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Option trading and individual investor performance ☆,☆☆

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ABSTRACT

This paper examines the impact of option trading on individual investor performance. The results show that most investors incur substantial losses on their option investments, which are much larger than the losses from equity trading. We attribute the detrimental impact of option trading on investor performance to poor market timing that results from overreaction to past stock market returns. High trading costs further contribute to the poor returns on option investments. Gambling and entertainment appear to be the most important motivations for trading options while hedging motives only play a minor role. We also provide strong evidence of performance persistence among option traders.

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1. Introduction

Over the last decade, Internet brokerage has dramatically changed the investment landscape. The professional traders who used to dominate financial markets now find themselves surrounded by a much larger and more divergent crowd: individual investors. To gain a better insight into the trading behavior of the increasing numbers of individual investors, financial economists examine their performance using trading records and position statements obtained from brokerage firms.[1]

A growing literature presents evidence of irrational behavior of individual investors in option markets. Poteshman (2001) shows that option market investors exhibit the same pattern of short-term underreaction and long-term overreaction to information that has been found in stock markets. In addition, Poteshman and Serbin (2003) find that customers of discount brokers regularly engage in irrational early exercise of stock options and Mahani and Poteshman (2008) document that discount clients act irrationally by entering option positions that load up on growth stocks a few days before earnings announcements, even though at earnings announcements value stocks usually outperform substantially. Moreover, Han (2008) finds that investor sentiment about the stock market affects option prices. Another strand of literature stresses the importance of irrational determinants of individual investors' trading activity in stock markets, like gambling (Kumar, 2008), entertainment (Dorn and Sengmueller, 2007), and sensation-seeking (Grinblatt and Keloharju, in press). However, options seem to be more attractive for these purposes than stocks due to the leverage they provide and the positive skewness of their

☆ An earlier draft of this paper was titled "The Performance and Persistence of Individual Investors: Rational Agents or Tulip Maniacs?".

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[1] Studies have considered the trading behavior and performance of individual investors in, among others, the United States (Barber and Odean, 2000), China (Ng and Wu, 2007), Israel (Shapira and Venezia, 2001; Venezia and Shapira, 2007), and Sweden (Anderson, 2006).

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payoffs. Indeed, Lakonishok et al. (2007) show that a large fraction of individuals' option activity is motivated by speculation on the direction of future stock price movements.

We extend this work by studying the impact of option trading on individual investor performance. Doing so gives us the opportunity to shed light on the question whether individual investors understand the risk and return characteristics of these more complex securities, and whether they are able to use these instruments successfully. Previous work (e.g., Barber and Odean, 2000) has shown that excessive trading by individual investors leads to substantial losses on their common stock investments. We therefore examine both the absolute returns of option traders and their performance relative to those who only trade stocks. In addition, we identify the determinants of option trading volume at the investor level to examine whether option trading is related to investor characteristics that have been linked to gambling and sensation-seeking in stock markets by Kumar (2008) and Grinblatt and Keloharju (in press). Furthermore, we investigate whether there is a group of option traders who are able to consistently earn abnormal returns. This is motivated by the findings of Coval et al. (2005), who present evidence of performance persistence among a small group of stock investors. We then analyze the characteristics and trading strategies of these skilled option investors.

We perform the empirical analysis using a unique database that comprises more than 68,000 accounts and more than eight million trades in stocks and options at a large online broker in the Netherlands. In terms of size, the sample is comparable to the data set often used in studies for the United States (see, e.g., Barber and Odean, 2000; Kumar, 2008). We examine investor behavior and performance from January 2000 to March 2006, which covers the top of the stock market boom in 2000, the subsequent bust in stock prices in 2001 and 2002, and the recovery from 2003 to 2006. Thus, we are able to examine whether major market movements affect trading behavior and investor performance.

We use several methods to deal with the specific risk and return characteristics of individual investor portfolios. First, to adjust returns for risk and style tilts, we use a multifactor model in the spirit of Agarwal and Naik (2004) to capture the nonlinear payoffs of options. Furthermore, we use a Kalman filter approach to allow for time variation in risk loadings and style preferences. Finally, we introduce an approach that allows us to control for risk and style exposures even when the number of time series observations for some investors is very small.

We find that option traders incur much larger losses on their investments than equity traders. The gross return difference between these two groups of investors equals more than 1% a month, after taking risk and style differences into account. Controlling for known determinants of investor returns like gender, age, turnover, account value, income, and experience does not explain the return differential between option investors and equity investors. Instead, we attribute the poor performance of option traders to bad market timing that results from overreaction to past stock market movements. We construct a call/put ratio based on the option trades of the clients of the broker and find this ratio to be highly correlated with two other sentiment indicators, the consumer confidence index and the VIX index. In addition, estimation results for a vector autoregressive model show that the call/put ratio is driven by past market returns.

We further document that the demographic (age and gender), socioeconomic (income) and portfolio characteristics (account value and turnover) of option traders and equity traders are very similar. In particular, the empirical results show that men are more likely than women to engage in both option trading and equity trading and also exhibit a higher trading intensity. Furthermore, we extend the result of Anderson (2006) that poorer investors trade most to the option market. However, an important difference between option traders and equity traders is the impact of past portfolio returns. Specifically, while past returns do not affect an individual's trading activity in stock markets, they have a significantly negative influence on option trading volume. This is related to the finding of Coval and Shumway (2005) that futures traders are highly loss-averse and take more risk following losses than following gains.

We link the option positions that investors take to their common stock holdings and show that most investors do not use options for hedging underlying stock positions, which confirms the results of Lakonishok et al. (2007) for the US market. Instead, our finding that single men with low income and little investment experience trade most suggests that gambling and sensation-seeking are important determinants of option trading, consistent with the results of Kumar (2008) and Grinblatt and Keloharju (in press) for equity investors. This is confirmed by the responses of a group of brokerage clients to several statements on investment attitude, which reveal that the majority of investors enjoy trading and only invest the money they do not directly need. The responses also show that only a small subset of investors uses the option Greeks when trading options. Hence, a lack of knowledge about the risk and return characteristics and the use of options might be another explanation for the detrimental impact of option trading on investor performance. Seru et al. (2008) provide support for this hypothesis by showing that inexperienced investors learn slowly.

Consistent with this interpretation, we identify a small group of sophisticated option traders who succeed in consistently outperforming other investors. Specifically, option traders who are in the top decile portfolio based on past 1-year performance continue to outperform investors in the bottom decile over the next year in terms of both gross and net alphas. Performance persistence is somewhat weaker on shorter horizons but still significant for 6-month periods. Persistence in trading costs explains only part of total performance persistence, as we also find persistence in gross performance. Analyzing the composition of the decile portfolios shows that investors in the bottom deciles tend to hold small accounts with high turnover. Furthermore, these accounts are predominantly held by men with low income and little investment experience.

The paper proceeds as follows: in Section 2 we give a short overview of individual investors and financial markets in the Netherlands and introduce the data set of investor accounts and trades that is used in the empirical analysis. Section 3 outlines the methods used for performance calculation and attribution and Section 4 presents the empirical results. Section 5 concludes.

2. Data

2.1. Individual investors and financial markets in the Netherlands

We use a data set of individual investor accounts at a large online discount broker in the Netherlands. At the end of 2006, 224 companies had listed their shares at Euronext Amsterdam, of which 128 were domestic firms and 96 were foreign.[2] The total market capitalization of these companies was 591 billion euros. Total equity turnover in 2006 was close to 687 billion euros of which 585 billion euros was turnover of stocks included in the AEX index. The Dutch AEX stock market index is a value-weighted index of the 25 most actively traded firms with a combined market value of 50 billion euros. On the Euronext Liffe Amsterdam exchange options on approximately 50 different stocks are traded. In 2006 a total of

[2] These statistics are retrieved from the Euronext Global factbook, available at http://www.euronext.com.

Table 1
Descriptive statistics on investor accounts and trades.

	Mean	Std. dev.	5th	25th	Median	75th	95th
Gender (male = 1)							
Option traders	0.78						
Equity traders	0.76						
Age (years)							
Option traders	45.28	12.98	26	36	44	55	67
Equity traders	44.72	13.29	25	36	44	54	66
Trades (#)							
Option traders	80.32	304.23	1	4	16	59	331
Equity traders	45.26	135.43	1	4	11	35	185
Turnover (%)							
Option traders	8.85	100.83	0	0	0	0	25.60
Equity traders	23.68	184.96	0	0	0	2.38	83.33
Portfolio value (€)							
Option traders	34,682	111,344	500	2700	9419	29,432	133,655
Equity traders	35,053	179,762	662	3343	10,004	28,351	129,812
Income (€)							
Option traders	2548	935	1500	1900	2300	2900	4300
Equity traders	2563	937	1500	2000	2400	2900	4400
Experience (months)							
Option traders	34.64	28.02	3.00	12.00	27.28	50.80	75.00
Equity traders	32.94	25.34	2.00	12.00	27.52	48.80	74.00

This table presents descriptive statistics for a sample of 68,146 investor accounts at a Dutch online broker. We split the sample into 26,266 option traders and 41,880 equity traders. The sample period is from January 2000 to March 2006. The variables are defined as follows: Gender and Age are the gender and age of the primary account holder. Trades is the total number of trades per account during the sample period. Turnover is the average of the value of all purchases and sales in a given month divided by the beginning-of-the-month account value. Portfolio value is the average market value of all assets in the investor's portfolio. Income is the average monthly income assigned to investors based on their zip-code. Experience is the number of months an investor has been trading. The table shows for each variable the mean, median, and standard deviation, as well as 5th, 25th, 75th, and 95th percentile values.

89 million stock option contracts and 25 million index option contracts were traded.

An annual survey performed by the marketing research agency Millward-Brown in 2006 among approximately 1000 Dutch investors characterizes the market of individual investors in the Netherlands. In total 1.5 million out of 7 million Dutch households invest their money in financial markets. The average Dutch retail investor trades securities at 1.4 different financial institutions (banks and online brokers). Thus, it is unlikely that the investors in our sample trade at many other institutions than the online broker. Almost half of Dutch retail investors trade through websites of banks and Internet brokers. These online investors trade almost three times as much as offline investors, in line with results documented by Barber and Odean (2002). The value-weighted asset mix of the average Dutch investor consists of 44% mutual funds, 34% stocks, 15% bonds, 5% derivatives and 2% other products. Investors indicate that they predominantly invest in mutual funds via a traditional bank. In contrast, online brokers are mostly used for trading stocks and derivatives. For the average (median) investor the total value of the investment portfolio is €60,000 (€35,000).

2.2. Data set

The raw data set contains the daily trades and end-of-the-month portfolio positions of all individual investor accounts that existed during the period from January 2000 to March 2006. Due to trading restrictions, we exclude accounts owned by minors (age <18 years). We further exclude accounts with a beginning-of-the-month value of less than €250 to reduce the impact of outliers. Imposing these restrictions leaves 68,146 accounts and more than two million monthly portfolio overviews. On average, investors are present in the sample for 36 months.

Table 1 presents summary statistics for the data set. The sample is split into 26,266 option traders and 41,880 equity traders. We define an option trader as an investor who trades options at least once during the sample period. The proportion of men among option investors and equity investors is similar (more than 75%). Thus, if we take gender as a proxy for overconfidence, as suggested by Barber and Odean (2001), option traders and equity traders exhibit the same level of overconfidence. The average age of option traders and equity investors is also very similar (45 years). For option investors the mean (median) number of trades during the sample period is 80 (16) and for those who only invest in stocks the average (median) number of trades is 45 (11). The 10 most traded stocks account for 34% of all stock transactions and almost half of the value of all stock trades. The four most frequently traded stocks all belong to the IT and Telecommunications sector, which reflects the heavy trading of these stocks during the tech bubble. Most other frequently traded stocks are those of large companies.[3] A striking feature of our sample is that almost half of all trades are in options.[4] More than 33 million option contracts are traded, which, based on historical statistics retrieved from NYSE Euronext Liffe, is 7.2% of all option contracts traded at the Amsterdam options exchange during the sample period. The 10 most traded underlyings account for 77.2% of all option trades and 72.0% of the value of all option trades. Options on the Dutch AEX index account for 47.8% of all option transactions and 34.3% of the value of all option trades. The most frequently traded stock options are those on the largest firms with the most liquid stocks.[5]

Table 1 also reports statistics for monthly turnover per account, which we define as the average of the value of all security purchases and sales divided by beginning-of-the-month account

[3] By constructing value-weighted factors for performance attribution we take into account that investors mainly hold large caps, since these stocks receive more weight in the construction of the factors.

[4] To make a clean comparison between the impact of option trading and equity trading on investor performance we disregard transactions in bonds and futures contracts, which constitute only a small fraction of all trades.

[5] The option-based factors that we include in the performance evaluation model are constructed using AEX index options. Large and liquid stocks receive more weight in the value-weighted AEX index. Therefore, the fact that options are not available for small and illiquid stocks does not affect the performance evaluation.

value. Average turnover for option traders is 8.9% but median turnover is zero. For equity traders the average (median) turnover is 23.7% (zero). These results show that although the majority of investors (65%) does not trade on a monthly basis, a subset of investors trades very often. The fact that for option investors the average number of trades is higher than for equity investors but the average turnover is lower, indicates that the value of each option transaction is smaller than the value of a stock transaction. Consequently, the average costs per transaction are higher for option traders than for equity traders (€32 and €22, respectively).

The average (median) portfolio size of option traders and equity traders is again close to each other, with a mean value of €35,000 and a median of €10,000. Combining the average account value with a total portfolio value of €60,000 for the average Dutch investor, as reported by Millward-Brown (2006), shows that the average client invests more than half of the total investment portfolio at the online broker. We also assign income to investors, based on their zip-code and income data retrieved from the Dutch Central Bureau of Statistics (CBS). The average gross income of both groups of traders is slightly higher than €2500 a month. Following Seru et al. (2008), we measure experience by the number of months that an investor has been trading. The results in Table 1 show that on average, option traders are a bit more experienced than equity traders (35 and 33 months of experience, respectively). In general, however, the descriptive statistics show a striking similarity between the demographic, socioeconomic, and portfolio characteristics of option traders and equity traders.

3. Methods

3.1. Measuring investor performance

We define investor performance as the monthly change in the market value of all stocks and options in an investor's account. End-of-the-month account value is net of transaction costs the investor incurred during the month. Since we measure performance on a monthly basis, we have to make an assumption concerning the timing of deposits and withdrawals of cash and securities. To be conservative, we assume that deposits are made at the beginning of the month and that withdrawals take place at the end of the month. We also performed the analysis under the assumption that deposits and withdrawals are made halfway the month and find that our results are robust to this assumption. Thus, we calculate net performance as

$$R_{it}^{net} = \frac{(V_{it} - V_{it-1} - NDW_{it})}{(V_{it-1} + D_{it})}, \quad (1)$$

where V_{it} is the account value at the end of month t, NDW_{it} is the net of deposits and withdrawals during month t, and D_{it} are the deposits made during month t.

We obtain gross returns by adding back transaction costs incurred during month t, TC_{it}, to end-of-the-month account value,

$$R_{it}^{gross} = \frac{(V_{it} - V_{it-1} - NDW_{it} + TC_{it})}{(V_{it-1} + D_{it})}. \quad (2)$$

We only consider direct transaction costs (commissions) and do not add back any indirect transaction costs (market impact and bid-ask spreads). The trades of most individual investors are relatively small, so their market impact is likely to be limited. In addition, Keim and Madhavan (1998) point out that quoted bid-ask spreads may be imprecise estimates of the true spread, because trades are often executed inside the quoted spread. Therefore, Barber and Odean (2000) estimate the bid-ask spread using transaction prices and closing prices. However, this approach is inappropriate for our purposes as the resulting estimate of the spread includes the return on the trading day, which can be substantial in the case of options.

3.2. Performance attribution

We attribute the returns on investor portfolios to different risk and style factors to obtain the abnormal performance. The Carhart (1997) four-factor model is used to adjust investor returns for exposures to the market, size, book-to-market, and momentum factors. We construct these factors for the Dutch market, since the investors in the sample mainly invest in Dutch securities.[6] To characterize the market risk of the equity component of the portfolio returns, we include the return on the MSCI Netherlands equity index. We construct the factor-mimicking portfolios SMB, HML, and MOM according to the procedure outlined by Kenneth French.[7]

To characterize the nonlinear exposure from options, we build on the theoretical framework developed by Glosten and Jagannathan (1994), who propose adding option-based factors to performance attribution models. Agarwal and Naik (2004) implement this approach to measure the risk exposure of hedge funds and find that many funds use strategies that result in option-like payoffs. Following these studies, we include the excess returns on liquid at-the-money (ATM) European call and put options on the Dutch AEX stock market index to capture the nonlinear systematic risk exposure of investors' portfolios. In particular, at the end of each month, ATM call and put index options that expire 2 months later are bought. These index options are sold 1 month later and new index options are purchased. As a proxy for ATM options we select options whose strike prices are closest to the current index value. This rolling strategy of buying and selling index calls and puts produces a time series of monthly returns on ATM calls and puts that we add to the performance attribution model.

We further include the value-weighted average return on Dutch stocks from the MSCI IT and Telecommunications sector to capture possible tech-related style tilts, since many economists, including Shiller (2005), argue that the technology bubble was fed by irrational euphoria among individual investors. Because the option-based factors and the IT factor are highly correlated with the market return, we orthogonalize them with respect to the market factor.

The general time series model we estimate to obtain risk- and style-adjusted returns is

$$R_{it} = \alpha_i + \sum_{k=1}^{K} \beta_{ik} F_{kt} + \epsilon_{it}, \quad (3)$$

where R_{it} is the excess return on the portfolio of investor i, β_{ik} is the loading of portfolio i on factor k, and F_{kt} is the month t excess return on the k'th factor-mimicking portfolio. The intercept α_i measures abnormal performance relative to the risk and style factors. The factor loadings indicate whether a portfolio is tilted towards a particular investment style.

Other studies on individual investor performance assume that factor loadings remain constant over time, i.e., they use unconditional or static models for performance attribution. However, a large body of empirical evidence shows that the systematic risk of stocks varies substantially over time as a function of the business cycle (see, e.g., Ferson and Harvey, 1999; Bauer et al., in press). Moreover, in a dynamic world it is unlikely that investors keep

[6] In terms of volume (value) 95% (85%) of all trades are transactions in Dutch securities. This suggests the presence of a home bias among Dutch investors, which has previously been documented by French and Poterba (1991) for the US, Japan, and UK and by Karlsson and Norden (2007) for Sweden. Consequently, we find that Dutch versions of the factor-mimicking portfolios lead to a better model fit than do international factors.

[7] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

their exposure to risk and style factors constant over time. Empirical support for this conjecture is provided by Kumar (in press), who finds that individual investors exhibit time-varying style preferences, driven by past style returns and earnings differentials. Hence, Ferson and Schadt (1996) argue that fluctuations in factor exposures should be taken into account when measuring portfolio performance. We treat the time-varying alphas and betas as latent state variables and infer them directly from portfolio returns using the Kalman filter. We assume a random walk process for the latent alphas and betas. Specifically, we consider the following state-space representation:

$$R_{it} = \alpha_{it} + \sum_{k=1}^{K} \beta_{ikt} F_{kt} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \sigma^2_{i\epsilon}), \tag{4}$$

$$\alpha_{it} = \alpha_{it-1} + \nu_{it}, \quad \nu_{it} \sim N(0, \sigma^2_{i\nu}), \tag{5}$$

$$\beta_{it} = \beta_{it-1} + \eta_{it}, \quad \eta_{it} \sim N(0, Q), \tag{6}$$

where ϵ_{it}, ν_{it}, and η_{it} are normally distributed mean zero shocks orthogonal to each other and with variance $\sigma^2_{i\epsilon}$, $\sigma^2_{i\nu}$, and diagonal covariance matrix Q, respectively. We test the null hypothesis of constant betas, which corresponds to the restriction that the diagonal elements of Q are zero, using a likelihood ratio test. Eq. (4) is the observation equation and Eqs. (5) and (6) are the state equations. The Kalman filter is a recursive algorithm for sequentially updating the one-step ahead estimate of the state mean and variance. We use it to calculate maximum likelihood estimates of the model parameters $\sigma^2_{i\epsilon}$, $\sigma^2_{i\nu}$, and Q along with minimum mean-square error estimates of the state variables α_{it} and β_{it}. We set the initial one-step-ahead predicted values for the states equal to the OLS estimates from the static model. We treat the initial one-step-ahead predicted values of $\sigma^2_{i\nu}$ and the covariance matrix Q as diffuse, setting them equal to arbitrarily large numbers. We use a smoothing algorithm to obtain Kalman smoothed estimates, conditioned on information from the full sample period (see, e.g., Hamilton, 1994).

4. Results

4.1. Option trading and investor performance

In this section we compare the raw returns and alphas of option traders and equity investors. Barber and Odean (2000) show that the common stock performance of individual investors is poor due to excessive trading and poor stock selection skills. This raises the question how these investors perform when trading options, which have a more complex payoff structure.

In Table 2, panel A shows that the average option investor loses 1.81% per month in gross terms during the sample period, which is

Table 2
Investment performance of option traders and equity traders.

	Gross			Net		
	Options	Stocks	Difference	Options	Stocks	Difference
Panel A: Performance full period: 2000/01–2006/03						
Raw return	−1.81	−0.58	−1.23	−4.46	−1.57	−2.89
	(−2.31)	(−0.49)	(−1.60)	(−6.83)	(−1.35)	(−3.24)
Static alpha	−1.01	0.03	−1.04	−3.72	−0.97	−2.75
	(−1.72)	(0.05)	(−2.00)	(−6.30)	(−2.08)	(−4.65)
Dynamic alpha	−0.93	0.03	−0.96	−3.59	−0.97	−2.62
	(−1.75)	(0.34)	(−2.08)	(−6.24)	(−2.17)	(−4.81)
Panel B: Performance subperiod 1: 2000/01–2003/03						
Raw return	−3.03	−3.70	0.67	−5.51	−4.78	−0.73
	(−3.02)	(−2.52)	(0.68)	(−5.60)	(−3.32)	(−0.78)
Static alpha	1.32	1.00	0.32	−1.28	−0.15	−1.13
	(1.17)	(1.23)	(0.39)	(−1.19)	(−0.10)	(−1.43)
Panel C: Performance subperiod 2: 2003/04–2006/03						
Raw return	−0.48	2.80	−3.28	−3.33	1.90	−5.23
	(−0.58)	(2.02)	(−2.65)	(−4.48)	(1.41)	(−4.45)
Static alpha	−1.82	−0.01	−1.81	−4.74	−0.87	−3.87
	(−2.92)	(−0.01)	(−2.15)	(−7.87)	(−1.29)	(−4.90)

	Full period		Subperiod 1		Subperiod 2	
	Options	Stocks	Options	Stocks	Options	Stocks
Panel D: Factor loadings						
R_M	0.94	1.48	1.20	1.46	0.71	1.14
	(5.55)	(19.39)	(4.69)	(10.48)	(2.52)	(3.70)
SMB	0.30	0.99	0.22	0.87	0.60	1.05
	(1.21)	(7.89)	(0.74)	(6.87)	(2.01)	(3.18)
HML	−0.13	0.23	−0.10	0.26	0.10	0.42
	(−0.63)	(2.31)	(−0.39)	(2.99)	(0.41)	(1.62)
MOM	0.16	0.01	0.21	0.15	0.16	−0.36
	(1.26)	(0.08)	(1.12)	(2.17)	(1.16)	(−2.65)
ATMC	0.37	0.06	0.66	−0.12	0.39	0.22
	(3.24)	(0.80)	(2.18)	(−0.59)	(2.58)	(1.79)
ATMP	0.04	−0.02	0.08	0.05	−0.15	−0.21
	(0.24)	(−0.26)	(0.44)	(0.53)	(−1.08)	(−1.15)
IT	0.31	0.41	0.25	0.48	0.17	0.24
	(2.89)	(6.35)	(1.44)	(5.46)	(0.99)	(1.28)
Adj. R^2 (%)	61.8	89.1	61.3	94.2	62.8	85.3

This table reports the raw returns and alphas of option traders and equity investors. Panel A presents the performance for the full sample period, January 2000 to March 2006, panel B for the first subperiod from January 2000 to March 2003, and panel C for the second subperiod from April 2003 to March 2006. The left-hand side of each panel shows the gross performance and the right-hand side displays the net performance of each group of investors. Static alphas are those produced by the static model in Eq. (3) and dynamic alphas are the average alphas produced by the dynamic model in Eqs. (4)–(6). Panel D reports the estimated factor loadings in the static model for the full period and the two subperiods for both groups of investors. t-Statistics based on Newey–West heteroskedasticity and autocorrelation robust standard errors are in parentheses.

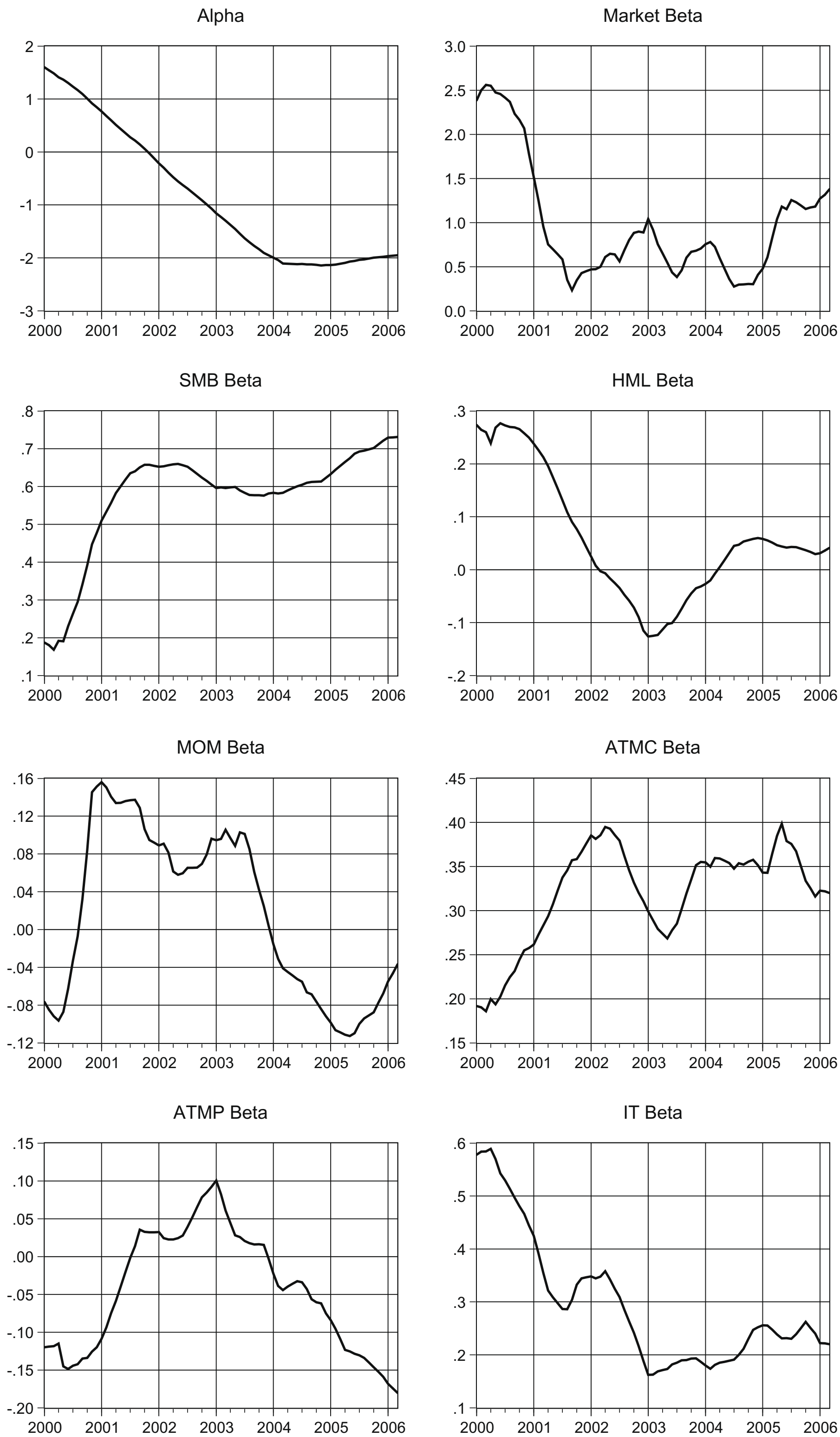

Fig. 1. Kalman smoothed alpha and betas for option traders. This figure plots the evolution of the Kalman smoothed alpha and betas for option traders over the period January 2000 through March 2006. The estimates are produced by the dynamic factor model in Eqs. (4)–(6) and are based on gross returns.

economically large and statistically significant at a 1% level. In contrast, equity investors only lose 0.58%, which is not significant at conventional levels. The second line in Table 2 shows that accounting for risk exposures and style tilts explains only part of the poor performance of option traders. Specifically, while the gross alpha of equity traders is close to zero, the risk- and style-adjusted return of option traders is −1.01%. In the third row of panel A, we adjust returns for time-varying risk and style exposures using the dynamic factor model in Eqs. (4)–(6). Although the average dynamic alpha of option traders is 10 basis points higher than their static alpha, they still underperform equity investors by almost a percent per month. Thus, allowing for time variation in risk and investment styles does not eliminate the underperformance of option traders.

The right-hand side of panel A indicates that the performance gap between option traders and common stock investors widens when transaction costs are taken into account. In particular, the net alphas of equity investors are 2.75% higher than those of option traders. Thus, option investors not only lose due to poor investment decisions but also suffer from higher trading costs. Part of this underperformance can be explained by the brokerage firm's commission fee structure. Trading costs for option contracts consist of a specific amount per contract, whereas trading costs for stocks are based on a fixed amount and a variable part that depends on the value of the transaction. Because option investors tend to trade many small contracts, trading options is more expensive than trading stocks in relative terms.

To shed more light on the poor performance of option traders we split the sample in two subperiods.[8] The first period, from January 2000 to March 2003, includes the huge stock market decline after the burst of the tech bubble. In the second subperiod, from April 2003 to March 2006, the market gradually recovers from the crash. Panel B shows that in the first subperiod option investors earn positive gross alphas and actually outperform equity traders. However, panel C reveals that in the second subperiod option traders underperform other investors by almost two percent in terms of gross alpha and almost four percent in terms of net alpha. These results suggest that option traders seem to miss the recovery of the market.

Panel D reports the beta estimates in the static performance evaluation model for both groups of investors. These betas are based on gross returns but loadings based on net returns are similar. The results indicate that the loadings of the portfolios held by option investors on the market and SMB factors are significantly lower than those of the equity-only traders. As expected, their exposure to the call option factor is higher. The positive loadings on the IT factor imply that, on average, investors' portfolios are tilted towards technology stocks. The subsample analysis shows that investors lower their exposure to the market, momentum and the IT factors but increase their exposure to the size and value factors in the second subperiod, in line with Kumar's (in press) finding that individual investors exhibit time-varying style preferences.

Fig. 1, which traces the evolution of time-varying alphas and betas for option traders, confirms our finding that these investors primarily underperform in the second subperiod. The plot further shows that although factor betas fluctuate heavily, investors often adjust their exposures too late.[9] For instance, in the first subperiod option traders increase their exposure to the call option factor when the market falls, but decrease their call option exposure at the beginning of the second subperiod when the recovery sets in. Interesting, however, is that option traders already lower their exposure to the IT factor in 2000 whereas equity traders keep their exposure constant throughout the first subperiod. A possible explanation for the slower response of equity investors to the burst of the IT bubble is that these traders are more prone to the disposition effect than option traders. Brunnermeier and Nagel (2004) show that hedge funds, which are considered to be managed by sophisticated investors, were also riding the bubble but reduced their exposure to the IT sector before stock prices collapsed.

Because the poor performance of option traders compared to equity investors is not explained by risk and style tilts, we consider several other potential explanations. First, we account for known determinants of investor performance by relating returns to a number of investor characteristics. We examine the cross-sectional relation between investor performance and characteristics using the cross-sectional approach of Fama and MacBeth (1973). Each month we run a cross-sectional regression of portfolio returns on investor characteristics,

$$R_{it} = \gamma_{0t} + \sum_{l=1}^{L} \gamma_{lt} Z_{ilt} + \xi_{it}, \tag{7}$$

where Z_{ilt} is the value of characteristic l for investor i in month t. We then calculate the Fama–MacBeth estimator for the characteristics, which is the time series average of the monthly cross-sectional parameter estimates. We calculate the standard error of the Fama–MacBeth estimator from the time series of these monthly estimates. We perform this analysis for the full sample period as well as the two subperiods defined before to assess the stability of the relations between performance and characteristics in different market conditions.

We include the following characteristics as independent variables: *options* and *stocks&options*, which are two dummy variables equal to one if investor i trades only options or both stocks and options, respectively, in month t; monthly portfolio *turnover*; *inactive*, a dummy variable equal to one if monthly portfolio turnover is zero; and *woman* and *joint*, which are two gender dummy variables equal to one if the account is held by a woman or jointly by a man and woman. We also include the *value* of the portfolio at the end of the previous month. Because the descriptive statistics in Table 1 show that the distributions of turnover and account value are skewed, we trim these characteristics at the 99th percentile and use their logarithmic transformations. We further include the *age* and the gross *income* of investors. Finally, we add *experience*, measured by the number of months an investor has been trading, to the regressions.

Table 3 reports results from the Fama–MacBeth regressions. Results on the left-hand side of the table correspond to regressions with raw returns as dependent variable. The first column shows that even after controlling for investor and portfolio characteristics, option traders continue to earn lower gross returns than those investors who only trade stocks. This is consistent with the observation in Table 1 that the demographic, socioeconomic, and portfolio characteristics of option traders and equity investors are very similar. The estimation results for the two subperiods reported in columns two and three confirm the result from Table 2 that the underperformance of option traders is concentrated in the second subperiod. The estimates in the next three columns show that also in the presence of control variables the return difference between option and stock investors increases when transactions costs are taken into account. In addition, the coefficient estimates on the control variables have the expected signs. Specifically, we find that trading lowers net performance, in line with the evidence of Barber and Odean (2000), and that portfolios held by women outperform those of men, confirming the results of Barber and Odean (2001). We also find a strong, positive relation between portfolio value and investor performance and between income and performance, which indicates that investors with larger portfolios and higher income outperform smaller investors.

The cross-sectional analysis above does not account for risk and style differences across investor portfolios. The standard approach to identifying the determinants of cross-sectional variation in risk- and style-adjusted returns consists of two steps. First, for every portfolio a time series regression of returns on risk and style factors is run to obtain alpha. Second, a cross-sectional regression of these alphas on investor characteristics is estimated. The main drawback of this approach is the errors-in-variables problem that arises be-

[8] We do not estimate dynamic models for subperiods because of the small number of time series observations.

[9] The likelihood ratio for testing whether factor loadings are constant in the dynamic model is 22.11, rejecting the null hypothesis that betas are constant at a 1% level.

Table 3
Investor performance and characteristics.

	Raw return						Alpha					
	Gross			Net			Gross			Net		
	Full	Sub 1	Sub 2	Full	Sub 1	Sub 2	Full	Sub 1	Sub 2	Full	Sub 1	Sub 2
Options	−1.34	0.40	−3.23	−3.38	−1.39	−5.55	−1.11	0.39	−1.96	−3.21	−1.54	−4.32
	(−1.88)	(0.37)	(−3.95)	(−4.73)	(−1.28)	(−7.10)	(−2.08)	(0.41)	(−2.77)	(−6.09)	(−1.58)	(−6.68)
Stocks & options	−0.91	−1.10	−0.70	−1.64	−1.77	−1.50	−0.79	−0.69	−0.64	−1.53	−1.39	−1.42
	(−3.96)	(−3.09)	(−2.47)	(−7.04)	(−5.01)	(−4.97)	(−3.61)	(−1.69)	(−2.25)	(−6.91)	(−3.45)	(−4.92)
Turnover	0.67	0.84	0.47	−0.08	0.08	−0.27	0.79	1.38	0.29	0.04	0.54	−0.42
	(4.54)	(3.34)	(3.57)	(−0.63)	(0.36)	(−2.20)	(5.72)	(5.05)	(2.10)	(0.28)	(1.16)	(−2.96)
Inactive	−1.16	−0.92	−1.42	0.79	1.05	0.52	−1.46	−2.07	−0.27	0.52	−0.02	1.64
	(−2.83)	(−1.57)	(−2.47)	(2.03)	(1.87)	(0.95)	(−4.26)	(−3.42)	(−0.57)	(1.60)	(−0.03)	(3.60)
Single woman	0.38	0.67	0.07	0.37	0.66	0.06	0.33	0.36	0.19	0.31	0.34	0.16
	(3.47)	(3.96)	(0.60)	(3.35)	(3.96)	(0.45)	(3.52)	(2.12)	(1.52)	(3.32)	(2.06)	(1.28)
Joint	0.18	0.19	0.16	0.23	0.25	0.20	0.13	−0.02	0.14	0.18	0.04	0.17
	(3.44)	(2.12)	(3.53)	(4.44)	(2.83)	(4.39)	(2.29)	(−0.21)	(3.89)	(3.75)	(0.42)	(2.76)
Portfolio value	0.28	0.38	0.17	0.55	0.66	0.44	0.22	0.02	0.23	0.50	0.31	0.41
	(2.52)	(2.03)	(1.96)	(5.21)	(3.48)	(5.35)	(2.01)	(0.07)	(2.45)	(5.07)	(1.48)	(3.97)
Age/10	−0.01	0.01	−0.03	−0.02	0.01	−0.05	−0.05	−0.05	−0.05	−0.07	−0.06	−0.07
	(−0.28)	(0.22)	(−1.03)	(−0.59)	(0.23)	(−1.78)	(−2.32)	(−1.39)	(−2.04)	(−2.78)	(−1.14)	(−2.19)
Income	0.47	0.73	0.19	0.50	0.77	0.21	0.43	0.84	0.35	0.46	0.89	0.37
	(5.16)	(5.42)	(1.80)	(5.55)	(5.81)	(2.03)	(3.54)	(4.09)	(5.25)	(4.87)	(5.67)	(3.50)
Experience	0.07	0.12	0.02	0.07	0.11	0.02	0.11	0.38	0.02	0.05	0.16	0.03
	(1.09)	(0.95)	(0.42)	(1.09)	(0.92)	(0.43)	(1.04)	(1.23)	(0.79)	(0.84)	(1.11)	(0.20)

This table reports Fama–MacBeth (1973) coefficient estimates. The left-hand side of the table uses raw returns as dependent variables and the right-hand side refers to alphas. Both gross and net returns are used in the estimation. We estimate the Fama–MacBeth regressions for the full period, January 2000 to March 2006, and for two subperiods, January 2000 to March 2003 and April 2003 to March 2006. The independent variables are investor characteristics. Options is a dummy variable equal to one if an investor only traded options in a given month. Stocks&options is a dummy variable equal to one if the investor trades both stocks and options in a particular month. Turnover is the average of the value of all purchases and sales of an investor in a given month divided by beginning-of-the-month account value. Inactive is a dummy variable equal to one if an investor does not trade in a given month. Single woman and joint are dummy variables equal to one if the account is held by a woman or jointly by a man and woman, respectively. Portfolio value is the market value of all assets in the investor's portfolio and is lagged by one month. Age is the age of the primary account holder. Income is the monthly income assigned to investors based on their zip-code. Experience is the number of months the investor has been trading. Turnover and portfolio value are expressed as natural logarithms. *t*-Statistics are in parentheses.

cause the factor loadings in the first-stage time series regression are estimated with error. Therefore, we introduce a new method that makes it possible to control for risk and style exposures even when the number of return observations for some investors is small. This approach is based on a purged estimator used in the asset pricing literature by Brennan et al. (1998). Each month, we run the cross-sectional regression (7) of returns on characteristics. We then regress the vector of monthly cross-sectional coefficients for each characteristic, γ_{lt}, on a constant and the risk and style factors F_{kt},

$$\gamma_{lt} = \delta_{l0} + \sum_{k=1}^{K} \delta_{lk} F_{kt} + \omega_{lt}. \tag{8}$$

In the Appendix we demonstrate that the intercept in this regression, δ_{l0}, is an unbiased estimate of the cross-sectional relation between characteristic l and alpha.

The right-hand side of Table 3 shows that the conclusion that option trading has a detrimental impact on investor performance also holds when alpha is used as a dependent variable. The bottom line is that controlling for differences in risk and style exposures and differences in the characteristics of investors and their portfolios does not explain the underperformance of option traders compared to equity investors.

4.2. Investor sentiment and market timing

The finding that the underperformance of option investors is concentrated in the second subperiod suggests that it is related to poor market timing. Market timing skills are especially important in the option market because options are effective instruments for betting on market moves due to the leverage they provide and the positive skewness of their payoffs. Since we find that option investors perform poorly when markets move upward, we conjecture that after the stock market decline in 2001 and 2002, investors became bearish about market prospects and expected a further fall. Since the brokerage firm restricts the ability of its clients to sell stocks short to the 50 largest and most liquid Dutch stocks and only allows intraday short selling, most investors use options to speculate on a market decrease. Therefore, we expect that at the end of 2002 investors took bearish positions in options.

Initial evidence supporting this hypothesis is provided in Fig. 2, which plots the return on the MSCI Netherlands equity index, the gross return difference between equity investors and option traders, and the ratio of short-term (3 months to expiration or less) option positions taken in anticipation of a market increase and positions taken in anticipation of a market decrease. We calculate this call/put ratio as the value of call options bought by the investors divided by the value of their put option purchases.[10] An increase (decrease) in the call/put ratio indicates that option investors become more optimistic (pessimistic) about stock market prospects. Fig. 2 indicates that the ratio is below one for most months in 2003 and 2004, which is exactly the period in which stock markets started to recover. This supports our hypothesis that, after the stock market crash in 2001 and 2002, option traders speculated on a further decline of the market. As a result, they missed part of the recovery of the market and consequently, common stock investors outperformed option traders during this period.

The importance of sentiment in option markets has recently been shown by Han (2008), who documents that investor sentiment about the stock market affects option prices. Fig. 3 relates the call/put ratio to the level of the MSCI Netherlands index and

[10] We also considered an extension of this ratio, defined as the sum of the value of call options bought and put options sold divided by the sum of the value of put options bought and call options sold. Using this ratio leads to similar results.

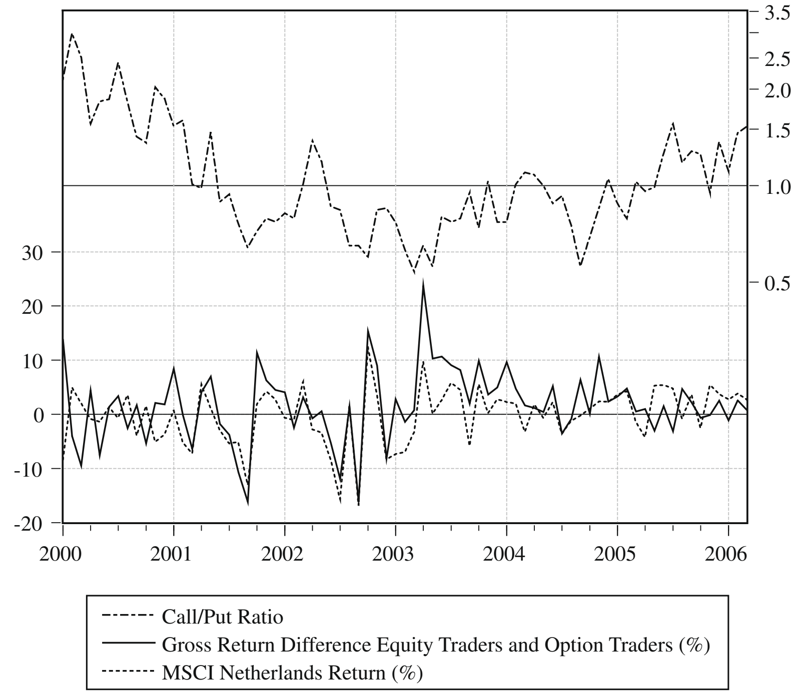

Fig. 2. Call/put ratio and return difference equity traders and option traders. This figure plots the evolution through time of the monthly call/put ratio, the return on the MSCI Netherlands equity index and the gross return difference between equity and option traders. We calculate the call/put ratio as the value of short-term (3 months to expiration or less) call options bought by the investors divided by the value of their put option purchases. The sample period is January 2000 to March 2006.

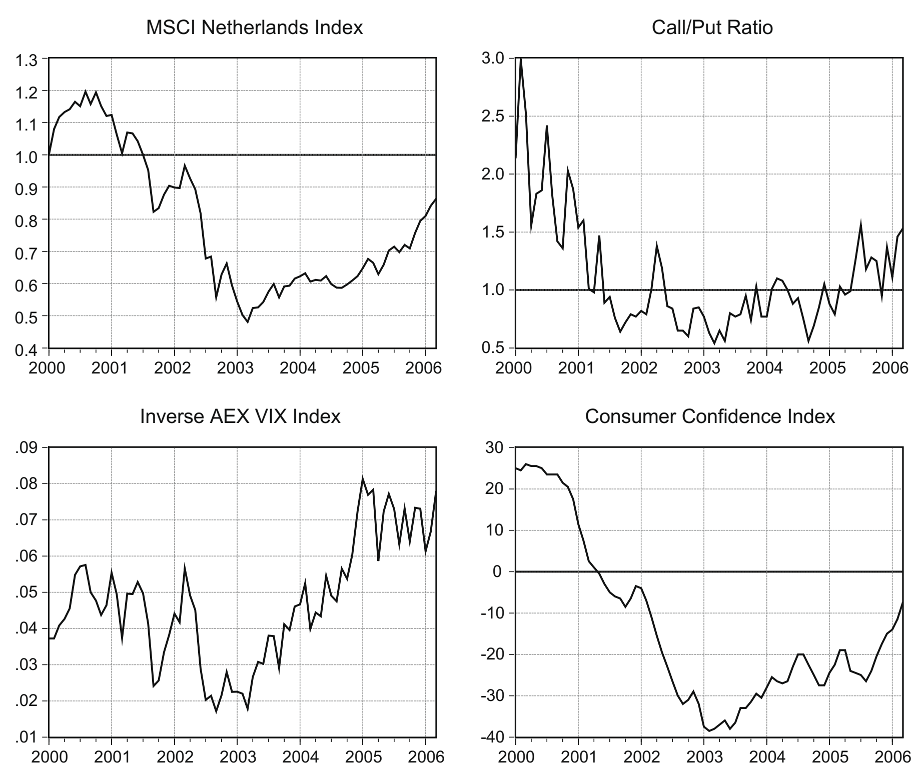

Fig. 3. MSCI Netherlands index and sentiment measures. This figure shows the evolution through time of the MSCI Netherlands Equity Index, scaled to 1 in January 2000, and of three sentiment measures. We define the call/put ratio as the value of short-term (3 months to expiration or less) call options bought by the investors divided by the value of their put option purchases. The AEX VIX index captures the implied volatility embedded in prices of options on the Dutch AEX stock market index. We plot the inverse of the VIX so that low values correspond to fear among investors. The Consumer Confidence Index is constructed by the investors divided by the value of their put option purchases. The AEX VIX index captures the implied volatility embedded in prices of options on the Dutch AEX stock market index. We plot the inverse of the VIX so that low values correspond to fear among investors. The Consumer Confidence Index is constructed by the Dutch Central Bureau of Statistics. The sample period is January 2000 to March 2006.

Table 4
Sentiment and market timing.

	Mean	Std. dev.	Autocorrelation	Pairwise correlations		
Panel A: Descriptive statistics on sentiment indicators						
Call/put ratio	1.12	0.49	0.79	1		
AEX VIX index	24.63	10.77	0.86	−0.60	1	
CC index	−13.45	19.74	0.97	0.43	−0.52	1
Gross return difference option traders and equity traders						
Panel B: Option trader performance and market timing						
Intercept	−1.91	−4.48	−1.99	−1.82	−1.97	−1.90
	(−3.08)	(−2.95)	(−4.16)	(−3.67)	(−4.00)	(−4.01)
Market	−0.77	−0.78	−2.14	−3.29	−2.35	−3.15
	(−6.57)	(−6.74)	(−10.00)	(−8.20)	(−9.10)	(−8.18)
Call/put		2.31				
		(1.85)				
Market×call/put			1.46			
			(7.06)			
Market×call/put index				3.14		1.79
				(6.45)		(2.70)
Market×call/put stocks					0.66	0.40
					(6.55)	(2.87)
Adj. R^2 (%)	37.1	38.3	61.8	59.0	59.5	62.8

Panel A of this table presents descriptive statistics for three sentiment indicators. We define the call/put ratio as the value of all call options bought by the investors divided by the value of their put option purchases. The AEX VIX index captures the implied volatility embedded in prices of options on the Dutch AEX stock market index. The CC index is the consumer confidence index constructed by the Dutch Central Bureau of Statistics (CBS). Panel B presents results for time-series regressions of the gross return difference between option traders and equity traders on the market return, the call/put ratio, and various interaction terms between the market return and the call/put ratio, constructed using index options, stock options, or both. t-Statistics based on Newey–West heteroskedasticity and autocorrelation robust standard errors are in parentheses.

to two other sentiment indicators, which are the consumer confidence index obtained from the Dutch Central Bureau of Statistics and the AEX volatility index (VIX) provided by Euronext. The VIX measures the market expectations of short term volatility implied by AEX index option prices. Since volatility often signals financial turmoil, the VIX is commonly interpreted as a measure of fear in the market.[11] We plot the inverse of the VIX so that high values correspond to optimism among investors. Fig. 3 shows a strong relation between the MSCI index on the one hand and the three sentiment measures on the other hand. Both the index and the sentiment indicators reach their lowest value in the beginning of 2003, which coincides with the start of the second subperiod. The plots also reveal that after the downfall of the market it takes considerable time before confidence of consumers and investors has been restored to normal levels.

Table 4 provides a more formal analysis of the relation between sentiment, market timing, and investor performance. The pairwise correlations between the three different sentiment measures reported in panel A confirm their strong relationships depicted in Fig. 3. In panel B we present results for time-series regressions of the gross return difference between option traders and equity investors on the market return, the call/put ratio, and interaction terms between these two variables. The first column shows that the market return alone explains more than 37% of the performance difference between these two groups of investors. The negative coefficient implies that option traders lose relative to stock investors when markets increase, which lends further support to the hypothesis that bad market timing is responsible for the underperformance of option traders in the second subperiod, when stock markets rose. The second column indicates that adding the call/put ratio only leads to a small increase in the adjusted R^2. In contrast, column 3 shows that adding an interaction term between the market return and the call/put ratio leads to a sharp increase in explanatory power. In fact, this two-factor model explains more than 60% of the underperformance of option traders. The positive coefficient on this interaction term means that for a given market return, an increase in the call/put ratio is related to an increase in the relative performance of option traders. This explains the poor performance of option investors in the second subperiod, when the call/put ratio of their trades was low.

In columns four and five we include call/put ratios constructed using index options and stock options, respectively, to examine whether the underperformance of option traders is driven by market sentiment (index options) or stock-specific sentiment (stock options). When including these variables separately, they are both significant at a 1% level. In column six we include both ratios simultaneously in the regression and find that they are still significant. This suggests that market sentiment and stock-specific sentiment are both important in explaining the underperformance of option traders.

The conclusion that option traders overreact to past stock market movements is in line with results of Lakonishok et al. (2007). These authors find that discount clients decreased their open interest in purchased puts at the height of the Internet bubble but sharply cut their bets that prices would increase after the burst of the bubble. In contrast, clients of full-service brokers and firm proprietary traders did not use the option market to speculate on rising prices during the boom.

To further investigate the relation between sentiment and market returns, we estimate vector autoregressive (VAR) models with the call/put ratio and the market return as dependent variables. The VAR model makes it possible to examine the dynamic interrelationships between sentiment and market returns. The methodology is similar to that used by Brown and Cliff (2004) and Schmitz et al. (2007), who find strong evidence that sentiment is driven by past stock market returns but little evidence that sentiment predicts returns.

The general VAR model is given by

$$Y_t = \phi_0 + \sum_{j=1}^{P} \phi_j Y_{t-j} + \eta_t, \tag{9}$$

where Y_t is a vector that contains the call/put ratio and the market return. We use the Schwarz criterion and the Akaike information criterion to determine the appropriate number of lags P. These cri-

[11] The construction of the AEX volatility index follows the current methodology of the CBOE for constructing the traditional VIX, which is based on the S&P500 index option prices listed on CBOE.

Table 5
VAR model of sentiment and market returns.

	2000/01–2006/03		2000/01–2003/03		2003/04–2006/03	
	Call/put	Market	Call/put	Market	Call/put	Market
Intercept	0.26	0.89	0.29	−3.58	0.18	2.02
	(3.71)	(0.55)	(2.28)	(−1.29)	(1.41)	(0.80)
Call/put$_{t-1}$	0.63	1.10	0.67	2.98	0.45	−0.26
	(6.13)	(0.47)	(4.60)	(0.95)	(2.64)	(−0.08)
Call/put$_{t-2}$	0.11	−2.03	0.05	−1.92	0.35	0.68
	(1.15)	(−0.91)	(0.40)	(−0.64)	(2.10)	(0.21)
Market$_{t-1}$	0.02	0.06	0.02	−0.06	0.02	−0.21
	(3.09)	(0.53)	(1.96)	(−0.36)	(2.48)	(−1.25)
Market$_{t-2}$	−0.01	0.10	−0.01	−0.02	0.00	−0.14
	(−0.84)	(0.81)	(−0.62)	(−0.09)	(0.35)	(−0.80)
Granger causality *F*	5.08	0.53	2.28	0.48	3.09	0.03
P-value	(0.01)	(0.59)	(0.12)	(0.62)	(0.06)	(0.97)
Adj. R^2 (%)	70.3	−2.4	70.5	−9.1	54.7	−5.2

This table presents estimation results for vector autoregressive models with two lags. The dependent variables are the call/put ratio and the market return. We estimate the VAR models for the full period, January 2000 to March 2006, and for two subperiods, January 2000 to March 2003 and April 2003 to March 2006. *t*-Statistics based on Newey–West heteroskedasticity and autocorrelation robust standard errors are in parentheses. Granger causality *F* is the *F*-statistic of a test that the coefficients on the lags of the independent variables other than the lags of the dependent variable are jointly equal to zero.

teria prefer a specification with two lags of the call/put ratio and the market return.

Table 5 presents the estimation results from the VAR model for the full sample period and the two subperiods. The first column shows that the first-order lags of the call/put ratio and the market return have a significantly positive impact on the current level of the call/put ratio. This is consistent with the hypothesis that option investors extrapolate recent market returns. In contrast, Schmitz et al. (2007) derive a sentiment measure from warrants and find that past returns have a negative impact on sentiment, while sentiment has a positive impact on future returns. However, these effects are short-lived (2 days), so sentiment measures do not seem to be useful to predict returns for longer horizons. Table 5 also reports *F*-statistics and *p*-values for Granger causality tests that the coefficients on the lags of the independent variables other than the lags of the dependent variable are jointly equal to zero. The results show that market returns Granger-cause the call/put ratio at the 1% level. In contrast, column two indicates that lags of the call/put ratio do not predict the return on the market. Estimation results for the two subperiods are similar and confirm the conclusion that sentiment among option investors, as measured by the call/put ratio,

Table 6
Trading behavior and investor characteristics.

	Probit		Fama–MacBeth		Panel	
	Options	Stocks	Options	Stocks	Options	Stocks
Intercept	−1.51	−1.09	−2.40	0.20	−3.12	0.02
	(−10.63)	(−5.19)	(−6.14)	(0.91)	(−4.56)	(0.06)
Net return$_{t-1}$	−0.33	0.06	−0.81	0.02	−0.76	0.04
	(−4.80)	(1.14)	(−10.06)	(0.52)	(−7.15)	(0.68)
Single woman	−0.20	−0.23	−0.33	−0.21	−0.40	−0.25
	(−9.15)	(−7.56)	(−8.79)	(−11.26)	(−6.34)	(−8.02)
Joint	−0.13	−0.07	−0.22	−0.06	−0.26	−0.07
	(−10.00)	(−3.61)	(−11.11)	(−8.34)	(−6.99)	(−5.39)
Portfolio value	0.16	0.23	0.35	0.25	0.38	0.27
	(38.35)	(20.58)	(14.56)	(14.64)	(8.86)	(10.86)
Age/10	0.04	0.00	0.09	0.02	0.10	0.02
	(7.57)	(0.22)	(12.02)	(6.84)	(8.48)	(4.98)
Income	−0.12	−0.17	−0.29	−0.25	−0.30	−0.26
	(−6.49)	(−7.09)	(−16.23)	(−27.27)	(−7.86)	(−11.42)
Experience/12	−0.08	−0.01	−0.25	−0.17	−0.17	−0.12
	(−14.17)	(−5.72)	(−7.12)	(−4.17)	(−7.42)	(−9.44)
Inverse Mills ratio			2.13	0.79	2.46	0.97
			(10.99)	(8.87)	(7.12)	(6.63)
Equity trades	0.22		0.48		0.53	
	(30.35)		(16.12)		(9.13)	
Option trades		0.23		0.18		0.20
		(9.03)		(11.72)		(15.13)
R^2 (%)	6.6	9.2	6.3	6.9	4.3	5.6

This table relates the trading behavior of individual investors to investor characteristics. Results in the columns labeled "Probit" are estimates for a pooled probit regression with standard errors clustered by investor and month to account for potential serial correlation and cross-correlation in parentheses. Results in the columns labeled "Fama–MacBeth" refer to Fama and MacBeth (1973) coefficient estimates with Newey–West heteroskedasticity and autocorrelation robust standard errors in parentheses. Results in the columns labeled "Panel" are pooled OLS panel regression estimates with standard errors clustered by investor and month in parentheses. The dependent variable in the probit model is a dummy variable equal to one if an investor trades options (column 1) or stocks (column 2) in a given month. The dependent variable in the Fama–MacBeth and panel regressions is the logarithm of the number of option trades per month per account (columns 3 and 5) or the logarithm of the number of equity trades (columns 4 and 6). The inverse Mills ratio is based on the estimates of the pooled probit regressions and is included to account for self-selection in trading decisions. The R^2 for the probit regressions is the pseudo R^2.

is driven by past market returns while the call/put ratio itself does not predict future market returns.

4.3. Hedging and gambling motivations for option trading

The large losses on option investments bring up the question why individual investors trade options. In this section we consider two alternative motivations for option trading. First, it is possible that investors use options for hedging the downward risk of their stock portfolio. Another possibility is that investors use options for gambling. Kumar (2008) links the preference of individual investors for lottery stocks to their socioeconomic characteristics. He defines lottery stocks as stocks with a low price, high idiosyncratic skewness, and high idiosyncratic volatility and shows that state lotteries and lottery stocks attract a similar socioeconomic clientele, which consists of poor, young, single men. However, options seem to be even more attractive for gambling purposes than stocks because of the leverage they provide and their skewed payoffs.

We examine this hypothesis by linking both option trading and equity trading to a number of investor and portfolio characteristics. Specifically, we regress different measures of trading on a gender dummy variable, lagged portfolio value, age, income, experience, and past portfolio returns. We also include the number of trades in the other asset class as a regressor to control for an investor's general propensity to trade. Furthermore, this allows us to investigate whether option investors also trade more stocks than equity-only investors.

The first two columns in Table 6 report estimates for a pooled probit model that measures the influence of the investor and portfolio characteristics on the decision to trade options (column one) and stocks (column two) in a given month. Standard errors are clustered by investor and by time period, as suggested by Petersen (in press), to account for both serial correlation and cross-sectional correlation. The results indicate that past portfolio returns have a significantly negative impact on the decision to trade options. In contrast, past returns have a positive but insignificant effect on the decision to trade stocks. The finding that lower past returns increase trading activity among option investors but decrease the intensity of trading among equity investors is consistent with a disposition effect being present among equity traders but absent among option traders. Another potential explanation for this finding is that option traders are loss-averse and take more risk following losses and less risk following gains. This is consistent with evidence documented by Coval and Shumway (2005), who show that professional future traders are highly loss averse.

Table 6 also shows that females have a lower propensity to trade both options and stocks, which generalizes the conclusion of Barber and Odean (2001) that men trade more than women to the option market. Portfolio value has a positive impact on the decision to trade, since large portfolios require more trades. We further find that older investors are more likely to trade stocks and options. A possible explanation for this result is that for older investors trading is a leisure activity.[12] Experience and income lower the probability of trading stocks and options, consistent with the view that less experienced investors and those with lower income are more inclined to gamble.

The probit regressions consider the decision to trade but not the intensity of trading. Therefore, in columns three and four we report Fama–MacBeth regression estimates in which the dependent variable is the logarithm of the number of option trades (column three) and equity trades (column four). Since the dependent variables exhibit serial correlation, we correct the Fama–MacBeth standard errors for serial correlation using the Newey–West procedure, as suggested by Cochrane (2005). In addition, we apply the Heckman (1976) two-stage procedure to account for self-selection in the trading decision. In the first stage, we use the estimates from the probit regressions to calculate the inverse Mills ratio. We then include the inverse Mills ratio as an additional regressor in the Fama–MacBeth regressions to obtain consistent estimates.

The Fama–MacBeth estimates are qualitatively similar to the results from the probit model. In particular, higher portfolio returns in the previous month decrease option trading activity but increase the intensity of equity trading. Single men, investors with large accounts, older investors, and those with low income and little experience tend to trade most. Furthermore, the results confirm the hypothesis that investors who trade more options (stocks) also trade more stocks (options). Although we correct the Fama–MacBeth standard errors for serial correlation, as a robustness check we also report estimation results for pooled panel regressions in the last two columns with standard errors clustered by investor and by time period. The results from the panel model are very similar to the Fama–MacBeth estimates and confirm the conclusion that investor and portfolio characteristics have the same influence on option trading as on equity trading, except for the impact of past portfolio returns. The finding that single men with low income and little experience trade most suggests that gambling and entertainment play an important role in explaining excessive trading by individual investors in both option and stock markets.

To dig further into the motivations for trading options, in Table 7 we classify all opening option trades into purchased call, written call, purchased put, and written put positions. Furthermore, a split is made between AEX index options and stock options. Panel A reports the percentage of option volume in a given category relative to the total of calls and puts traded. When looking at trading volume in all options, purchased call options dominate, followed by written calls, written puts and purchased put positions. The result that call positions are more prevalent than put positions is consistent with results documented by Lakonishok et al. (2007). However, differentiating between index options and stock options shows that purchased put positions dominate for index options but are least prevalent for stock options. Similarly, Schmitz et al. (2007) find that for index warrants, trading volume of calls equals volume of puts but that for stock warrants, volume of calls is much larger than volume of puts. The finding that purchased puts are the least frequently traded category of stock options suggests that most investors do not use options for hedging their underlying stock portfolio. Panel B shows the percentage of the value of option trades in a given category relative to the total value of calls and puts traded. These results are qualitatively similar to those reported in panel A. In particular, most investments in index options are purchased put positions while for stock options the highest amount of money is invested in long call positions.

In Panel C we display the moneyness of the options in each category, defined as the strike price divided by the price of the underlying asset. The results indicate that investors have a strong preference for out-of-the-money options. This holds for both calls and puts and for index options and stock options. The tendency to take out-of-the-money option positions is consistent with a gambling motive for option trading, since these options are cheap and offer a small probability of a large gain, similar to a lottery ticket.

Panel D reports the percentage of stock options for which the investor holds the underlying stock. These results provide direct evidence that most investors do not use options for hedging. In fact, more than 70% of all purchased puts are naked positions.

[12] Another reason could be that their risk aversion is lower because they tend to have more wealth. We thank the referee for pointing this out.

Table 7
Descriptive statistics on option positions.

	Call			Put		
	Purchased	Written	Total	Purchased	Written	Total
Panel A: Option volume (%)						
All	40.4	21.3	61.7	17.9	20.3	38.3
Index	30.3	17.4	47.6	33.1	19.2	52.4
Stock	45.2	23.2	68.4	10.8	20.8	31.6
Panel B: Option value (%)						
All	34.4	16.9	51.3	28.1	20.6	48.7
Index	26.3	16.2	42.5	37.9	19.5	57.5
Stock	49.6	18.3	67.8	9.5	22.7	32.2
Panel C: Option moneyness (K/S)						
All	1.02	1.03	1.02	0.97	0.94	0.96
Index	1.03	1.03	1.03	0.98	0.95	0.97
Stock	1.01	1.03	1.02	0.96	0.94	0.95
Panel D: Underlying stock holdings (%)						
Yes	14.5	34.3	21.1	27.3	27.1	27.2
No	85.5	65.7	78.9	72.7	72.9	72.8

In this table we classify all 2,497,378 opening option trades into purchased call, written call, purchased put, and written put positions. Furthermore, a split is made between index options (1,148,148 trades) and stock options (1,349,230 trades). Panel A reports the percentage of option volume in a given category relative to the total of calls and puts traded. Panel B shows the percentage of the value of option trades in a given category relative to the total value of calls and puts traded. In Panel C we display the moneyness of the options in each category, defined as the strike price divided by the price of the underlying asset. Panel D reports the percentage of stock options for which the investor holds the underlying stock.

The option category with the highest percentage of options for which the investor has a long position in the underlying stock is that of written calls, which suggests that some investors use a strategy of covered call writing. Although written calls can be used for hedging, the protection they provide against a price decline of the underlying asset is limited to the option premium. Given the restrictions imposed by the broker on short-selling stocks, it is unlikely that investors use purchased call and written put positions for hedging short-stock positions. Panel D indeed shows that most positions taken in these categories are also naked positions. Our conclusion that most individual investors primarily use options for speculation reinforces results documented by Lakonishok et al. (2007) for the US market.

We use survey data to complement the information derived from the trades and portfolio positions of the investors. In September 2005, a questionnaire was sent to all clients of the brokerage firm. In total 4516 clients responded, which we split into 2323 option traders and 2193 equity-only traders. Panel A in Table 8 reports the responses to statements related to investor experience and to the importance of the portfolio held at the online broker. An important difference between option traders and equity investors is that only a small proportion of option traders consider themselves novice investors while more than half of all equity traders think they are novice investors. However, the average option investor indicates that she has been trading for just 4 years, which is only slightly longer than the investment experience of equity traders. This suggests that option traders are overconfident about their investment experience and skills. Panel A further shows that both option and equity traders indicate that they invest more than half of their portfolio at the broker. This implies that the losses investors incur on accounts held at the broker can have a serious impact on their total financial wealth.

Table 8
Responses to statements on investment attitude and option trading.

Statement	Option traders	Equity traders
Panel A: Investor experience (% agree or amount x)		
"I consider myself a novice investor"	18.2	50.7
"I already invest for *x* years"	4.0	3.5
"I invest *x*% of my portfolio at another bank or broker"	48.8	46.0
Panel B: Investment attitude (% agree)		
"Investing is just a hobby for me"	55.7	43.6
"I only invest the money I have left"	80.9	65.3
"My main investment objective is short-term speculation"	17.2	9.4
Panel C: Option trading (% agree)		
"Option trading is too risky"	11.6	67.8
"When trading options I use the option Greeks"	11.2	–
"I primarily use options to hedge my risks"	19.6	–

This table shows the responses of 4516 clients of the brokerage firm to statements on investor experience (panel A), investment attitude (panel B), and option trading (panel C). We split the respondents into 2323 option traders and 2193 equity traders. The questionnaire was sent to clients in September 2005.

Panel B shows the responses to statements that measure the investment attitude of the clients. More than half of all option traders indicate that investing is just a hobby for them. Consistent with this result, over 80% of the option investors and 65% of the equity traders state that they only invest the money they have left. Moreover, whereas 17.2% of the option traders agree to the statement that short-term speculation is their main investment objective only 9.4% of the equity investors agree. The overall picture that emerges from the results reported in panel B is that for both groups of investors entertainment and sensation-seeking are important reasons for investing. However, option traders seem to be affected most by these factors.

Panel C presents the responses to three statements on option trading. As expected, only a small proportion of option investors and a majority of equity traders consider option trading too risky. A striking result is that only 10% of those who do invest in options indicate that they use the option Greeks when trading options. This finding suggests that a lack of knowledge about the risk and return characteristics and the use of options might also contribute to the poor performance on option investments. Finally, panel C reveals that only 20% of the option traders indicate that they use options primarily for hedging their risks, which confirms the conclusion from Table 7 that little option volume can be attributed to hedging.

4.4. Option trading skills

Although the previous sections have shown that on average option traders perform poorly, it is possible that some sophisticated investors do possess trading skills and are able to exploit inefficiencies in the option market. Coval et al. (2005) present strong evidence of performance persistence among a small group of common stock investors. They note that although it is unlikely that individual investors are better informed than professional fund managers, they are better able to exploit superior information for two reasons. First, individual investors usually trade smaller positions, so the price impact of their trades is limited. Second, individual investors face fewer asset allocation constraints, since they are not required to hold a diversified portfolio or track a specified benchmark. In this section we perform persistence tests to investigate whether their findings can be extended to option traders. Subsequently, we examine the characteristics and trading behavior of successful and unsuccessful option investors.

We first sort option traders into decile portfolios based on their performance during a ranking period. We then calculate returns for each of these deciles over an evaluation period. Repeating the ranking procedure using nonoverlapping intervals produces a time series of post-ranking returns for each decile. We include investors who drop out of the sample during the evaluation period in the portfolios until they disappear, after which we readjust the portfolio weights. We test whether past winners continue to outperform past losers by performing a t-test on the return difference between decile 1 (past winners) and decile 10 (past losers). We also calculate Spearman rank correlation coefficients between the formation period ranking and the evaluation period ranking. The null hypothesis of the Spearman test is that there is no relation between formation and evaluation period ranking, i.e., no performance persistence.

Table 9
Performance persistence of option traders.

Decile	Gross		Net		Factor loadings							Adj. R^2
	Return	Alpha	Return	Alpha	R_M	SMB	HML	MOM	ATMC	ATMP	IT	
Winner	0.07	0.22	−0.05	0.03	1.03	0.16	0.13	0.01	−0.11	−1.85	−0.06	84.8
	(0.08)	(0.73)	(−0.07)	(0.13)	(11.35)	(1.07)	(1.27)	(0.22)	(−0.15)	(−2.25)	(−1.31)	
2	0.39	0.49	−0.09	0.23	0.81	0.17	0.20	−0.10	−1.13	0.55	0.05	91.5
	(0.51)	(2.34)	(−0.12)	(1.18)	(13.52)	(2.53)	(4.59)	(−2.78)	(−2.60)	(0.97)	(1.01)	
3	−0.07	0.16	0.02	0.08	0.79	0.13	−0.05	−0.02	−0.04	−0.43	0.06	94.4
	(−0.10)	(0.90)	(0.03)	(0.37)	(23.44)	(4.29)	(−1.15)	(−0.99)	(−0.17)	(−1.44)	(2.25)	
4	0.28	0.44	−0.12	0.03	0.97	0.38	0.14	0.05	0.80	0.32	0.21	95.2
	(0.35)	(1.82)	(−0.16)	(0.14)	(25.32)	(9.81)	(3.39)	(1.49)	(2.68)	(0.05)	(5.46)	
5	−0.08	0.09	−0.44	−0.30	1.19	0.47	0.10	0.03	−1.29	0.82	0.19	94.0
	(−0.09)	(0.31)	(−0.45)	(−0.97)	(17.56)	(4.20)	(1.18)	(0.52)	(−3.22)	(0.13)	(3.75)	
6	−0.31	0.02	−0.48	−0.23	1.16	0.57	−0.01	0.11	0.57	−1.21	0.32	87.6
	(−0.32)	(0.08)	(−0.50)	(−0.79)	(18.32)	(3.72)	(−0.14)	(1.53)	(0.89)	(−1.82)	(5.18)	
7	−0.42	−0.13	−0.87	−0.77	1.25	0.90	0.15	0.25	−0.76	1.71	0.39	87.2
	(−0.44)	(−0.35)	(−0.84)	(−1.44)	(19.22)	(8.95)	(1.50)	(3.99)	(−1.40)	(2.23)	(6.61)	
8	−0.39	−0.17	−1.05	−0.68	1.51	1.17	0.08	0.27	0.37	0.05	0.59	90.8
	(−0.32)	(−0.34)	(−0.91)	(−1.14)	(18.83)	(12.35)	(0.70)	(3.99)	(0.59)	(0.05)	(7.88)	
9	−1.64	−1.37	−2.30	−2.23	1.34	0.91	0.17	0.24	−0.19	0.19	0.64	79.4
	(−1.33)	(−2.61)	(−1.77)	(−3.36)	(12.29)	(5.72)	(1.06)	(2.59)	(−0.25)	(0.13)	(5.62)	
Loser	−3.59	−3.47	−4.91	−4.82	1.01	0.93	0.05	0.14	0.48	−3.19	0.72	52.7
	(−2.82)	(−5.13)	(−3.98)	(−7.82)	(5.10)	(3.15)	(0.21)	(1.14)	(0.35)	(−1.45)	(2.95)	
Winner–loser	3.66	3.69	4.86	4.85	0.02	−0.77	0.08	−0.13	−0.59	1.34	−0.78	11.3
	(4.43)	(4.48)	(5.79)	(6.30)	(0.06)	(−1.98)	(0.27)	(−0.82)	(−0.31)	(0.51)	(−2.73)	
Rank correlation	0.93***	0.93***	0.96***	0.94***								

At the end of every year from 2000 to 2004 we sort option investors into equal-weighted decile portfolios based on returns earned over the year. Each portfolio is held for 1 year and subsequently rebalanced. This table shows the average monthly raw returns, alphas and factor loadings for each decile portfolio in the post-formation period. Decile 1 contains the 10% of investors with the highest return during the ranking period and decile 10 includes the worst 10% performers in the ranking period. Columns labeled "gross" ("net") refer to deciles formed and evaluated based on gross (net) returns. t-Statistics based on Newey–West heteroskedasticity and autocorrelation robust standard errors are in parentheses. Rank correlation is the Spearman rank correlation coefficient that measures the relation between formation period ranking and evaluation period ranking. *** denotes its significance at the 1% level.

Table 10
Characteristics of successful and unsuccessful option traders.

Decile	Value (€)	Turnover (%)	Men (%)	Age (years)	Income (€)	Experience (months)
Winner	26,341	15.9	70.6	44.1	2706	41.2
2	25,604	5.9	64.5	46.9	2611	41.8
3	27,023	3.7	71.2	47.0	2714	42.0
4	18,853	5.3	67.1	49.5	2473	41.8
5	12,401	8.1	73.7	44.9	2552	41.7
6	14,001	8.7	76.3	54.1	2498	41.9
7	4261	9.6	84.1	42.1	2316	41.0
8	5382	8.4	83.0	46.8	2323	40.7
9	3235	16.0	84.6	45.3	2404	39.5
Loser	1813	76.7	85.1	48.1	2279	34.8
Winner–loser	23,106	−60.8	−14.5	4.0	427	6.4

This table reports time series averages of monthly cross-sectional averages of investor characteristics for decile portfolios of option investors formed on the basis of past 1-year net return. As an exception, the numbers we report for account value and income are time series averages of monthly cross-sectional median values. Decile 1 contains the 10% of investors with the highest return during the ranking period and decile 10 includes the worst 10% performers in the ranking period. Value is the market value of all assets in the investor's account. Turnover is the average value of purchases and sales in a given month divided by beginning-of-the-month account value. Men is the percentage of accounts in a given decile portfolio held by a man and Age is the age of the primary account holder. Income is the monthly gross income assigned to investors based on their zip-code. Experience is the number of months the investor has been trading.

To examine whether consistency in returns, if any, is due to persistence in transaction costs, we perform the analysis using both gross and net returns. If we only find evidence of performance persistence when we sort on net returns we conclude that it is related to costs. We consider 3-, 6-, and 12-month ranking and evaluation periods. This choice is based on mutual fund studies showing that performance persistence is usually short term (e.g., Busse and Irvine, 2006). Using longer periods also means that we can include fewer investors in the analysis, because we require an investor to be present in the sample during the complete ranking period and at least 1 month in the evaluation period. On the other hand, results for periods shorter than 3 months are likely to be dominated by noise and luck.

Table 9 presents post-formation returns and alphas for portfolios of option investors sorted on past 1-year return. The columns labeled "gross" ("net") refer to deciles formed and evaluated on the basis of gross (net) performance. The results indicate that on average, option traders in the top decile continue to outperform those in the bottom decile in the year subsequent to the formation year by more than 3.5% per month in terms of gross return and almost 5% in terms of net return. The consistency in gross returns indicates that persistence in costs explains only part of total performance persistence. A substantial part of the performance differential is driven by the extremely poor performance of the option investors in decile 10. Gross and net returns for these investors are 2% and 2.5% lower, respectively, than for those in decile 9. The Spearman rank correlation is significant at the 1% level, which indicates a strong relation between formation and evaluation period ranking.[13]

The difference in performance between past winners and losers also shows up when we consider risk- and style-adjusted returns. Investors in decile 1 earn gross and net alphas that are almost 4% and 5% higher, respectively, than those earned by investors in decile 10. These differences are significant at a 1% level. Spearman rank correlation coefficients exceed 0.9 and are also significant at the 1% level, providing strong evidence of performance persistence among option traders. Although gross and net alphas for option investors in the top deciles are positive but insignificant, alphas are significantly negative for those in the bottom two deciles. Table 9 also reports the exposures of the returns on the decile portfolios to the factors in the performance attribution model. Loser deciles tend to have significantly higher loadings on the SMB and IT factors than winner deciles, indicating strong tilts in their portfolios towards small tech stocks.

Since the performance difference between winners and losers cannot be explained by risk and style tilts, we investigate whether it can be linked to heterogeneity in the characteristics of investors and their portfolios. Table 10 presents the characteristics of the investors in the decile portfolios formed on past 1-year returns. We find that the median account value decreases uniformly with ranking, i.e., the bottom decile consists of investors who hold the smallest accounts. Furthermore, those in the bottom deciles have much higher turnover than successful option traders. Table 10 also shows that a higher proportion of accounts in the bottom deciles is held by men with low income and little investment experience.

5. Conclusion

This paper shows that option trading has a detrimental impact on the performance of individual investors. The losses investors incur on their option investments are much larger than those from equity trading. Risk and style tilts and differences in demographic and socioeconomic characteristics do not explain the poor performance of option traders relative to equity investors. Instead, we attribute the poor performance of option traders to bad market timing due to overreaction to past stock market movements. In particular, after the collapse of the Internet bubble, option traders speculated on a further market decrease when markets actually started to recover. High trading costs also contribute to the losses suffered by option investors.

We also show that various demographic, socioeconomic, and portfolio characteristics that have been linked to gambling by Kumar (2008) have a similar influence on the trading intensity of option investors and equity investors. Specifically, we find that single men with low income and little investment experience are most likely to engage in both option trading and equity trading. However, an important difference between option traders and equity investors is that the trading activity of the former increases after past losses while past performance has a positive, but insignificant effect on the trading volume of equity investors. By linking option trades to the common stock holdings of individual investors we rule out hedging as an important motivation for trading options. Instead, investors tend to take naked, out-of-the-money option positions, suggesting a gambling motive for trading options. Options are particularly attractive for gambling because of the leverage they provide and their skewed payoffs, thereby resembling lottery tickets. Responses of investors to statements on investment attitude confirm that entertainment and sensation-seeking are important reasons for trading options.

Despite the poor performance of the average option trader, we do identify a small group of investors who consistently manage to outperform the others. Option traders who are in the top decile portfolio based on past 1-year performance continue to outperform investors in the bottom decile over the next year. We further show that persistence in trading costs explains only part of total performance persistence. The bottom deciles tend to consist of male investors with little experience and low income who hold small accounts with high turnover. These results suggest that most option traders lose money due to excessive trading and a lack of knowledge. We conclude that trading hurts investor performance and that trading options hurts most.

Appendix A. Cross-sectional risk and style adjustment

In this appendix we show how to obtain an unbiased estimate of the relation between alphas and characteristics without estimating first-stage time series regressions for every investor. Each month, we estimate a cross-sectional regression of returns on investor characteristics. We then regress the vector of monthly cross-sectional coefficients γ_{lt} for each of the l investor characteristics on a constant and the time series of risk and style factor realizations F_{kt},

$$\gamma_{lt} = \delta_{l0} + \sum_{k=1}^{K} \delta_{lk} F_{kt} + \omega_{lt}. \tag{10}$$

To see that the intercept δ_{l0} in this time series regression is an unbiased estimate of the cross-sectional relation between alpha and investor characteristic l, consider the following. Suppose that portfolio returns are generated by the factor model

$$R_{it} = \alpha_i + \sum_{k=1}^{K} \beta_{ik} F_{kt} + \epsilon_{it}. \tag{11}$$

We are interested in the cross-sectional relation between α_i and Z_{ilt}, the value of characteristic l for investor i at time t. Denote the true coefficient vector of this relation between alphas and the

[13] Results for the 3- and 6-month ranking and evaluation periods (not reported to save space) show that persistence is still significant on 6-month horizons but absent for shorter periods. Spearman coefficients are significant at the 5% level for 6-month periods but not significant for 3-month periods.

characteristics by $\boldsymbol{\delta}$. The cross-sectional regression of portfolio returns in month t on investor characteristics produces the following coefficient vector

$$\gamma_{\mathbf{t}} = (\mathbf{Z}_{\mathbf{t}}'\mathbf{Z}_{\mathbf{t}})^{-1}\mathbf{Z}_{\mathbf{t}}'\mathbf{R}_{\mathbf{t}} = \delta + \mathbf{F}_{\mathbf{t}}[(\mathbf{Z}_{\mathbf{t}}'\mathbf{Z}_{\mathbf{t}})^{-1}\mathbf{Z}_{\mathbf{t}}'\beta]. \tag{12}$$

Therefore, as noted by Brennan et al. (1998), the intercept δ_{l0} from the time series regression of the monthly cross-sectional parameter estimates γ_{lt} on the vector of factor realizations $\mathbf{F_t}$ is an unbiased estimate of δ_l if the factor premia are serially uncorrelated. Intuitively, the time series regression (10) purges the cross-sectional coefficients of their factor dependent component. The standard error of δ_{l0} is the standard error of the purged estimator. The coefficients on the factor premia $\mathbf{F_t}$ are unbiased estimates of $(\mathbf{Z}_{\mathbf{t}}'\mathbf{Z}_{\mathbf{t}})^{-1}\mathbf{Z}_{\mathbf{t}}'\beta$ and measure the relation between factor loadings and investor characteristics.

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