day, market makers tend to frame morning profits as part of a bigger frame, which is exactly what distinguishes the house money effect from the static implication of the prospect theory. Furthermore, another independent study by O'Connell and Teo (2005) on mutual fund managers, who consider a longer evaluation period than day traders, also finds a positive relationship between prior outcome and subsequent risk taking. As a result, their study provides a support for myopic loss-aversion and partly resolves the difference in the extant results.

In addition to investment horizons, we note that our sample market makers at TAIEX are a unique type of investors in a sense that they are obligated to provide quotations and respond to RFQs. Because market makers trade actively, their views of risk and performance may differ from those of proprietary traders who have the option of

temporarily staying out of the market. In addition, market makers also differ from proprietary traders in the sense that they have to satisfy the exchange's expectation to provide liquidity and maintain price continuity. However, we believe such differences are not driving our main findings, as communications with different types of market participants confirmed that trading profits are the most important criteria on which market makers are evaluated. We further examine the relationship between prior outcomes and subsequent risk taking for the other two types of investors, namely proprietary traders and individual investors. Our unreported analyses confirm that these two types of traders at TAIEX also exhibit a significant, albeit weaker, house money effect. Hence, our findings are not limited to market makers.

Overall risk levels of securities

Extant literature shows that risk-taking behavior can depend heavily on the general perception of risk levels. (Eeckhoudt et al. 1996, Xie and Wang, 2003). When return movement is relatively smooth (less volatile) in a market, an investor with morning profit is eager to lock in her morning profit, in anticipation of reversals in the afternoon. In contrast, higher volatility at the market level implies that the investor with disappointing morning session may suffer even greater losses if the trend in morning trading were to persist into the afternoon. The same mechanism also holds for morning gains: an investor with morning gains are more likely to take on more risks in hope that the profitable trading in the morning session will persist in the afternoon. Hence, higher level of volatility at the market level is likely to lead a positive link between prior trading outcome and subsequent risk-taking.

The TAIEX option index is indeed much riskier than the securities examined in previous studies. The volatility for TAIEXE was 34.64 percent per annum between 1993 and 2003. During the more stable period in our sample between 2001 and 2004, the average annual volatility was still quite high at 24.44 percent per annum. In contrast, previous studies using U.S. data witness much lower volatilities. For example, U.S. Treasury bonds, the underlying securities of the treasury futures studied in Coval and Shumway (2005), are generally considered as relatively safe investments. The annual

volatility for 30 year treasury bonds was 7.7 percent for 1998 and averaged 8.5 percent for the decade between 1990 and 1999.³⁴ Using data on institutional investors trading U.S. equities, O'Connell and Teo (2005) document increased risk-taking after net profits, consistent with the current findings. Therefore, it seems that differences in general perception of risks among markets may also explain the difference among existing studies.

(Insert Table 9 about here)

Market development

Although the financial market in Taiwan has a history of more than 50 years, the derivatives market where TAIEX options are traded is still a fairly recent phenomenon. As Dhar and Zhu (2005) and List (2003) find that experience helps alleviate certain behavioral biases, it is possible that the house money effect that we observed in Taiwan may come from a lack of experience for market makers, compared to investors studied in the U.S. market.

One natural way to test the hypothesis is to examine whether the house money effect changes over time at TAIEX. We split the whole sample into three one-year sub-periods.³⁵ Table 9 indeed points in the opposite direction: there is a very weak house money effect in the first year and a similarly strong evidence of the house money effect in 2003 and 2004. It is possible that only after forming an opinion on their average performance early on, did market makers start responding to their performance relative to a perceived benchmark. Because we have only about three years' of data, claim about the impact of market development on the house money effect should be taken with great caution.

³⁴ <http://www.cbot.com/cbot/pub/page/0,3181,1665,00.html>

³⁵ We include the six trading days at the end of 2001 into the 2002 sub-period.

Culture

Finally, a common explanation for the differences in investor behavior among international markets is the difference in cultures (Grinblatt and Keloharju 2001, Feng and Seasholes, 2005). Although Taiwan resembles the United States in its market infrastructure and transparent regulations (see Barber et al. 2005), fundamental differences exist in the attitude toward gambling. Existing studies document that the Asian population has a strong appetite for gambling and gaming activities both within their home countries and among immigrant communities in developed economies³⁶. If gambling indeed plays a greater role in the Taiwanese population, it is likely that Taiwanese may be more likely to frame investment in the context of gambling and hence more likely to treat earlier gain as ‘house money’ and increase their wager in subsequent trading.

6. Conclusions

The question about how people respond to risks is fundamental to understand various economic phenomena. As it becomes more accepted that individuals do not simply treat uncertainty and risks as simply probabilistic calculations, it remains unclear whether a single behavioral theory can describe decisions under uncertainty. Prospect theory and many of its implications have had great successes in explaining many circumstances in more or less static background. As a result, more efforts need be devoted to understanding how people make decisions when they face a sequence of tasks. Such dynamic decision-making process closely resembles what professional investors (i.e. day traders, market makers, and fund managers, etc.) would face, in that such market participants constantly watch the market movement, prior trading outcome, and adjust their decisions accordingly. Therefore, studying professional investors’ behavior provides ways to understand decision-making in a dynamic context.

³⁶ http://www.abgaminginstitute.ualberta.ca/pdfs/asian_gambling.pdf provides a comprehensive list references on related academic journal articles.

We utilize the complete order and trade record of market makers, a very important type of professional investors, at the Taiwan TAIEX option market. In addition, we document that they take on greater risks after profitable mornings and reduce risk-taking after morning losses. Behavior of this nature is at odds with the standard expected utility function and provides support for the house money effect proposed by Thaler and Johnson (1990). Our findings emphasize that it is important to study not only how the reference point is determined and influences behavior in isolated context, but also how people frame a series of related events relative to dynamic benchmarks. The fact that extant studies using different time horizons obtain different results on how investors respond to prior outcomes highlights the complexity of human decision-making and the importance of evaluation horizon (Benartzi and Thaler 1995) and framing. Consequently, future studies on behavioral decision-making from a broader spectrum of financial markets, securities and investors are needed to generate a more generalized framework of investor behavior.

Consistent with Coval and Shumway (2005), such behavioral biases exert significant impact on asset prices. We find that the shift in market makers' afternoon risk-taking behavior, in response to their morning trading performance results, changes subsequent liquidity and volatility at the market level. Two current findings distinguish our study and call for future research in behavioral finance. First, we find a different mechanism by which professional investors bias their decisions from Coval and Shumway (2005), although such a different bias (the house money effect) influences volatility and liquidity in a similar fashion as reported by the previous study. Such findings confirm Thaler and Johnson (1990)'s assertion that "making generalization about risk-taking preferences is difficult" and calls into study a wider range of behavioral patterns in the financial market.

Secondly, different from the results drawn from competitive market maker mechanism (in which price distortions are quickly reversed by other peer investors), our findings show that the biases exhibited by designated market makers can collectively influence return properties in a persisting fashion. Professional traders such as market

makers are often assumed to behave rationally and eliminate impacts generated by individual investors' biases. Our findings are important since they reveal that market makers indeed exhibit behavioral biases themselves and can shift asset price formation through their behavior. Such findings motivate future studies to incorporate behavioral patterns into asset price formation process.

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Appendix A. Overview of Taiwan Futures Exchange

The Taiwan Future Exchange conducts a fully electronic trading system, which is similar to that of EURONEXT/LIFFE. The trading hours are 8:45 a.m. to 1:45 p.m. Traders submit orders electronically to the central limit order book. All entering orders before the market open are executed by a call method. Orders are matched by a continuous mechanism during the rest of the trading sessions. Incoming orders are automatically matched with orders in the order book to produce trades. Orders are given priority according to price and time.

Only designated market makers can submit orders directly to the trading system, and they can trade on their own account. Designated market makers are obligated to continuously provide quote with firm commitment and respond to request-for-quotes by investors. Upon receiving the quote requests from market participants, all market makers are obligated to give a quote. If an inquirer thinks the quote given is acceptable, the market maker may proceed to place an order into the trading system. A quote is a two-way (bid and ask) limit order placed by a market maker. The quote entered into the system by a market maker is a firm order and will enter the order book to compete with the orders from the public. The bid-ask spreads and quantity orders are set by the relevant requirement by the TAIFEX. Each quote entered by market makers will be good for a certain period of time (e.g., 20 seconds). If the order is not executed, it will be deleted from the order book automatically.

The TAIFEX discloses the quote information and best five quotes and depths in real-time to the public. Information on the opening price, closing price, market price, execution volume, number of contract, bid/order prices and order volume, day high and day low of each option series and total contracts executed are disseminated by the TAIFEX in real-time. Trading is anonymous both before and after a trade and no information is available on the identity of the order submitter.

Appendix B. Regulations on Market Maker Commission Concession at TAIEX

TAIFEX requires that the monthly total market-making volume in the market-making account shall reach a minimum of 10,000 contracts. The number of quotes given in response to the inquiries (RFQs) shall reach at least 70% of the total number of inquiries in each month. Market makers can enjoy fee reduction of up to 100% for their trades in the quote account, depending on the level of market making trading volume if they meet the requirements specified by TAIEX. The schedule for commission concession is listed below:

Commission Concession at TAIEX	
Types of market makers	Fee discount rate
2001/12/24~2002/12/31	
All market makers	free
2003/01/01~2004/7/8	
2000<=market making volume<5000	85% off
5000<=market making volume<10000	90% off
10000<=market making volume<20000	95% off
20000<=market making volume	free
2004/7/9~Present	
10000<=market making volume<20000	20% off
20000<=market making volume<30000	30% off
30000<=market making volume<40000	40% off
40000<=market making volume	50% off

Appendix C. Profit on a First-in-First-out Basis

Zero Inventory Position										
Date	Time	Price	Purchase	Sales	Inventory	Profit	Morning	Afternoon	Morning	Afternoon
			Quantities	Quantities			Realized Profit	Realized Profit	Paper Profit	Paper Profit
20011226	103655	135	2	0	2	.				
20011226	111500	145			2		.		20	
20011226	123712	151	0	1	1	16				
20011226	123737	160	3	0	4	.				
20011226	123839	165	0	5	-1	45				
20011226	123839	170	3	0	2	-5				
20011226	134500	180			2			56		20
20011227	092727	193	0	1	-1					
20011227	093318	185	0	1	-2					
20011227	111500	185			-2		.		8	

Table 1. Summary Statistics

There are a total of 21 market makers and 753 trading days during the sample period between 2001/12/24 and 2004/12/31. Paper profit is calculated by estimating the profit/loss for the total positions held at 11:15 a.m. at each trading day for each market maker. Paper profit is recorded if the current price is higher/lower for long/short positions for an existing position. Realized profit is the profit that each market maker realizes by liquidating positions in the morning. Total profit is the sum of paper profit and realized profit. Number of trades and orders are the number of all index options trades/orders that each market maker executed during the respective time period. Average trade size is the average number of contracts per trade, defined as the total number of transacted contracts divided by the number of trades. Average order size is the average number of contracts per order, defined as the total number of contracts in orders divided by the number of orders.

Variable	Morning			Afternoon		
	Mean	Median	St. Dev.	Mean	Median	St. Dev.
All Trader-Days						
Whole Period 2001/12/24-2004/12/31 (N=15813)						
Realized Profits	\$31316.40	\$2100.00	\$436970.14	\$63554.33	\$2000.00	\$858369.92
Paper Profits	\$72130.29	\$195.00	\$1337633.7	\$106818.61	\$1150.00	\$2390423.2
Total Profits	\$95065.46	\$1887.50	\$1522673.2	\$156930.49	\$3750.00	\$2675744.1
Number of Trades	296.27	75.00	583.70	229.87	62.00	454.72
Average Trade Size	6.16	5.38	5.43	6.28	5.35	5.59
Number of Order	377.80	24.00	2015.67	298.48	18.00	1965.66
Average Order Size	19.44	11.34	23.20	18.87	10.00	23.52
Trade to Order Ratio	11.69	1.70	63.34	10.79	1.89	59.48
Sub-Period 2001/12/24-2002/12/31 (N=5334)						
Realized Profits	\$6580.84	\$1375.00	\$53668.85	\$6458.16	\$950.00	\$117591.00
Paper Profits	\$44722.55	\$100.00	\$761852.79	\$45410.61	\$540.00	\$458251.72
Total Profits	\$46905.38	\$650.00	\$751457.31	\$48178.72	\$1800.00	\$495199.74
Number of Trades	76.27	17.00	154.69	62.95	16.00	131.45
Average Trade Size	45.68	25.08	59.10	39.24	22.00	49.87
Number of Order	71.70	11.00	180.67	55.71	7.00	151.31
Average Order Size	160.40	29.63	436.68	139.33	22.17	427.75
Trade to Order Ratio	56.790	5.760	193.604	68.096	5.000	268.339

Variable	Morning			Afternoon		
	Mean	Median	St. Dev.	Mean	Median	St. Dev.
Sub-Period 2003/1/1-2003/12/31 (N=5229)						
Realized Profits	\$28814.33	\$2500.00	\$259181.13	\$45719.18	\$2500.00	\$672818.65
Paper Profits	\$78040.09	\$500.00	\$1086497.54	\$143504.22	\$800.00	\$1667138.80
Total Profits	\$99648.56	\$2700.00	\$1225536.88	\$179268.48	\$4725.00	\$2015064.04
Number of Trades	320.80	64.00	600.42	248.06	58.00	464.61
Average Trade Size	70.09	36.25	89.08	64.31	32.36	82.55
Number of Order	164.38	16.00	512.46	121.13	13.00	393.36
Average Order Size	326.41	73.63	791.70	297.45	61.00	778.57
Trade to Order Ratio	105.50	14.19	324.27	122.33	12.63	411.10
Sub-Period 2004/1/1-2004/12/31 (N=5250)						
Realized Profits	\$43498.82	\$2550.00	\$603031.95	\$104942.93	\$2712.50	\$1141724.02
Paper Profits	\$82076.49	\$0.00	\$1725665.53	\$110606.74	\$2735.00	\$3389818.74
Total Profits	\$118680.89	\$3037.50	\$2006364.42	\$203218.38	\$5805.00	\$3748575.17
Number of Trades	417.55	166.00	694.82	322.70	138.00	544.21
Average Trade Size	119.82	82.62	116.04	107.38	72.84	108.11
Number of Order	789.93	66.00	3191.22	633.72	47.00	3141.87
Average Order Size	512.61	176.77	1088.66	454.39	150.67	1037.99
Trade to Order Ratio	137.51	25.40	398.19	154.31	24.43	485.17

Table 2. Risk Taking for Profitable and Losing Morning

There are 4,841 market maker/day observations with morning profits and 4,039 market maker/day observations in with morning losses between 2001/12/24 and 2004/12/31. Total profit is the sum of paper morning profit and morning realized profit. Total profit is normalized by dividing the raw total profit observation by the standard deviation of total profit for each market maker. Paper profit is calculated by estimating the profit/loss for the total positions held at 11:15 a.m. of each trading day for each market maker. A profit is recorded if the current price is higher/lower for long/short positions. Realized profit is the profit that each market maker realizes by liquidating positions in the morning. Number of trades and orders are the number of all index options trades/orders that each market maker executed during the respective time period. Average trade size is the average number of contracts per trade, defined as the total number of transacted contracts divided by the number of trades. Average order size is the average number of contracts per order, defined as the total number of contracts in orders divided by the number of orders. Number of trades, trade size, number of orders, and order size are first demeaned and then standardized by dividing the raw observation by market-maker-specific standard deviation.

Variable	Morning			Afternoon		
	Mean	Median	St. Dev.	Mean	Median	St. Dev.
Observations with Morning Profits (N=4841)						
Normalized by Trader						
Total Profits	0.347	0.081	1.095	0.248	0.041	1.049
Number of Trades	0.112	-0.213	1.065	0.127	-0.219	1.098
Average Trade Size	0.069	-0.108	0.942	0.045	-0.123	0.957
Number of Order	0.093	-0.314	1.058	0.096	-0.257	1.094
Average Order Size	0.069	-0.224	1.031	0.043	-0.230	0.994
Trade to Order Ratio	-0.004	-0.203	0.922	0.006	-0.212	0.984
Observations with Morning Losses (N= 4039)						
Normalized by Trader						
Total Profits	-0.294	-0.086	0.750	-0.157	-0.024	0.908
Number of Trades	-0.097	-0.415	0.925	-0.111	-0.382	0.886
Average Trade Size	-0.070	-0.273	1.016	-0.044	-0.281	1.021
Number of Order	-0.082	-0.332	0.935	-0.084	-0.299	0.898
Average Order Size	-0.060	-0.305	0.964	-0.038	-0.281	1.002
Trade to Order Ratio	0.009	-0.209	1.082	-0.007	-0.207	1.016

Table 3. Morning Profits and Afternoon Risk Taking (Order Account)

We present parameter estimates and the corresponding t-statistics in Panel A, B, and C by fitting the data with pooled OLS regression, panel regression with corrected standard deviation, logit regression, respectively. The independent variables are the same for all specifications. The regressions in Panels (A) and (B) follow the specification of Equation (1) in Section 4.2,

$$RISK_d = a + b_1 * PROFIT_m + b_2 * |INV_m| + b_3 * PROFIT_m * |INV_m| + b_4 * RISK_m + e, \quad (1)$$

where $RISK_d$ is the measure of risk-taking in the afternoon. We adopt five different measures of risk-taking: the number of trades, trade size, the number of orders, order size, and the ratio of number of trades to number of orders. $PROFIT_m$ is the total morning profit for each market maker calculated by summing the realized gains/losses and paper gains/losses. $|INV_m|$ is the absolute value of the market maker's inventory at 11:15 am of each trading day. $RISK_m$ is the corresponding risk-taking measure in the morning.

The logit regression in Panel C follows the specification of Equations (2) and (3) in Section 4.2,

$$\Pr(Risk_{i,t}^A > 0) = \frac{\exp(X'B)}{1 + \exp(X'B)}, \quad (II)$$

where $X'B = a + b_1 * PROFIT_m + b_2 * |INV_m| + b_3 * PROFIT_m * |INV_m| + b_4 * RISK_m + e$, and the dependent variable equals 1 if the market maker takes above-average risks in the afternoon and 0 otherwise. Independent variables are defined similarly to those in the linear regressions. T-statistics are in parentheses.

Model	Panel A				Panel B				Panel C							
	Equation (I)				Equation (I)				Equation (II)							
Method	Pooled OLS Regressions				Panel Regressions with Fixed Effect				Logit Regressions							
Dependent Variable	a	b_1	b_2	b_3	b_4	a	b_1	b_2	b_3	b_4	a	b_1	b_2	b_3	b_4	
Afternoon Number of Trades	coef	0.021	0.076	-0.024	-0.004	0.664	-	0.078	-0.024	-0.004	0.661	-0.6467	0.245	-0.103	-0.014	1.880
	t-stat	2.341	5.250	-2.328	-2.922	79.608	-	3.692	-1.553	-1.891	31.053	-21.833	4.609	-2.571	-2.607	40.123
Afternoon Average Trade Size	coef	0.021	0.014	0.021	-0.001	0.311	-	0.017	0.019	-0.001	0.302	-0.495	0.066	0.066	-0.005	0.823
	t-stat	1.870	0.767	1.724	-0.798	30.860	-	1.136	1.896	-1.153	11.780	-20.033	1.706	2.366	-1.492	25.326
Afternoon Number of Orders	coef	0.012	0.052	-0.012	-0.002	0.668	-	0.055	-0.013	-0.002	0.666	-0.826	0.125	-0.011	-0.007	2.016
	t-stat	1.358	3.675	-1.180	-1.431	82.369	-	2.961	-1.069	-1.541	29.299	-27.020	2.464	-0.310	-1.597	41.058
Afternoon Average Order Size	coef	0.006	0.010	0.021	-0.000	0.563	-	0.011	0.021	-0.000	0.558	-0.548	0.089	0.036	-0.006	1.369
	t-stat	0.645	0.627	2.000	-0.019	63.903	-	0.656	1.660	-0.051	33.666	-20.418	2.017	1.224	-1.559	37.579
Afternoon Trade/Order Ratio	Coef	-0.003	0.0301	-0.003	-0.003	0.354	-	0.030	-0.002	-0.003	0.354	-0.532	0.125	0.020	-0.017	1.188
	t-stat	-0.233	1.756	-0.216	-1.687	31.994	-	1.945	-0.179	-2.247	17.752	-18.802	2.621	0.566	-2.898	30.854

Table 4. Morning Profits Indicator and Afternoon Risk Taking (Order Account)

We present parameter estimates and the corresponding t-statistics in Panel A, B, and C by fitting the data with pooled OLS regression, panel regression with corrected standard deviation, and logit regression, respectively. The independent variables are the same for all specifications. The linear regression is specified as follows:

$$RISK_a = a + b_1 * Dummy(PROFIT_m) + b_2 * |INV_m| + b_3 * PROFIT_m * |INV_m| + b_4 * RISK_m + e, \quad (III)$$

where $RISK_a$ is the measure of risk-taking in the afternoon. We adopt five different measures of risk-taking: the number of trades, trade size, the number of orders, order size, and the ratio of number of trades to number of orders. $Dummy(PROFIT_m)$ is a dummy variable that equals to 1 if the total normalized morning profit for a market maker is greater than 0, and 0 otherwise. $PROFIT_m$ is calculated by summing the realized gains/losses and paper gains/losses.

$|INV_m|$ is the absolute value of the market maker's inventory at 11:15 am of each trading day. $RISK_m$ is the corresponding risk-taking measure in the morning.

The logit regression in Panel C is specified as follows:

$$\Pr(Risk_{i,t}^A > 0) = \frac{\exp(X'B)}{1 + \exp(X'B)}, \quad (IV)$$

where $X'B = a + b_1 * Dummy(PROFIT_m) + b_2 * |INV_m| + b_3 * PROFIT_m * |INV_m| + b_4 * RISK_m + e$, and the dependent variable equals 1 if the market maker takes above-average risk in the afternoon and 0 otherwise. Independent variables are similarly defined as in the linear regressions. T-statistics are provided in parentheses.

Model	Panel A				Panel B				Panel C											
	Equation (III)								Equation (IV)											
Method	Pooled OLS Regressions								Panel Regressions with Fixed Effect								Logit Regressions			
Dependent Variable	a	b_1	b_2	b_3	b_4	a	b_1	b_2	b_3	b_4	a	b_1	b_2	b_3	b_4					
Afternoon Number of Trades	coef	-0.003	0.081	-0.058	0.059	0.661	-	0.087	-0.056	0.057	0.658	-0.708	0.127	-0.228	0.231	1.881				
	T-stat	-0.274	4.274	-3.548	3.068	78.591	-	4.003	-2.666	1.886	30.741	-15.616	2.129	-3.539	2.940	40.103				
Afternoon Trade Size	coef	0.005	0.046	0.022	-0.007	0.311	-	0.039	0.019	-0.004	0.301	-0.501	0.019	0.050	0.020	0.823				
	T-stat	0.379	2.014	1.136	-0.298	30.761	-	1.705	1.170	-0.190	11.743	-13.516	0.376	1.131	0.374	25.334				
Afternoon Number of Orders	coef	0.012	0.011	-0.054	0.075	0.668	-	0.005	-0.056	0.078	0.667	-0.879	0.106	-0.060	0.088	2.017				
	T-stat	1.075	0.563	-3.352	3.934	81.947	-	0.274	-4.164	3.362	29.201	-19.123	1.730	-1.149	1.370	41.093				
Afternoon Order Size	coef	-0.015	0.061	0.020	0.003	0.561	-	0.062	0.020	0.003	0.556	-0.584	0.073	0.020	0.029	1.370				
	T-stat	-1.257	3.075	1.165	0.145	63.618	-	2.918	0.927	0.134	33.485	-14.390	1.343	0.395	0.497	37.592				
Afternoon Trade to Order Ratio	coef	-0.015	0.038	0.002	-0.011	0.353	-	0.045	0.004	-0.013	0.353	-0.604	0.141	0.051	-0.075	1.188				
	T-stat	-1.092	1.649	0.108	-0.453	31.913	-	1.918	0.305	-0.771	17.706	-14.213	2.507	1.031	-1.280	30.889				

Table 5. Morning Profits and Afternoon Risk-Taking for Observations with Morning Profits and Morning Losses

We run pooled OLS regressions for observations with morning profits in Panel A and morning losses in Panel B. The regressions given below follow the specification of Equation (1) in Section 4.2:

$$RISK_a = a + b_1 * PROFIT_m + b_2 * |INV_m| + b_3 * PROFIT_m * |INV_m| + b_4 * RISK_m + e,$$

where $RISK_a$ is the measure of risk-taking in the afternoon. We adopt five different measures of risk-taking: the number of trades, trade size, the number of orders, order size, and the ratio of number of trades to number of orders. $PROFIT_m$ is the total morning profit for each market maker by summing the realized gains/losses and paper gains/losses. $|INV_m|$ is the absolute value market maker's inventory at 11:15 a.m. of each trading day. $RISK_m$ is the corresponding risk-taking measure in the morning. T-statistics are provided in parentheses.

Model		Pooled OLS Regressions				
Panel A: Observations with Morning Profits						
		a	b_1	b_2	b_3	b_4
Dependent Variable						
Number of Trades	Coefficient	0.037	0.0244	0.028	-0.005	0.704
	T-stat	(2.711)	(0.5089)	(0.527)	-(2.631)	(56.659)
Average Trade Size	Coefficient	0.010	0.0493	0.036	-0.006	0.306
	T-stat	(0.652)	(0.9036)	(0.595)	-(2.671)	(22.082)
Number of Orders	Coefficient	0.021	-0.0232	0.073	-0.003	0.700
	T-stat	(1.593)	-(0.5043)	(1.424)	-(1.665)	(61.632)
Average Order Size	Coefficient	-0.017	0.0775	0.006	-0.004	0.552
	T-stat	-(1.296)	(1.6660)	(0.115)	-(2.380)	(47.535)
Trade to Order Ratio	Coefficient	-0.006	0.1026	-0.078	-0.003	0.367
	T-stat	-(0.402)	(1.9892)	-(1.355)	-(1.283)	(24.907)
Panel B: Observations with Morning Losses						
Number of Trades	Coefficient	-0.018	-0.067	-0.068	0.004	0.608
	T-stat	-(1.268)	-(1.228)	-(1.134)	(1.523)	(52.875)
Average Trade Size	Coefficient	-0.004	-0.104	-0.001	0.009	0.313
	T-stat	-(0.235)	-(1.437)	-(0.007)	(2.650)	(20.758)
Number of Orders	Coefficient	-0.003	-0.106	-0.135	0.001	0.623
	T-stat	-(0.183)	-(1.899)	-(2.196)	(0.253)	(52.475)
Average Order Size	Coefficient	0.001	-0.074	0.010	0.008	0.564
	T-stat	(0.083)	-(1.130)	(0.146)	(2.690)	(40.573)
Trade to Order Ratio	Coefficient	-0.018	0.097	0.116	0.003	0.340
	T-stat	-(0.874)	(1.281)	(1.384)	(0.687)	(20.167)

Table 6. Afternoon Market Volatility and Market Maker Aggregate Morning Profits

We perform time series regressions relating aggregate morning profits to the volatility of afternoon price changes. All regressions have the basic form as given in Equation (4) of Section 4.2,

$$\sigma_{h,t}^A = \alpha + \beta_{\sigma} \sigma_{h,t}^M + \beta_{\lambda} \lambda_t^M + \varepsilon_t,$$

where $\sigma_{h,t}^A$ is the volatility of afternoon price changes on date t measured at frequency h , $\sigma_{h,t}^M$ is the volatility of morning price changes on date t measured at frequency h , and λ_t^M is the fraction of market makers with gains at 11:15 a.m. In Panel A, the fraction is calculated for all market makers and in Panel B, the fraction is calculated only for market makers displaying house money effect. To identify market makers with house money effect, we employ the time-series regression model (1) given below for each market maker,

$$RISK_a = a + b_1 * PROFIT_m + b_2 * |INV_m| + b_3 * PROFIT_m * |INV_m| + b_4 * RISK_m + e.$$

We classify a market maker to be displaying house-money effect if her morning profit coefficient (b_1) is significantly positive. The sample size is 753 trading days. All estimates are corrected for first-order autocorrelation, and t-statistics are in parentheses.

	Panel A			Panel B		
	$\lambda_t^M =$ fraction of all market makers with morning gains			$\lambda_t^M =$ fraction of house-money market makers with morning gains		
Frequency	α	β_{σ}	β_{λ}	α	β_{σ}	β_{λ}
Dependent Variable: Abnormal Afternoon Volatility($\sigma_{h,t}^A$)						
1 min	-0.05 (-1.40)	0.14 (3.92)	0.35 (2.07)	-0.06 (-1.59)	0.14 (3.81)	0.28 (2.12)
5 mins	-0.07 (-3.24)	0.10 (4.84)	0.23 (1.69)	-0.08 (-3.67)	0.10 (4.92)	0.19 (1.90)
10 mins	-0.07 (-3.34)	0.13 (5.86)	0.27 (1.97)	-0.08 (-3.70)	0.12 (5.81)	0.23 (2.24)
30 mins	-0.06 (-2.28)	0.10 (3.49)	0.34 (1.86)	-0.07 (-2.58)	0.10 (3.45)	0.22 (1.64)

Table 7. Afternoon Market Liquidity and Market Maker Morning Profits

We perform time series regressions relating aggregate morning profits to afternoon spread at the market level. All regressions have the basic form as given in Equation (5) of Section 4.2,

$$Spread_t^A = \alpha + \beta_s Spread_t^M + \beta_\lambda \lambda_t^M + \varepsilon_t,$$

where $Spread_t^A$ is the afternoon spread and $Spread_t^M$ is the morning spread of day t at the market level. Market spread is calculated as an equal average of the spread of all option contracts traded in day t . We use four different measures of spread: normalized percentage of spread, normalized spread, percentage spread, and dollar spread calculated as the difference between best bid and best ask orders. Percentage spread is calculated as the dollar spread divided by the mid-point quote. Normalized percentage spread and normalized dollar spread are calculated as percentage spread and dollar spread divided by respective standard deviation. λ_t^M is the fraction of market makers with gains at 11:15 a.m. In Panel A, the fraction is calculated for all market makers and in Panel B, the fraction is calculated only for market makers displaying house money effect. To identify market makers with house money effect, we employ the time-series regression model (1),

$$RISK_a = a + b_1 * PROFIT_m + b_2 * |INV_m| + b_3 * PROFIT_m * |INV_m| + b_4 * RISK_m + e.$$

We also classify a market maker to be displaying house-money effect if her morning profit coefficient (b_1) is positive. The sample size is 745 trading days. All estimates are corrected for first-order autocorrelation, and t-statistics are in parentheses.

	Panel A			Panel B		
	$\lambda_t^M =$ fraction of market makers with morning gains			$\lambda_t^M =$ fraction of house-money market makers with morning gains		
Frequency	α	β_s	β_λ	α	β_s	β_λ
Dependent Variable: Afternoon Spread ($Spread_t^A$)						
Normalized Percentage Spread	0.004 (0.25)	0.503 (12.75)	-0.140 (-2.13)	0.004 (0.27)	0.512 (12.59)	-0.084 (-1.61)
Normalized Spread	0.004 (0.18)	0.517 (9.98)	-0.253 (-2.27)	0.014 (0.55)	0.519 (10.14)	-0.252 (-2.91)
Percentage of Spread	0.002 (2.15)	0.462 (11.97)	-0.008 (-2.14)	0.002 (2.16)	0.469 (11.82)	-0.005 (-1.66)
Spread	1.066 (4.31)	0.370 (8.23)	-3.067 (-2.71)	1.163 (4.67)	0.372 (8.43)	-2.885 (-3.31)

Table 8. Market Maker Risk-Taking and Previous-Day Trading Outcome

We run pooled OLS regressions for observations with morning profits in Panel A and morning losses in Panel B. The regression given below follows the same form of Equation (1) in Section 4.2.

$$RISK_{t} = a + b_1 * PROFIT_{t-1} + b_2 * |INV_t| + b_3 * PROFIT_t * |INV_t| + b_4 * RISK_{t-1} + e_t,$$

where $RISK_t$ is the measure of risk-taking in the afternoon. We adopt five different measures of risk-taking: the number of trades, trade size, the number of orders, order size, and the ratio of number of trades to number of orders. $PROFIT_{t-1}$ is the total profit for each market maker from the previous trading day. $|INV_t|$ is the absolute value market maker's inventory of each trading day. $RISK_{t-1}$ is the corresponding risk-taking measure in the previous trading day. T-statistics are provided in parentheses.

Model	Panel A: Yesterday Total Profits/Losses				Panel B: Yesterday with Profits				Panel C: Yesterday with Losses							
	Pooled OLS Regressions				Pooled OLS Regressions				Pooled OLS Regressions							
Method																
Incl. Var.	a	b_1	b_2	b_3	a	b_1	b_2	b_3	b_4	a	b_1	b_2	b_3	b_4		
Afternoon Risk Measure																
Number of Trades	coef t	0.015 1.477	-0.057 -4.089	0.017 1.433	0.006 3.496	0.609 62.129	0.003 0.195	-0.246 -3.658	0.243 3.359	0.003 0.754	0.580 39.359	0.020 1.260	-0.032 -0.423	0.006 0.078	0.004 1.753	0.640 44.838
Average Trade Size	coef t	0.014 1.269	-0.027 -1.536	0.029 2.461	0.004 2.074	0.324 33.016	-0.025 -1.459	-0.089 -1.241	0.191 2.460	-0.011 -2.788	0.328 23.583	0.022 1.316	0.002 0.025	0.069 0.800	0.006 2.780	0.345 23.929
Number of Orders	coef t	0.014 1.476	-0.035 -0.262	0.012 1.063	0.003 2.155	0.668 76.427	0.025 1.590	-0.177 -2.774	0.109 1.580	0.011 3.081	0.664 50.688	0.023 1.611	0.024 0.339	0.030 0.409	-0.000 -0.108	0.684 55.077
Average Order Size	coef t	0.008 0.800	-0.006 -0.413	0.005 0.482	0.002 1.380	0.570 63.666	-0.014 -0.862	-0.121 -1.810	0.182 2.509	-0.008 -2.070	0.581 44.366	0.004 0.309	0.018 0.255	0.050 0.681	0.005 2.417	0.559 45.410
Trade to Order Ratio	coef t	0.019 1.736	0.005 0.335	0.003 0.290	-0.000 -0.024	0.425 43.463	0.020 1.112	-0.221 -2.960	0.254 3.137	-0.005 -1.194	0.433 29.686	-0.004 -0.241	0.085 1.099	0.106 1.311	0.002 0.954	0.427 32.254

Table 9. Afternoon Risk-Taking and Morning Profits (Sub-Samples by Year)

We run pooled OLS regressions for observations with morning profits in Panel A and morning losses in Panel B. The regression given below follows Equation (1) in Section 4.2.

$$RISK_a = a + b_1 * PROFIT_m + b_2 * |INV_m| + b_3 * PROFIT_m * |INV_m| + b_4 * RISK_m + e,$$

where $RISK_a$ is the measure of risk-taking in the afternoon. We adopt five different measures of risk-taking: the number of trades, trade size, the number of orders, order size, and the ratio of number of trades to number of orders. $PROFIT_m$ is the total morning profit for each market maker by summing the realized gains/losses and paper gains/losses. $|INV_m|$ is the absolute value market maker's inventory at 11:15 a.m. of each trading day. $RISK_m$ is the corresponding risk-taking measure in the morning. T-statistics are provided in parentheses.

Model	Panel A: 2001 and 2002				Panel B: 2003				Panel C: 2004							
Method	Pooled OLS Regressions				Pooled OLS Regressions				Pooled OLS Regressions							
Ind. Var.	a	b_1	b_2	b_3	b_4	a	b_1	b_2	b_3	b_4	a	b_1	b_2	b_3	b_4	
Dep. Var.																
Afternoon Number of Trades	coef	-0.037	0.044	-0.041	-0.002	0.784	-0.008	0.047	0.013	-0.010	0.593	0.097	0.092	-0.032	-0.003	0.659
	t	-2.829	1.388	-3.04	-0.694	43.490	-0.550	1.520	0.422	-2.919	40.803	5.826	4.646	-2.123	-1.786	50.998
Afternoon Average Trade Size	coef	-0.174	-0.044	0.010	0.003	0.244	-0.019	0.049	0.037	-0.007	0.218	0.131	0.001	0.000	0.001	0.379
	t	-7.223	-0.668	0.357	0.529	11.205	-0.732	1.318	1.042	-1.548	13.583	7.323	0.024	0.029	0.260	23.218
Afternoon Number of Orders	coef	0.012	-0.014	-0.047	0.002	0.732	-0.035	0.019	0.017	-0.003	0.604	0.054	0.070	-0.015	-0.002	0.673
	t	0.820	-0.372	-2.889	0.578	41.453	-2.640	0.677	0.634	-0.862	44.698	3.168	3.440	-1.010	-1.162	52.504
Afternoon Average Order Size	coef	-0.150	-0.124	0.023	0.009	0.670	0.026	0.041	0.016	-0.003	0.491	0.117	0.010	0.005	0.000	0.527
	t	-9.028	-2.984	1.299	3.082	37.224	1.527	1.765	0.482	-0.850	32.393	7.095	0.506	0.348	0.225	37.706
Afternoon Trade to Order Ratio	coef	-0.274	-0.035	0.012	0.003	0.261	0.143	0.071	0.006	-0.009	0.263	0.003	0.020	-0.008	-0.002	0.391
	t	-14.996	-0.748	0.652	0.734	12.068	6.899	1.613	0.158	-1.469	14.218	0.141	0.952	-0.526	-0.896	22.159

Figure 1. Standardized Afternoon Number of Orders after Morning Gains and Morning Losses

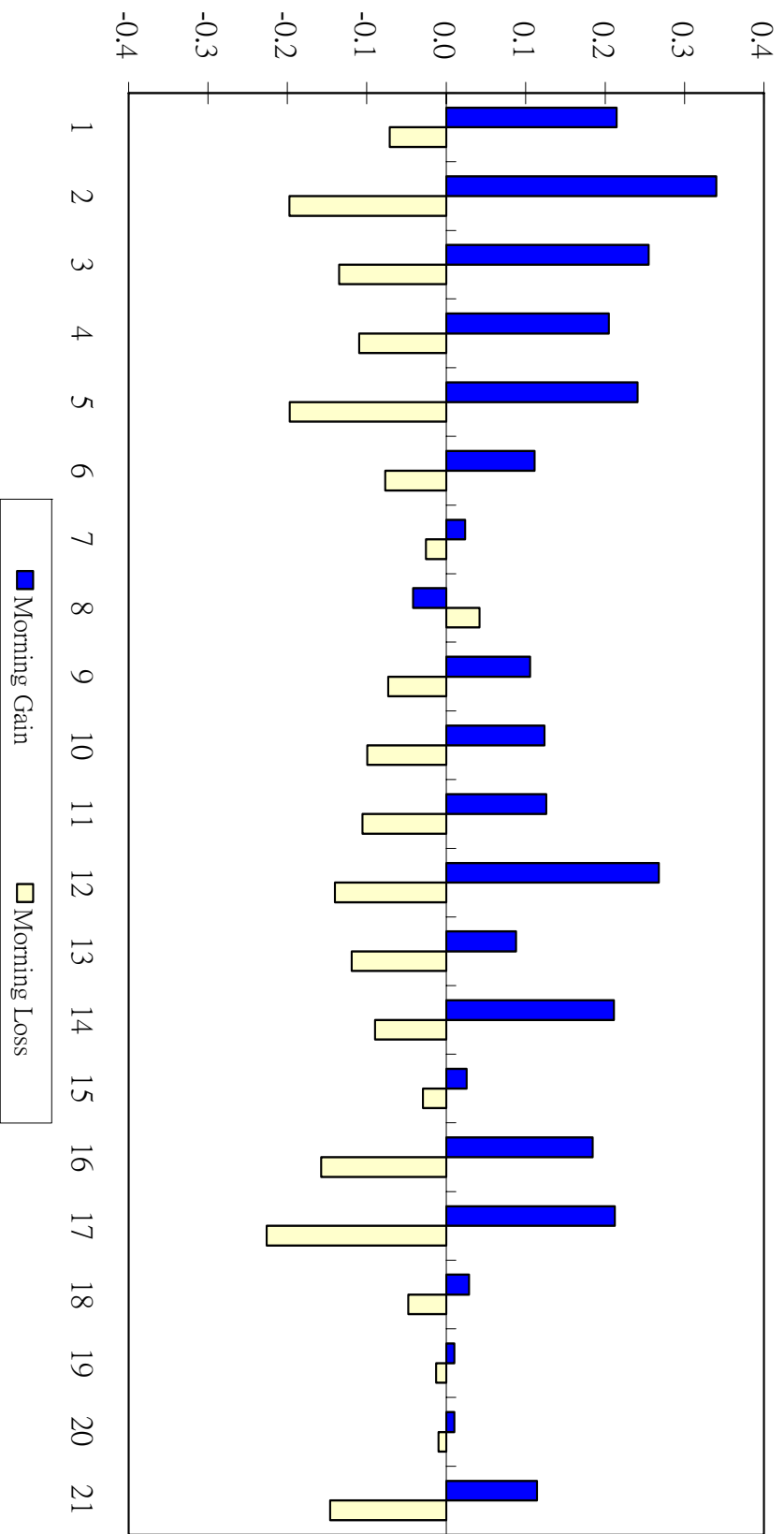


Figure 2. Standardized Afternoon Order Sizes after Morning Gains and Morning Losses

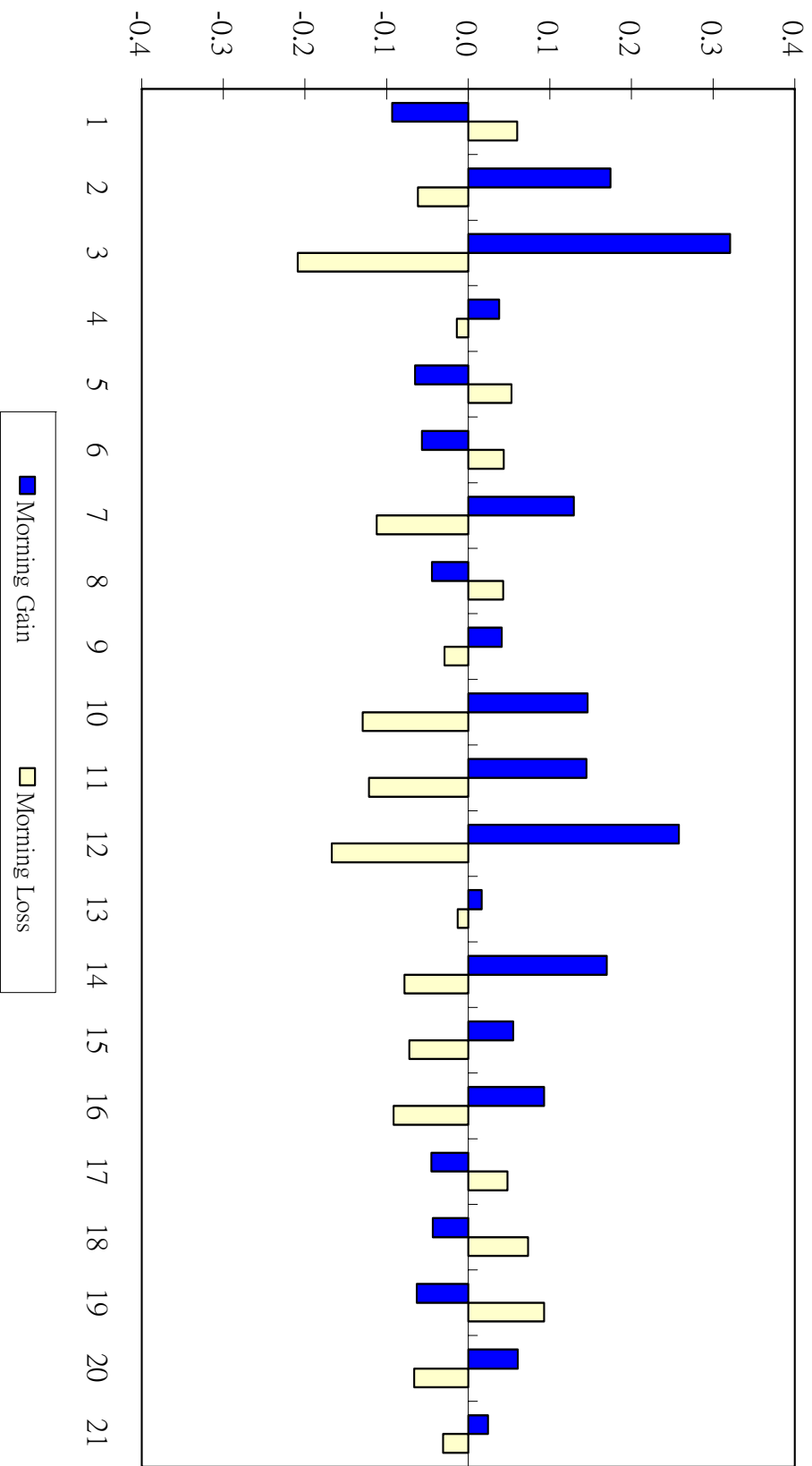


Figure 3. Standardized Afternoon Number of Trades after Morning Gains and Morning Losses

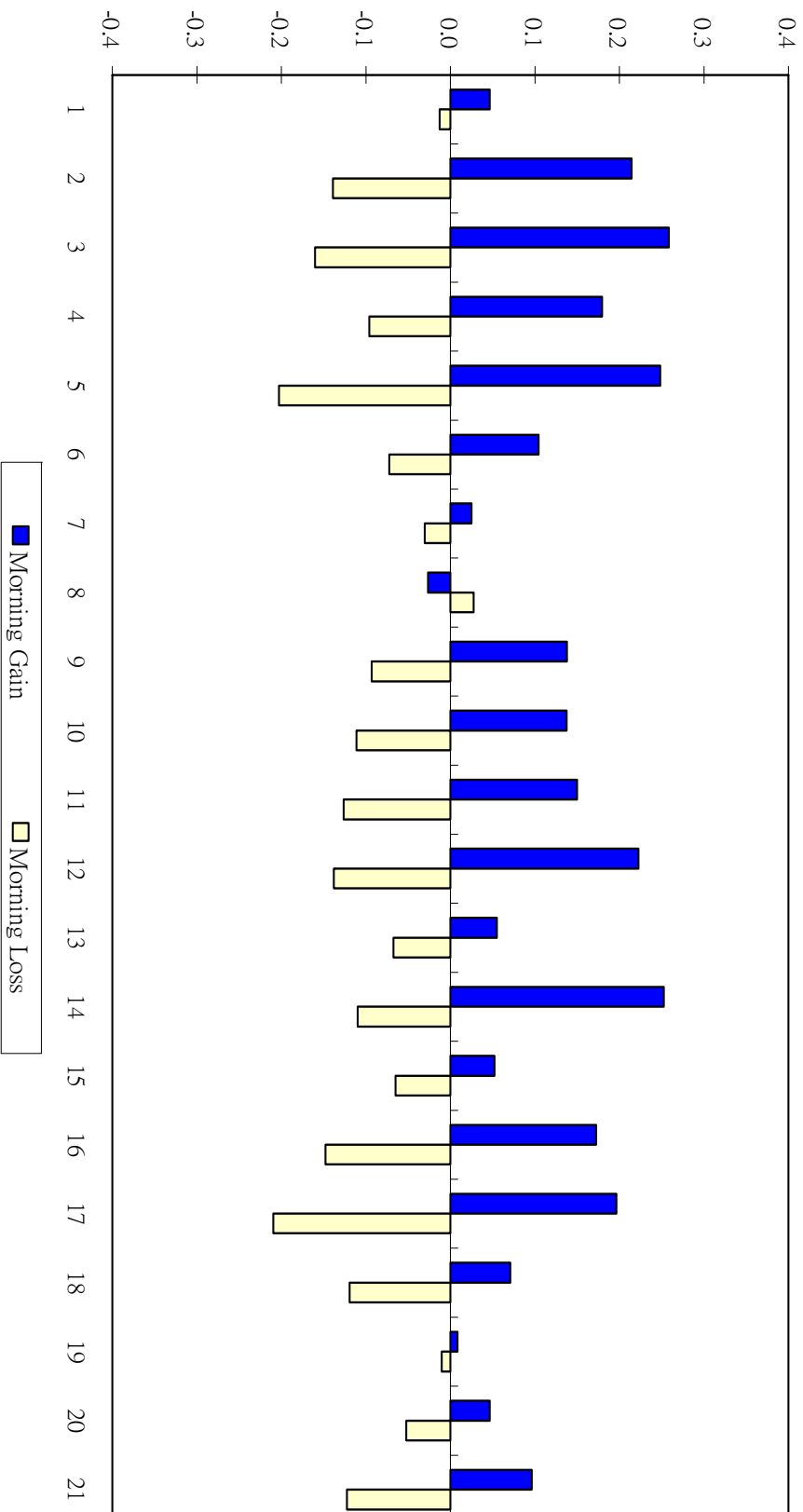


Figure 4. Standardized Afternoon Trade Sizes after Morning Gains and Morning Losses

