Differences in Trading and Pricing between Stock and Index Options

Michael Lemmon*

Sophie Xiaoyan Ni*

ABSTRACT

We find that the demand for stock options that increases exposure to the underlying is positively related to the individual investor sentiments and past market returns, whereas the demand for index options is invariant to these factors. These differences in trading patterns are also reflected in the differences in the composition of traders with different types of options—options on stocks are actively traded by individual investors, whereas trades in index options are more often motivated by the hedging demand of sophisticated investors. Consistent with a demand-based view of option pricing, the individual investor sentiments and past market returns are related to time-series variations in the slope of the implied volatility smile of stock options, but have little impact on the prices of index options. The pricing impact is more pronounced in options with a higher concentration of unsophisticated investors and those with higher delta hedging costs. Our results provide evidence that factors not related to fundamentals also impact security prices.

JEL Classification Code: G1, G12, G13

Key Words: Options, Volatility Smile, Sentiment, Speculation, Behavior

---

* Lemmon is at the University of Utah, email: michael.lemmon@business.utah.edu. Ni is at the Hong Kong University of Science and Technology, email: sophieni@ust.hk. We benefited from the comments and support of Bing Han (AFA discussant), Mark Grinblatt, John Griffin, Ohad Kadan (IDC Caesarea discussant), Neil Pearson, Allen Poteshman, Maik Schmeling (EFA discussant), Mark Seasholes, Jason Wei, Ning Zhu and anonymous referees. We bear full responsibility for any errors. The financial support from a Hong Kong RGC Research Grant (Project # 642908) is gratefully acknowledged.

Individual stock options in aggregate and index options are similar securities in the sense that their underlying securities are driven by same fundamentals and their prices are affected by the jump and the volatility risks in similar ways. However, the literature suggests that these two types of options serve different purposes. Bollen and Whaley (2004) show that most trading in S&P500 index options involves puts. They attribute this fact to the hedging demand of institutional investors, who purchase index puts as portfolio insurance against market declines. Lakonishok, Lee, Pearson and Poteshman (2007) document that hedging motivated trading accounts for only a small fraction of trading in stock options and a majority of non-market maker stock option trading involves naked positions.

The purpose of this study is to investigate what factors drive stock and index options trading and how these factors influence their prices. We begin our study by showing that if stock and index options markets are integrated, risk factors will influence their prices in a same manner. Adopting a model that uses stochastic volatility with jumps, we simulate the implied volatility functions (IVF) of stock and index options responding to variations in jump and volatility risks in similar ways. This result implies that if a factor influences the IVF of index options, it should also affect the average IVF of stock options in the same way, and vice versa.

We then pursue two strands of empirical investigation to examine the extent to which stock and index options trades differ and how the factors that influence option trading affect option prices. Our first empirical investigation examines how the trading activities of stock and index options respond to individual investor sentiment measured as AAII, Conference Board or Michigan consumer sentiment index, and past month market returns. We use these measures of sentiment because in our data, trading by individual investors accounts for more than 30% of the non-market maker stock options volume, and only 3% of the index options volume. We use lagged market returns to capture the idea that changes in stock valuations are likely to be associated with hedging demand for index puts and the potential for the overreactions of unsophisticated traders.[1] Consistent with the latter view, Lakonishok, Shleifer and Vishny (1994) argue that the value premium in stock returns arises from investors over-extrapolating past performances.

To measure options trading, we construct two variables: the positive exposure demand for individual stock options (*PDS*) and the positive exposure demand for S&P500 index options (*PDI*). *PDS* and *PDI* measure the monthly non-market maker public investor option demand with positive exposure to the

[1] In addition, individual investor sentiment is also driven by past stock returns and we wish to separate the components of sentiment that are unrelated to market returns from those that are associated with changes in stock market valuations.

underlying. Our results indicate that over the period from 1990 through 2010, the time-series variation in *PDS* is related to individual investor sentiments and lagged market returns. When individual sentiments and past returns are high, investors increase their exposure to individual stocks by purchasing calls and selling puts. In contrast, *PDI* is not related to sentiment or past market returns. We also find that changes in *PDS* are most strongly related to changes in the sentiments and the lagged returns for trades initiated by less sophisticated investors.

Our second empirical investigation examines the pricing impact of the individual sentiments and the lagged market returns on stock and index options. If they are proxies for variations in volatility and jump risks, the slopes of the implied volatility function (IVF) of stock and index options should respond in similar ways. In contrast, if the individual sentiments and the lagged market returns are proxies for the behavioral biases of noise investors, they should only influence the IVF of stock options, as Gârleanu, Pedersen and Poteshman (2009) show, the demand imbalances generated by the trades of the end users of options can affect option prices.[2]

The dependent variables are slopes of the IVF computed as the differences in implied volatilities between OTM calls and OTM puts. Our results show that both the individual sentiments and lagged market returns are positively related to the slope of the IVF of stock options. In contrast, we find no evidence that individual sentiments or lagged market returns are related to the slope of the IVF of index options. Similar to Han (2008), our results show that the slope of index options is related to a measure of institutional investor sentiment, but that institutional investor sentiment is not significantly related to the slope of stock options.

Also consistent with the view that the individual sentiments and the past market returns affect stock option prices, we find evidence of positive abnormal returns from contrarian trading strategies that trade calls and puts on individual stocks following large changes in the individual sentiments and the market returns. In some cases these abnormal returns exceed options transaction costs.

Finally, we examine whether the effects of individual sentiments on stock options trading and prices vary cross-sectionally. As models of limited arbitrage predict, we find that options with a higher proportion of trading from less sophisticated investors and those with higher arbitraged costs exhibit prices that are more sensitive to the individual sentiments.

[2] We focus on how differences in demand for different types of options can affect prices. Nevertheless, significant literature exists that examines other determinants of option prices. For example, Bates (1991, 2000); Heston (1993); Jackwerth and Rubinstain (1996); Coval and Shumway (2001); Pan (2002); Bakshi, Kapadia and Madan (2003); Bollen and Whaley (2004); and Liu, Pan and Wang (2005), among others.

Our results suggest that individual stock and index options markets are segmented because of differences in the composition of investor types. These results are consistent with the notion that factors not related to fundamentals affect security prices from a unique angle. The ideal setting for testing the efficient market hypothesis (EMH) and the behavioral hypothesis (BH) would be the existence of two identical securities in a frictional market with the only difference being that one security is traded by rational investors and the other is held by noise traders. It is difficult, however, to find such a setting in the stock market, with the exception of the close end fund. Securities traded mainly by noise traders tend to be different from those traded by rational investors. Any return disparity between these two types of securities can be attributed to the fundamental differences in the securities rather than to the types of investors trading them (Fama 1970).

Stock options in aggregate and index options are close to identical in the sense that their prices are affected by jump and volatility risks in similar ways. The fact that less sophisticated investors trade stock options much more actively than index options gives us an ideal setting to test EMH and BH. In addition, high transaction costs, margin requirements and short selling difficulties are more likely to impede arbitrage activities in option markets (Figlewski, 1989; Pontiff, 1996).

Our interpretation does not require any assumptions about the economic meaning of the individual sentiments or the lagged market returns. EMH predicts that stock options in aggregate and index options will respond to the individual sentiments or lagged market returns in a similar manner regardless of what they stand for. BH predicts that if these variables are associated with correlated noise trader biases, we will observe different reactions from stock and index options, and no conclusions can be drawn otherwise. The different responses in the prices of stock and index options to the individual sentiments and the lagged market returns in a certain direction suggest not only that BH is valid, but also that the sentiments and the lagged market returns can be proxies for the correlated biases of noise traders.

The argument above relies on the prices of aggregate stocks and S&P500 index options being driven by the same fundamentals in a rational setting. It is possible that there are systematic factors other than behavior biases that influence stock and index option prices differently. For example, stock options are less liquid than index options. However, for our findings to be driven by liquidity, liquidity would have to be exclusively associated with the trading and price of stock options. It is unclear why aggregate liquidity does not impact index options, given Cherks, Sagi and Stanton (2009) and Bao, Pan and Wang's (2010) documenting that liquidity commoves more closely with VIX index than it does with the Michigan consumer sentiment.[3]

Our findings are related to studies that document behavioral biases in options markets. Stein (1989) shows that the long-term implied volatilities of S&P100 options overreact to changes in short-term volatility. Constantinides, Jackwerth and Perrakis (2009) find no evidence that prices in the S&P500 options have become more rational over time. Han (2008) shows a positive relationship between the risk-neutral skewness in S&P500 options prices and the measures of institutional investor sentiments. Amin, Coval and Seyhun (2004) document S&P100 index call (put) prices are overvalued following large upside (downside) market movements. Barraclough and Whaley (2011) show that investors do not early exercise stock puts when they should. Xiong and Yu (2011) document speculation drives the warrants prices in China too high to be justified by any pricing model. Some of these studies above suggest that the prices of index options are subject to behavior biases. Our study does not contradict these findings, but rather focuses on the differences in index and stock options trading and infers that the prices of index options are less subject to the behavioral biases of noise traders.

Our study also relates to the work that investigates the relation between stock and index options. Bollen and Whaley (2004) note that the excess implied volatility of S&P500 index options is much higher than that of stock options. They attribute this fact to the hedging demand for index put options as portfolio insurance against market declines. Gârleanu, Pedersen and Poteshman (2009) confirm these findings and model how demand imbalances generated by the trades of end users can affect option prices. Bakashi, Kapadia and Madan (2003) show that the risk neutral skewness of stock option prices is less negative than that of index option prices due to the idiosyncratic components of stock returns. Dennis and Mayhew (2002) reveal that stock option-implied skewness is more negative when market volatility is high and when the risk-neutral density of index options is more negatively skewed.

Our study also relates to the literature that examines cross-sectional differences in stock options. Lakonishok, Lee, Pearson and Poteshman (2007) find that stocks with high past returns have high option volumes of both purchased calls and puts, and that during the bubble in the late 1990s the least sophisticated investors increased their purchase of calls on growth stocks. They do not, however, examine how the individual sentiments or the lagged market returns relate to the aggregate positive exposure demand or the prices of stock options. Nor do they compare the differences in stock and index options. Pan and Poteshman (2006), Yan (2011) and Zhang, Zhao and Xing (2010) document that stock options

[3] In the unreported results, we find that liquidity factor in Pastor and Stambaugh (2003) is not an alternative explanation for the roles individual sentiments and lagged market returns.

put-call ratios and the implied volatility slopes contain information about future stock returns. Duan and Wei (2009) find that systematic risk also impacts the IVF of the thirty largest stocks. The above studies focus on the cross-sectional differences in stock options, whereas our study is based on time-series variations in the aggregate trading and pricing of all stock options. Roll, Schwartz and Subrahmanyam (2009) investigate the relative volume in options and stock markets and argue that the determinants of options volume are not well understood. Our study partially addresses this issue.

Finally, our study relates to the literature examining the relation between investor sentiments and security prices. For example, Lee, Shleifer and Thaler (1991) and Pontiff (1996) propose that fluctuations in the discounts of closed-end funds are driven by changes in the individual investor sentiments. Baker and Wurgler (2006) and Stambaugh, Yu and Yuan (2011) present evidence that investor sentiments have significant effects on the cross-section of stock prices. Lemmon and Portniaguina (2006) show that Michigan consumer sentiment predicts the returns of small stocks and Kumar and Lee (2006) document that individual investor trades are systematically correlated and can explain the return co-movements of stocks with high concentration of retail investors.

The remainder of this paper is structured as follows. Section 1 shows that risks affect the prices of stock and index options in similar ways. Section 2 presents our data and the variable construction. Section 3 presents the summary statistics and trading activity of different investors on stock and index options. Section 4 presents results and Section 5 offers conclusions.

1. Index and Stock Options Prices

In this section, we show that the risks that affect the IVF of index options have the same impact on the IVF of stock options. Adopting a model with stochastic volatility and return jumps, we assume the following data-generating process for index price I under physical probability measure (to simplify exposition, we assume zero dividend and a constant risk free rate):

$$dI_t = \left[r + \eta^s V_t + \lambda \eta_t^J\right] I_t dt + \sqrt{V_t} I_t dW_t^1 + I_t dZ_t - \lambda \mu I_t dt, \quad (1)$$

$$dV_t = \kappa(\bar{v} - V_t)dt + \sigma_v \sqrt{V_t}\left(\rho_{12} dW_t^1 + \sqrt{1 - \rho_{12}^2} dW_t^2\right), \quad (2)$$

where r is the interest rate; $W = [W^1, W^2]'$ is a standard Brownian motion in $\mathbb{R}^2$; Z is the index price jump process with jump probability λ, jump volatility σ^J and average jump size μ; η^s is the premium for conventional return risks; and $\lambda \eta_t^J$ is the premium for the jump risk. In this model, we set jump size premia η_t^J time varying to reflect the variations in jump risk. Eq. (2) models the stochastic volatility with constant long-run mean $\bar{v}$, mean-reversion rate κ, instantaneous variance V_t, volatility coefficient σ_v and correlation coefficient of the return and the variance ρ_{12}.

Suppose an individual stock has beta one on index excess returns.[4] Its price S has the following data-generating process under physical probability measure *P*:

$$dS_t = \left[r + \eta^s V_t + \lambda \eta_t^J\right] S_t dt + \sqrt{V_t^S} S_t \left(\rho_{13} dW_t^1 + \sqrt{1-\rho_{13}^2} dW_t^3\right) + S_t dZ_t - \lambda \mu S_t dt + S_t dZ_t^S, \quad (3)$$

$$dV_t^S = dV_t + dV_t', \quad (4)$$

$$dV_t' = \kappa' \left(\bar{v}' - V_t'\right) dt + \sigma_v' \sqrt{V_t'} \left(\rho_{34} dW_t^3 + \sqrt{1-\rho_{34}^2} dW_t^4\right) \quad (5)$$

where V_t^S is the stock variance, $W' = [W^3, W^4]'$ is a standard Brownian motion in $\mathbb{R}^2$ and is uncorrelated with $[W^1, W^2]'$, ρ_{13} is the correlation coefficient between index and stock Brownian motion. We assume when an index jump occurs, the stock price S appreciates or depreciates by same return as the index price I. Z^S, uncorrelated with index jump Z, is the stock idiosyncratic jump with jump probability λ^S, average jump size 0 and jump size volatility $\sigma^{S,J}$.

Eq. (4) shows that the change in the stock variance is the sum of changes in the index variance (V_t) and the stock idiosyncratic variance (V_t') because $[W^1, W^2]'$ and $[W^3, W^4]'$ are uncorrelated and the stock market beta is 1. Eq. (5) indicates that the stock idiosyncratic variance follows its own mean reversion stochastic process.

Based on the above setting, the corresponding dynamic of index price *I* under risk neutral probability measure *Q* is as follows:

$$dI_t(Q) = rI_t dt + \sqrt{V_t} I_t dW_t^{1Q} + I_t dZ_t^Q - \lambda\left(\mu - \eta_t^J\right) I_t dt, \quad (6)$$

$$dV_t(Q) = [\kappa(\bar{v} - V_t) dt + \eta_t^v V_t] dt + \sigma_v \sqrt{V_t} \left[\rho_{12} dW_t^{1Q} + \sqrt{1-\rho_{12}^2} dW_t^{2Q}\right], \quad (7)$$

where $W(Q) = [W^{1Q}, W^{2Q}]$ is a Brownian motion under Q and η_t^v is the time varying volatility premium. The jump process Z^Q has a similar distribution as *Z* under *P*, except that the average jump size of Z^Q is $\mu - \eta_t^J$.

The corresponding dynamic of stock price S under the risk neutral probability measure is as follows:

$$dS_t(Q) = rS_t dt + \sqrt{V_t^S} S_t \left(\rho_{13} dW_t^{1Q} + \sqrt{1-\rho_{13}^2} dW_t^{3Q}\right) + S_t dZ_t^Q - \lambda\left(\mu - \eta_t^J\right) S_t + S_t dZ_t^S \quad (8)$$

[4] We ignore other factors affecting stock prices as our focus is on the aggregate performance of all stocks, not on the cross sectional differences.

$$dV_t^S(Q) = dV_t(Q) + dV_t^{'}, \tag{9}$$

where $V_t(Q)$ is the variance of index under Q and $V_t^{'}$ is the idiosyncratic variance under P.[5]

To investigate how the systematic risks affect prices of index and stock options, we assume that they influence option prices through the time varying jump size premium (η_t^J) and the variance premium (η_t^v). and use a simulation to examine their impact on the IVFs. We omit the pricing impacts from changes in physical jump size, jump probability or physical volatility because the effects of these changes are similar to the variations in the jump size or variance premium.

Figure 1 shows that systematic risks have the same impact on the IVFs of index and stock options. When the jump size premium increases,[6] the slopes of the IVFs are more negative for both index and stock options. Similarly, when the variance premium increases,[7] the levels of the IVFs increase for both options. These patterns suggest that if a systematic risk influences options prices, it must also affect the IVFs of stock and index options in similar ways. Indeed, Dennis and Mayhew (2002) empirically show that the implied skewness of stock options is more negative when the risk-neutral density for index options is more negatively skewed.

Figure 1 also shows that the slope of the IVF of stock options is flatter than that of index options. This result is consistent with those documented in Bakshi, Kapadia and Madan (2003). They model the idiosyncratic components of stock returns drive the risk neutral skewness of stock options to be less negative than that of index options.

2. Data and Variables

2.1. Option trading and price data

We obtain option trading data from the CBOE. The data contain daily non-market maker volumes for all CBOE-listed options from January 1990 to December 2010. The number of stocks having CBOE traded options in each month increases from 239 in January 1990 to 2,831 in December 2010, which reflects the dramatic growth in the options market during the sample period.

We obtain option price data from the Berkeley Option Database for the period from 1990 to 1995, and from OptionMetrics for the period from 1996 to 2010. For the first period, we follow Bollen and Whaley (2004) and compute daily option implied volatilities from the midpoint of the last bid-ask price

[5] Idiosyncratic variance earns zero risk premium, and its dynamic under Q is same as that under P.

[6] The variance risk premium, h^v, is fixed at 3.1.

[7] The jump size risk premium, h^J, is fixed at 0.17.

quote before 3:00 PM Central Standard Time.[8] Starting in January 1996, we use the implied volatilities supplied by OptionMetrics.

We use implied volatilities on the last trading day of the month for options that meet the following conditions: (1) the option is traded on that day, (2) the bid or the ask price is above zero and within standard no-arbitrage bounds,[9] (3) the time to expiration is within 10 to 60 trading days and (4) from the options on the same stock satisfying conditions (1)-(3) we retain those that have more than two strike prices for at least one maturity. We then choose the maturity with the highest number of strikes. If options of different maturities have the same number of strike prices, we choose the maturity with the highest trading volume. The final sample for stock options consists of 147,266 stock end-of-month days from 4,872 different firms.

2.2 Option trading and price variables

In each month t, we compute two measures we call the positive exposure demand for stock options (PDS_t) and the positive exposure demand for S&P500 index options (PDI_t). PDS_t and PDI_t measure the newly established net option positions that have positive exposure to the underlying and are computed as follows:

$$PDS_t = PDS\_C_t + PDS\_P_t, \qquad \text{where} \tag{10.1}$$

$$PDS\_C_t = lo\,g\left(\sum_i \sum_\tau \sum_T \sum_K OpenBuyCall^i_{t,\tau,T,K}\right) - \,log\left(\sum_i \sum_\tau \sum_T \sum_K OpenSellCall^i_{t,\tau,T,K}\right),$$

$$PDS\_P_t = log\left(\sum_i \sum_\tau \sum_T \sum_K OpenSellPut^i_{t,\tau,T,K}\right) - \,log\left(\sum_i \sum_\tau \sum_T \sum_K OpenBuyPut^i_{t,\tau,T,K}\right),$$

$$PDI_t = PDI\_C_t + SID\_P_t, \qquad \text{where} \tag{10.2}$$

$$PDI\_C_t = log\left(\sum_\tau \sum_T \sum_K OpenBuyCall^{SPX}_{t,\tau,T,K}\right) - \,log\left(\sum_\tau \sum_T \sum_K OpenSellCall^{SPX}_{t,\tau,T,K}\right),$$

$$PDI\_P_t = log\left(\sum_\tau \sum_T \sum_K OpenSellPut^{SPX}_{t,\tau,T,K}\right) - \,log\left(\sum_\tau \sum_T \sum_K OpenBuyPut^{SPX}_{t,\tau,T,K}\right),$$

[8] For American-style stock options we use the dividend-adjusted binomial method with the actual dividends paid as a proxy for the expected dividends. For SPX index options, which are European, we compute implied volatilities by inverting the Black-Scholes (1973) formula. We use linearly interpolated LIBOR as the risk free rate.

[9] For a call, the ask price is not less than *S-K-PV(D)* and the bid price is not larger than *S*. For a put, the ask price is not less than *K-S+PV(D)* and the bid price is not larger than *K*. For the European SPX options, we adjust the arbitrage bound by replacing *K* with Ke^{-rT}.

where i indexes stock, τ is the τth trading day in month t, T indexes the options maturities and K indexes strike prices. $OpenBuyCall^{i}_{t,\tau,T,K}$ is the number of call contracts open purchased by non-market maker public investors in month t on stock i across all maturities and strike prices and the remaining terms $OpenSellCall^{i}_{t,\tau,T,K}$, $OpenBuyPut^{i}_{t,\tau,T,K}$ and $OpenSellPut^{i}_{t,\tau,T,K}$ are computed in an analogous manner.[10]

The measures of *PDS* and *PDI* are different from option *NetDemand* examined in Bollen and Whaley (2004) and Gârleanu, Pedersen and Poteshman (2009). In their studies, *NetDemand* is measured as the difference between buy and sell option volumes or open interests as follows:

$$\begin{aligned} NetDemand &= buyOptions - sellOptions \\ &= (buyCall - sellCall) + (buyPut - sellPut)\,, \end{aligned}$$

PDS and *PDI* have positive exposure to the underlying, whereas *NetDemand* has positive exposure to the volatility. We use *PDS* and *PDI* because speculating and hedging on the directional movement of the underlying are the main motivations for options trading (Lakonishok, Lee, Pearson and Poteshman, 2007).

We do not use close volume in our main test because investors might close existing option positions not solely based on their perceptions of the future. Other conditions, such as the past performance of the position, time to expiration and margin requirements, can also cause investors to close a position. In some of the tests we use PDS computed from close volume.

Another reason for using only open volumes is that PDS can be linked to *NetDemand* for options of different strikes and the slope of implied volatility. In contrast no similar relation can be drawn for PDS computed from the close volume. In specific, for PDS and *NetDemand* from options of high strikes (ITM puts and OTM calls), we have:

$$PDS^{\text{high}K} = (BuyCall^{\text{OTM}} - SellCall^{\text{OTM}}) - \left(BuyPut^{\text{ITM}} - SellPut^{\text{ITM}}\right)$$

$$NetDemand^{\text{high}K} = (BuyCall^{\text{OTM}} - SellCall^{\text{OTM}}) + \left(BuyPut^{\text{ITM}} - SellPut^{\text{ITM}}\right)$$

In our data, the open volume of OTM options is far greater than the open volume of ITM options; the percentage of open OTM volume is above 30% of all nonmarket maker volumes, and that of open ITM volume is below 10% for both stock calls and puts. So we can omit the trading of open ITM options. Then,

[10] We do not use delta adjusted volume because OTM options are the most heavily traded options and ITM options have much smaller volume and liquidity than ATM/OTM options. Also If we use delta weighted volumes, we cannot differentiate the demand for options with high and low strike prices or link the demand to the variations in the slopes of implied volatilities.

$$PDS^{\text{high}K} \approx \left(\text{BuyCall}^{\text{OTM}} - \text{SellCall}^{\text{OTM}}\right) \approx NetDemand^{\text{high}K}. \tag{11.1}$$

Similarly if we omit the volume open ITM options of low strikes options (OTM puts and ITM calls), we have

$$-PDS^{\text{low}K} \approx (BuyPut^{\text{OTM}} - SellPut^{\text{OTM}}) \approx NetDemand^{\text{low}K} \ . \tag{11.2}$$

Equations (11.1) and (11.2) show that when we use the open volume, $PDS^{\text{low}K}$ and $NetDemand^{\text{low}K}$ are mainly driven by demand for puts, while $PDS^{\text{high}K}$ and $NetDemand^{\text{high}K}$ are mainly driven by demand for calls. If sentiment increases, investors buy more calls, and sell more puts, $NetDemand^{\text{high}K}$ increases, and $NetDemand^{\text{low}K}$ decreases. According to demand based pricing theory, the implied volatilities of high (low) strike options increase (decrease), and the slopes increase.

On the other hand, we cannot draw the same conclusion for PDS computed from close volumes because there're similar amounts of close ITM and close OTM volumes. In our data, the percentage of close OTM or ITM volume is both around 10% of all nonmarket maker volumes.

The primary measure we use to examine option prices is the slope of the IVF, i.e. the implied volatility difference between OTM calls and OTM puts.[11] For individual stock options, the slope measure is the average slope across all stocks. Specifically, the slope measures are given by:

$$SlopeS_t = \frac{1}{N_t}\sum_{i}^{N_t}\left(\frac{1}{Nk_t^{i,C}}\sum_{K_t^{i,C}} IV\_OTM^{i,C}_{t,K_t^{i,C}} - \frac{1}{Nk_t^{i,P}}\sum_{K_t^{i,P}} IV\_OTM^{i,P}_{t,K_t^{i,P}}\right) \tag{12.1}$$

$$SlopeI_t = \frac{1}{Nk_t^{SPX,C}}\sum_{K_t^{SPX,C}} IV\_OTM^{SPX,C}_{t,K_t^{SPX,C}} - \frac{1}{Nk_t^{SPX,C}}\sum_{K_t^{SPX,C}} IV\_OTM^{SPX,P}_{t,K_t^{SPX,P}}, \tag{12.2}$$

where N_t is the number of stocks with traded OTM calls and puts on the last day of month *t*, $Nk_t^{i,C}$ is the number of OTM call options for stock *i* on date *t*, $IV\_OTM^{i,C}_{t,K_t^{i,C}}$ is the implied volatilities of OTM calls for stock *i* on the last day of month *t* with strike $K_t^{i,C}$, and $IV\_OTM^{i,P}_{t,K_t^{i,P}}$ is the same variable for OTM puts. The slope measures are similar to the ones used by Han (2008) and are essentially equivalent to the risk neutral skewness embedded in option prices (Bakshi, Kapadia and Madan, 2003). We use the slope of the volatility smile instead of the model free risk neutral skewness developed in Bakshi, Kapadia and

[11] We consider options with $0.125 \ll \Delta_C \leq 0.375$ (or $-0.375 \ll \Delta_P \leq -0.125$) to be OTM calls (or OTM puts). When computing the option delta, i.e. Δ_C and Δ_P, we estimate volatility using the previous 60 trading days stock or index returns. We obtain similar results by using the implied volatilities to compute delta or by using K/S to classify moneyness.

Madan (2003) because most stocks do not have a sufficient number of strike prices to generate the integral necessary to compute the risk-neutral skewness. The median number of strike prices for optionable stocks in our sample is only three.

2.3 Individual Sentiment Measures

We use three measures of individual investor sentiments, namely the indices of AAII, Conference Board, and University of Michigan. The AAII sentiment index (AAII) measures the percentage of individual investors who are bullish, bearish, and neutral on the stock market. Individuals are polled from the ranks of the AAII membership on a weekly basis. To avoid the look-ahead bias, we compute the monthly AAII index as the average of the first three weekly indices.

The Conference Board index is a barometer of the health of the U.S. economy from the perspective of consumers. The index is based on consumers' perceptions of business conditions, employment and income. The Conference Board mailing is scheduled so that the questionnaires reach sample households on or about the first of each month. Returns flow in throughout the collection period, with the sample close-out for preliminary estimates occurring around the eighteenth of the month. Any returns received after then are used to produce the final estimates for the month, which are published with the release of the following month's data. We use the final estimates as the preliminary data are not available.

The University of Michigan consumer sentiment is a consumer confidence index based on household telephone interviews about their attitudes toward US economy. Preliminary numbers are released on the second Friday and revised final figures are reported at 10.00am Eastern Time on the fourth Friday each month. We use final figures in the analysis. Lemmon and Portniaguina (2006) find that the consumer sentiment predicts returns on stocks with small size and low institutional ownership.

All these three measures of individual sentiments are highly auto-correlated and influenced by macro conditions. In the main test we use the residuals after regressing changes of raw sentiment indices with changes of proxies for macro factors including unemployment rates, credit spreads and industrial productivity.

3. Index and Stock Option Trading

3.1 Summary statistics

Table 1 presents the summary statistics of the main variables. The level and monthly change of positive exposure demand for stock options are close to zero on average. The level (*PDS*) has high autocorrelation, while the change (*dPDS*) has no significant autocorrelation. The positive exposure demand for stock calls (*PDS_C*) is positive and the positive exposure demand for stock puts (*PDS_P*) is negative, implying that the average stock option open buy volume exceeds the open sell volume in both calls and puts (Breen and Figlewski, 1999). The positive-exposure demand for S&P500 index options (*PDI*, *PDI_C* and *PDI_P*) are all negative, especially for puts (*PDI_P*). The negative sign of *PDI* and *PDI_P* highlights the difference of our positive demand from the net demand in Grleanu, Pedersen and Poteshman (2009). In their study, the net demand for index options are positive as put purchases comprise the bulk of index option trading. The slope of the implied volatility function (IVF) for stock options (*SlopeS*) is -416 basis points, which indicates that the implied volatility of out-of-the-money calls lies below that of out-of-the-money puts on average. The average slope of the IVF for index options (*SlopeI*) is -697 basis points, and more negative than *SlopeS*.

The raw measure of AAII sentiment index has a mean value of 90.19 and strong auto correlation, while its monthly change adjusting macro factors, *dAAII*, has a mean close to zero and lower autocorrelation. Similarly, raw measures of Conference Board (*CB*) and Michigan (*Mich*) sentiments are highly auto-correlated, and their macro-adjusted changes have close to zero auto-correlation. Table 1 also reports summary statistics for the ATM implied volatility for stocks and the S&P500 index at the end of each month (σ^S or σ^I) and the monthly excess returns on the value-weighted CRSP index (*Rm*).

Figure 2 plots the time series of *PDS*, *PDI*, the level of the S&P500 index, and the raw measures of three sentiments. We present here *PDS* and *PDI* computed from options volumes without logarithm. In the regression analysis, we use *PDS* and *PDI* computed from the logarithm of volumes shown in Eq. (10) to control for any long-term trends in options volumes. Figure 2 shows that investors increase their exposure to individual stocks through the options market, i.e. buy stock calls and sell stock puts, in periods of high market returns and individual sentiment. The correlations of *PDS* with the level of various measures of the sentiments are particularly evident. In contrast, there is some evidence that investors reduce their exposure to the index when market returns have been high. The correlations between *PDI* and the sentiments are less evident.

3.2 Option trading behavior of different investor types

A number of studies associate noise traders with small unsophisticated individual investors, while institutional investors are generally assumed to act as more rational arbitrageurs (Lee, Shleifer and Thaler, 1991; Kumar and Lee, 2006; Lemmon and Portniaguina, 2006). The Option Clearing Corporation divides non-market maker option transactions into trades from firm proprietary traders and those from public customers. An example of a firm proprietary trader would be an employee of Goldman Sachs trading for the bank’s own account. For the period from 1990 to 2001, the CBOE further subdivides the public customer data into orders that originated from the customers of discount brokerages, full-service brokerages and other public customers. The clients of brokerage firms, such as E-Trade, are an example of discount brokerage customers, while the clients of Merrill Lynch are an example of full-service brokerage customers. For the remaining part of the sample period from 2002 to 2010, the CBOE changes its classification scheme and subdivides public customer volumes into volumes associated with small, medium and large trades corresponding to orders for less than 100, between 100 and 199, and larger than 199 contracts, respectively.

Among public customers, we consider discount brokerage customers or small size trades as the most likely to be associated with unsophisticated investors and full-service customers or large trades as more likely to be associated with sophisticated investors, i.e. hedge funds trading through full-service brokerages. Pan and Poteshman (2005) provide evidence that discount brokerage customers are less sophisticated by showing that full-service brokerage customers and other public customers have a greater propensity than discount customers to open purchased call (put) positions before stock price increases (decreases). However, it is worth noting that some investors in the full-service category are also individual investors and are subject to irrational behavioral. As Poteshman and Serbin (2003) show, the full-service customers also engage in the irrational early exercising of American options.

Figure 3 depicts the percentage of non-market maker volume attributable to each class of investors. The percentage volume is computed as the volumes from a particular type of investors divided by the volumes from all non-market maker investors. We can see that discount/small customers trade stock options much more actively than index options, while more rational, full-service customers are active traders of both stock and index options. Trading generated from discount customers (small trades) constitutes 14% (32%) of the non-market maker trading of stock options, but only 2% (4%) of S&P500 index options. Full-service customers constitute around 60% of both stock and index trading, and large trades comprise 41% of stock options trading and 53% of index options trading.

4. Results

In this section, we examine how individual sentiments and lagged market returns are related to option demand and pricing. We then investigate the profitability of a trading strategy and conclude with an examination of the cross-sectional effects of the sentiments and lagged market returns on the demand and prices of stock options.

4.1. Determinants of stock and index options trading

According to our previous analysis, we argue that the positive exposure demand for stock options (*PDS*) is likely to be driven by the sentiment of noise traders speculating on the direction of stock prices, whereas the positive exposure demand for index options (*PDI*) is more likely to be driven by rational investors for hedging purposes. To investigate the demand for stock and index options, we estimate the following time-series regression specifications:

$$PDS_t = a^S + b^S Sentiment_t + c^S Rm_{t-1} + d^S Rm_t + f^S PDS_{t-1} + \varepsilon_t^S \tag{13.1}$$

$$PDI_t = a^I + b^I Sentiment_t + c^I Rm_{t-1} + d^I Rm_t + f^I PDI_{t-1} + \varepsilon_t^I, \tag{13.2}$$

where PDS_t is computed from Eq. (10.1) and measured as the sum of non-market maker open buy call and sell put logarithm volumes minus the sum of open sell call and buy put logarithm volumes across all stock options, and PDI_t is the same variable for S&P500 index options. Because *PDS* and *PDI* have high autocorrelations, we use their monthly changes in some specifications. *Sentiment*, measured as *dAAII*, *dBC* or *dMich*, is the changes in individual sentiments adjusted for changes in unemployment rates, credit spreads, and industrial productivity. Rm_{t-1} is lagged market excess returns. The regressions also include contemporaneous market excess returns, Rm_t, and the lagged dependent variable as controls.[12]

The results are presented in Table 2. When the dependent variable is *PDS*, the coefficient estimates on three measures of sentiment and market lagged returns are all positive and statistically significant. The estimates on lagged market returns are around three times as large as those on contemporaneous market returns. When the dependent variable is the monthly change of *PDS* (*dPDS*), the coefficients of the sentiments and the lagged market return remain positive and statistically significant. In economic terms, a one standard deviation change in *dAAII* is associated with a 5.5 unit change in *dPDS*, amounting to 32% of the unconditional standard deviation of *dPDS*. And a one standard deviation change in the lagged market return is associated with a 6.8 unit change in *dPDS*.

Panels C and D present the results based on *dPDS* from puts (*dPDS_P*) and calls (*dPDS_C*), separately. The results show *dAAII* is similarly related to calls and puts, while *dCB* and *dMich* are more strongly related to puts than to calls. *dPDS_P* and *dPDS_C* are both positively related to lagged market returns, which indicates that investors increase their exposure to stocks by selling puts and buying calls after high market returns.[13]

[12] We also include specifications such as underlying volatilities and bull-bear sentiment. The coefficient estimates on these variables are not statistically different from zero.

[13] We also test the delta-adjusted *dPDS*. The coefficient estimates on sentiment and market returns remain qualitatively the same.

In contrast, as the right side of Table 2 reveals, *PDI* is not related to either the sentiments or lagged market returns; all the estimates of their coefficients are insignificant. Breaking-down *dPDI* into the demand from puts and calls separately shows a similar pattern.

The results presented in Table 2 confirm the visual observations from Figure 2. *PDS* and *PDI* do not follow the same pattern. *PDS* is driven by individual sentiments and prior market returns. When the sentiments and past returns are high, investors increase their exposure to individual stocks by purchasing calls and selling puts. In contrast, *PDI* is not related to individual sentiments or past market returns.

Referring back to Figure 3, relatively unsophisticated investors, such as those who use discount brokerages or make smaller trades, are important participants in the stock options market, but not in the index options market. If unsophisticated investors are more prone to be sentiment driven, we expect that their demand for options that increase their exposure to underlying stocks will be more sensitive to individual sentiments and past returns, compared to the demand of other investors.

Table 3 reports the results where the dependent variables are the monthly changes of positive exposure demand for stock options from different types of investors or trades. Panel A is for the period from 1990 to 2001 and panel B is for the period from 2001 to 2010, corresponding to the change in the CBOE's reporting of trader types. The coefficient estimates for three measures of the individual sentiments are all positive and statistically significant for discount, small and medium investors. The estimates for lagged market returns are positive and statistically significant for discount, small and investors and remain positive but insignificant for full and large investors. Meanwhile, the coefficient estimates for the sentiments or lagged returns are negative for firm proprietary. Panel C reports the results where *dPDS* are computed from options of different moneyness or close volumes. The positive relation between *dPDS* and the sentiments or lagged market returns presents in all moneyness category. OTM *dPDS* is the most closely related to the sentiments and lagged returns, and ITM *dPDS* is the least. *dPDS* computed from close volumes is negatively related to the sentiments, and positively related to the lagged market returns, both with marginal statistical significance.

Overall, the results suggest that less sophisticated investors, in particular, tend to increase their exposures to individual stocks through opening options positions, especially for OTM options, when individual sentiments are high and following high market returns. In contrast, firm proprietary traders appear to act more like market makers and take the opposite side of these trades.

4.2. Option Prices

The previous section documents that the individual sentiments and past market returns are related to the positive-exposure demand for stock options, but are unrelated to index options. To the extent that market-makers in options cannot perfectly hedge their positions, supply curves for options become upward sloping. In this case, the demand imbalances generated by the trades of end users can affect option prices (Garleneau, Pedersen and Poteshman (2009)). If individual sentiments and market returns reflect changes in the aggregate demand for stock options, as indicated by our results in the last section, we expect that changes in these variables will also be reflected in option prices.

Specifically, our previous results show that investors increase their exposure to underlying stocks through the options market when the individual sentiments and past market returns are high. Given that the volume of OTM options is far greater than that of ITM options, the results suggest that the demand for high strike options goes up and the demand for low strike options goes down following increases in the sentiments or high market returns. Based on this argument, we expect the slope of the IVF of stock options, measured as the implied volatility difference between OTM (high strike) calls and OTM (low strike) puts, to be positively associated with the individual sentiments and past market returns.[14] In contrast, we expect the sentiments and past returns to be unrelated to the prices of index options which, as we have shown, are largely immune to the demand imbalances associated with changes in the sentiments or lagged market returns.

In contrast, if the individual sentiments and past returns are proxies for changes in fundamentals such as jump or volatility risks, as shown in Section 1, the slopes of the IVF of stock and index options will respond to the individual sentiments and lagged market returns in similar ways.

The empirical specification used to investigate the impact on option prices is as follows:

$$SlopeS_t = \alpha^S + g^S Sentiment_t + h^S Rm_{t-1} + q^S Rm_t + l^S BB_t + j^S \sigma_t^S + k^S IVRV_t + l^S SlopeS_{t-1} + \varepsilon_t^S \quad (14.1)$$

$$SlopeI_t = \alpha^I + g^I Sentiment_t + h^I Rm_{t-1} + q^I Rm_t + l^I BB_t + j^I \sigma_t^I + k^I IVRV_t + l^I SlopeI_{t-1} + \varepsilon_t^I, \quad (14.2)$$

where $SlopeS_t$ and $SlopeI_t$ are the slopes of the IVF of stock and index options and are calculated based on Eqs. (12.1) and (12.2), respectively. If the individual sentiments and past market returns affect option prices through demand, the coefficients g^S and h^S will be significantly positive and the coefficients g^I and h^I will be insignificant. Alternatively, if the sentiments and past market returns influence option prices through risk preferences, the coefficients g^S and g^I or h^S and h^I will be similar because risk innovations are expected to affect the prices of index and stock options in similar ways.

The regressions also control for a number of other factors. Han (2008) finds that institutional investor sentiment proxied by the level of bull-bear spread (*BB*) is related to the prices of SPX index

[14] Note that to the extent that the sentiment-related demands for purchasing calls and selling puts are roughly equal, there will be no effect of sentiment on the prices of at-the-money options. In unreported results, this is indeed what we find.

options. Dennis and Mayhew (2002) and Han (2008) find that volatility is related to the slope of the volatility smile. We control for volatility using the monthly change of implied volatility of the underlying stock or index measured at the end of every month ($\Delta\sigma^{S}$ or $\Delta\sigma^{I}$). $IVRV_t$ is the volatility premia used Bollerslev, Tauchen and Zhou (2009). *Rm*, the contemporaneous market premium; Amin, Coval and Seyhun (2004) document that S&P100 index call (put) prices are overvalued following large upside (downside) market movements.

As shown in Table 4, for stock options (Panel A), the coefficients on individual sentiments and lagged market returns are all positive and significant. For example, a one standard deviation increase in *dAAII* is associated with a 55 basis point increase in the slope of the implied volatility smile for stock options (*SlopeS*), a magnitude equivalent to 18% of the unconditional standard deviation of *SlopeS*. A one standard deviation change in lagged market returns is associated with a 41 basis point increase in *SlopeS*. For a one month OTM call with 1.1 K/S and 0.4 volatility, these variations in volatility will drive around 3% changes in the call price.

The results for index options (Panel B) exhibit a different pattern. None of the coefficient on the individual sentiments or lagged market returns is statistically significant. These findings show that the individual sentiments and lagged market returns affect stock and index option prices in a manner consistent with the idea that fluctuations in sentiments of noise traders influences prices of securities mainly traded by individual investors, but are unrelated to the prices of securities dominated by sophisticated investors.

The coefficient on *BB* (a measure of institutional investor sentiment) is positive and significantly related to the slope of IVF for index options, which is consistent with Han's (2008) findings. This coefficient is also positive, but not statistically significant, for stock options. The coefficient on volatility and volatility premia are negative. This negative relation is consistent with the theoretical prediction of Bakshi, Kapadia and Madan (2003). Table 4 also reveals that there is no consistent relation between contemporaneous market returns (*Rm*) and the slope of IVF for either stock or index options.

If the only channel for sentiment to affect option prices is through demand, then controlling for demand pressure measured as PDS should eliminate the significance of investor sentiment. We report the results of adding PDS in explaining SlopeS in Table 4 Panel C. The fact that the sentiment variable remains statistically significant after controlling for option demand suggests biased beliefs distort the prices end-users are willing to pay for the options.

4.3. Trading Strategy

The results from the previous section suggest that stock OTM calls are more (less) expensive than OTM puts when the individual sentiments and lagged market returns are high (low). To provide further evidence of how the sentiments and past returns affect the relative prices of options, we compute returns from a trading strategy that trades calls and puts conditional on AAII sentiment and lagged market returns. We choose AAII because we compute monthly AAII index as the average of its first three weekly indices. It is well available before the trading strategy is conducted. In particular, we sell OTM calls and buy OTM puts in the last three trading days of the month if the changes in the raw measures of AAII ($dAAII^{Raw}$) for that month are larger than 0.05 or 0.015 and the previous month's market risk premium minus 0.5% (Rm_{t-1}-0.5%) is higher than 1% or 2%. We buy OTM calls and sell OTM puts when $dAAII^{Raw}$ is less than -0.05 or -0.15 and Rm_{t-1}-0.5% is lower than -1% or -2%. We choose 0.5% because average market risk premium is around 0.5% per month. In selecting the OTM call and put pairs for each underlying stock, we require options to have: (i) the same maturity of less than 60 trading days; (ii) non-zero trading volume; (iii) larger than $0.125 bid price; and (iv) a bid ask spread below 15% of the mid price. If more than one call or put satisfies above conditions for a pair, we choose the call (or put) with the largest trading volume.

For each call and put pair we compute the returns from holding the options to maturity, with and without delta hedging. The return without delta hedging is the profit of holding the position to maturity scaled by the average of call and put prices. The return with delta hedging is the proceeds from the daily delta hedged position divided by the average of call and put prices.[15]

As Table 5 shows, all of the strategies yield significant positive abnormal returns before accounting for options transaction costs.[16] For example, the strategy that conditions on absolute value of $dAAII^{Raw}$ ($|dAAII^{Raw}|$) larger than 0.05 and $|Rm$-0.5$|$>2% has returns of 11.49% before delta hedging and returns of 5.91% after delta hedging. The returns increase further to 21.50% (un-hedged) and 9.17% (hedged), when

[15] We use closing stock and option prices to estimate delta. Battalio and Schultz (2006) argue that non-synchronous stock and option prices at the end-of-day plague the OptionMetrics database. To address this issue, we re-estimate the delta hedge profit with simulated closing stock prices adjusted for the potential error arising for non-synchronous trading in unreported test. In specific:

$$S'_{i,t} = S_{i,t} + \epsilon_{i,t} = S_{i,t} + \tilde{R} * (0.1/356)^{0.5} * \sigma_{i,t}$$

where $S_{i,t}$ is the closing stock price, $\tilde{R}$ is a random variable with standard normal distribution and $\sigma_{i,t}$ is the volatility. We choose 0.1/356 as a conservative assumption about the difference between the times when options and the stock prices are recorded. The results are remain qualitatively the same and available upon request.

[16] The profit of unconditional strategy of buying OTM calls and selling OTM puts at mid is 5.73% (t statistics 2.07) without delta hedging, and 2.72% (t statistics 1.89) with delta hedging.

we condition on $|dAAII^{Raw}|>0.15$ and $|Rm\text{-}0.5|>2\%$. Even after accounting for transaction costs, all of the unhedged strategies and those of the hedged strategies with $|dAAII^{Raw}|>0.15$ yield positive returns.

Table 5 also reports the returns after we break down months into periods when investors are too optimistic and when investors are too pessimistic. For the strategies without delta hedge, when there's relative mild variations in $AAII^{Raw}$ ($|dAAII^{Raw}|>0.05$), returns during pessimistic periods are higher than those during optimistic periods; while when $|dAAII^{Raw}|>0.15$, the opposite is true. For delta hedged strategies, the returns from optimistic periods are higher than the returns from pessimistic periods.

To summarize, the results from the trading strategy show that positive returns are generated by strategies that sell options that end users' demand. And the strategy earns higher returns in periods when investors are optimistic than when investors are pessimistic. This analysis provides additional evidence that individual investor sentiments and past returns alter the time-series variations in the slope of the IVF of stock options.

4.4 Cross-Sectional Analysis

If the positive relations of the individual sentiments and past market returns with *PDS* and *SlopeS* arise from demand imbalances driven by the speculation of individual investors, the association between the sentiments and *PDS* or *SlopeS* should be stronger for stocks where trading by individual investors is more concentrated. And the effects of the sentiments and past market returns on *SlopeS* should be stronger for stocks where market-makers face higher arbitrage and hedging costs. We estimate the concentration of individual trading using the open volume of discount investors/small trades divided by the volume of all non-market makers. We use volatility and volatility of volatility, measured as the standard deviation of daily returns and absolute returns of the month, respectively, as proxies for the costs of arbitrage.

The results are reported in Table 6. When the dependent variable is $dPDS_{it}$, the coefficients on the interactions with concentration of individual investor ($Ratio_{it}$) are positive and statistically significant, while the coefficients on the interactions with volatility or volatility of volatility are insignificant. When the dependent variable is $SlopeS_{it}$, coefficients on the interaction terms are all positive and significant. These results indicate that the effects of sentiment and past returns on *PDS* are positively associated with concentration of individual investors, and their effects on *SlopeS* are associated with both concentration of individual investors and costs of hedging in the predicted direction.

5. Conclusion

We show that the demand for stock options positions that increase exposure to the underlying is positively related to individual sentiment and past market returns, whereas the demand for index options is invariant to individual sentiment and returns. These differences in trading patterns are reflected in the differences in the composition of traders in the different types of options. Options on individual stocks are actively traded by unsophisticated investors who appear to use options largely to speculate on future price movements while trades in index options are more often motivated by the hedging demand of sophisticated investors. Consistent with a demand-based view of option pricing, we find that individual sentiment and lagged market returns are related to time-series variations in the slope of the implied volatility smile of stock options, but have little impact on the prices of index options. The pricing impact is more pronounced in options with a higher concentration of speculative trading, higher stock return volatility and those with higher volatility of volatility. Our results provide new evidence that sentiments and lagged market returns as behavioral biases affect the demand for and prices of securities traded actively by individual investors, but have little effect on the prices of securities in which demand is driven by the hedging motives of more rational investors.

References

Amin, K., J. D. Coval and H. Seyhun, 2004, "Index Option Prices and Stock Market Momentum," *Journal of Business,* 77, 835-873.

Baker, M. and J. Wurgler, 2006, "Investor Sentiment and the Cross-section of Stock Returns," *Journal of Finance,* 61, 1645-1680.

Bakshi, G, N. Kapadia and D. Madan, 2003, "Stock Return Characteristics, Skew Laws, and Differential Pricing of Individual Equity Options," *Review of Financial Studies,* 16, 101-143.

Bao, J., J. Pan and J. Wang, 2010, "The Illiquidity of Corporate Bonds," *Journal of Finance,* forthcoming.

Barraclough, K. and R. E. Whaley, 2011, "Early Exercise of Put Options on Stocks," *Journal of Finance,* forthcoming.

Bates, D., 1991, "The Crash of 87: Was It Expected? The Evidence from Options Markets," *Journal of Finance,* 46, 1009-1044.

Bates, D., 2000, "Post-87 Crash Fears in S&P 500 Futures Options," *Journal of Econometrics,* 94,181-238.

Battalio, R. and P. Schultz, 2006, "Options and the Bubble," *Journal of Finance* 61.

Black, F. and M. Scholes 1973, "The Pricing of Options and Corporate Liabilities," *Journal of Political Economy,* 81, 637-645.

Bollen, N. P. and R. E. Whaley, 2004, "Does Net Buying Pressure Affect the Shape of Implied Volatility Functions?" *Journal of Finance,* 59, 711-753.

Bollerslev, T., G. Tauchen and H. Zhou, 2009, "Expected Stock Returns and Variance Risk Premia", Review of Financial Studies, 22, 4463-4492.

Cherkes, M., J. S. Sagi and R. H. Stanton, 2009, "A Liquidity-Based Theory of Closed-End Funds," *Review of Financial Studies,* 22, 257-299.

Constantinides, G. M., J. C. Jackwerth and S. Perrakis, 2009, "Mispricing of S& P 500 Index Options," *Review of Financial Studies,* 22,1247-1277.

Coval, J. and T. Shumway, 2001, "Expected Option Returns," *Journal of Finance,* 56, 983-1009.

Duan, J-C. and J. Wei, 2009, "Systematic Risk and the Price Structure of Individual Equity Options," *Review of Financial Studies.* 22, No 5,1982-2006.

Dennis, P. and S. Mayhew, 2002, "Risk-neutral Skewness: Evidence from Stock Options," *Journal of Financial and Quantitative Analysis,* 37, 471-493.

DeLong, J.B., A. Shleifer, L. H. Summers and R. J. Waldmann, 1990, "Noise Trader Risk in Financial Markets," *Journal of Political Economy,* 98, 703-738.

Fama, E., 1970, "Efficient Capital Markets, A Review of Theory and Empirical Work," *Journal of Finance,* 25, 383-417.

Figlewski, S., 1989, "Options Arbitrage in Imperfect Markets," *Journal of Finance,* 44, 1289-1311.

Gârleanu, N., L. H. Pederson and A. Poteshman, 2009, "Demand-based Option Pricing," *Review of Financial Studies,* 22, 4259-4288.

Breen, C. and S. Figlewski, 1999, "Market Risk and Model Risk for a Financial Institution Writing Options," *Journal of Finance* 54.

Han, B., 2008, "Investor Sentiment and Option Prices," *Review of Financial Studies,* 21,387-414.

Heston, S., 1993, "A Closed-from Solution for Options with Stochastic Volatility with Applications to Bond and Currency Options," *Review of Financial Studies,* 6, 327-343.

Jackwerth, J. and M. Rubinstein, 1996, "Recovering Probability Distributions from Option Prices," *Journal of Finance,* 51, 1611-1631.

Kumar, A. and C. M. C. Lee, 2006, "Retail Investor Sentiment and Return Comovements," *Journal of Finance*, 61, 2451-2486.

Lakonishok, J., I. Lee, N. D. Pearson and A. M. Poteshman, 2007, "Option Market Activity," *Review of Financial Studies*, 20, 813-857.

LaPorta, R., J. Lakonishok, A. Shleifer and R. Vishny, 1997, ''Good News for Value Stocks: Further Evidence on Market Efficiency,'' *Journal of Finance*, 62, 859-874.

Lee, C. M. C., A. Shleifer and R. H. Thaler, 1991, "Investment Sentiment and Close-end Fund Puzzle," *Journal of Finance*, 46, 75-109.

Lemmon, M. and E. Portniaguina, 2006, "Consumer Confidence and Asset Prices: Some Empirical Evidence," *Review of Financial Studies*, 19(4), 1499-1529.

Liu, J., J. Pan and T. Wang, 2005, "An Equilibrium Model of Rare-event Premia and Its Implication for Option Smirks," *Review of Financial Studies*, 18, 131-164.

Newey, W. K. and K. D. West, 1987, "A Simple Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimator," *Econometrica*, 55, 703-708.

Pan, J., 2002, "The Jump-risk Premia Implicit in Options: Evidence from an Integrated Time-Series Study," *Journal of Financial Economics*, 63, 3-50.

Pan, J. and A. M. Poteshman, 2006, "The Information in Option Volume for Future Stock Prices," *Review of Financial Studies*, 19, 871-908.

Pontiff, J., 1996, "Costly Arbitrage: Evidence from Closed-End Funds," *Quarterly Journal of Economics*, 111, 1135-1151.

Poteshman, A. M. and V. Serbin, 2003, "Clearly Irrational Financial Market Behavior: Evidence from the Early Exercise of Exchange Traded Stock Options," *Journal of Finance*, 58, 37-70.

Roll, R., E. Schwartz and A. Subrahmanyam, 2009, "Relative Trading Activity in Options and Stock," *Journal of Financial Economics*, forthcoming.

Shleifer, A. and R. W. Vishny, 1997, "The Limits of Arbitrage," *Journal of Finance*, 52, 35-55.

Stambaugh, R. F., J. Yu and Y. Yuan (2011), "The Short of It: Investor Sentiment and Anomalies," working paper, University of Pennsylvania, University of Minnesota and University of Iowa.

Stein, J., 1989, "Overreactions in the Options Market," *Journal of Finance*, 44, 1011-1023.

Stein, E. and J. Stein, 1991, "Stock Price Distributions with Stochastic Volatility," *Review of Financial Studies*, 4, 727-752.

Xiong, Wei and Jialin Yu, 2011, "The Chinese Warrants Bubble," *American Economic Review*, 101, 2723-2753.

Yan, S., 2011, "Jump Risk, Stock Returns, and Slope of Implied Volatility Smile," *Journal of Financial Economics*, 99 (1), 216-233.

Zhang, X., R. Zhao and Y. Xing, 2010, "What Does Individual Option Volatility Smirk Tell Us About Future Equity Returns?" *Journal of Financial and Quantitative Analysis*, forthcoming.

Table 1 Summary Statistics

	Mean	Std	Min	Max	Auto
Positive exposure demand for stock options (*PDS*)	-1.46	26.64	-128.49	82.57	0.79
Change of *PDS* (*dPDS*)	0.16	17.34	-54.85	96.45	-0.07
PDS from calls (*PDS_C*)	13.79	15.99	-35.79	73.77	0.70
Change of *PDS_C* (*dPDS_C*)	0.03	12.43	-75.53	62.65	-0.29
PDS from puts (*PDS_P*)	-15.24	17.65	-112.88	41.82	0.73
Change of *PDS_P* (*dPDS_P*)	0.13	12.90	-68.89	73.09	-0.21
Positive exposure demand for index options (*PDI*)	-34.40	21.84	-134.14	8.97	0.61
Change of *PDI* (*dPDI*)	0.16	17.58	-64.41	60.88	-0.37
PDI from calls (*PDI_C*)	-8.13	14.85	-74.46	21.17	0.62
Change of *PDI_C* (*dPDI_C*)	0.13	12.49	-46.57	*44.14*	-0.33
PDI from puts (*PDI_P*)	-26.27	14.54	-68.56	4.94	0.49
Change of *PDI_P* (*dPDI_P*)	0.03	11.64	-52.80	51.26	-0.34
Slope of smile of stock options (*SlopeS*) (bp)	-416.04	304.06	-1529.20	773.42	0.30
Slope of smile of index options (*SlopeI*) (bp)	-697.42	379.33	-2721.26	-148.96	0.48
AAII sentiment, raw measure ($AAII^{Raw}$)	0.09	0.17	-0.43	0.53	0.79
Change of *AAII*, macro adjusted (*dAAII*)	0.00	0.15	-0.41	0.49	-0.21
Conference Board sentiment, raw measure (CB^{Raw})	91.93	28.28	25.30	144.71	0.97
Change of *CB*, macro adjusted (*dCB*)	-0.31	6.28	-21.62	21.58	0.01
Michigan sentiment, raw measure ($Mich^{Raw}$)	86.99	13.35	56.40	112.00	0.95
Change of $Mich_t$, macro adjusted ($dMich_t$)	-0.07	4.16	-12.96	16.97	-0.02
Volatility of Stocks σ^S (bp)	4932.47	1099.96	2381.76	12270.93	0.92
Change of σ^S ($\Delta\sigma^S$) (bp)	7.46	429.85	-1559.35	4120.69	0.08
Volatility of Index σ^I (bp)	2048.42	793.05	486.62	6989.00	0.85
Change of σ^I ($\Delta\sigma^I$) (bp)	1.76	427.12	-1528.00	2050.00	0.00
Market excess returns (*Rm*) (%)	0.46	4.53	-18.54	11.04	0.13

The positive-exposure demand for stock options (*PDS*) is the monthly sum of the public investor open buy call and sell put logarithm volumes minus the sum of open sell call and buy put logarithm volumes across all stock options. *PDS_C* or *PDS_P* is *PDS* computed exclusively from stock calls or stock puts. *PDI*, *PDI_C* and *PDI_P* are similar variables for S&P500 index options. *SlopeS* is the cross-sectional average slope of the IVF for stock options computed as the difference between the implied volatilities of OTM calls and the implied volatilities of OTM puts. *SlopeI* is the slope of the implied volatility of S&P500 index options. Variables are monthly from January 1990 to December 2010.

Table 2 Determinants of *PDS* and *PDI*

	Sentiment	Rm_{t-1}	Rm_t	Lag	Obs/R^2	Sentiment	Rm_{t-1}	Rm_t	Lag	Obs/R^2
Panel A dependent:			$\boldsymbol{PDS_t}$					$\boldsymbol{PDI_t}$		
$dAAII_t$	31.25**	1.45**	0.38*	0.78**	251	5.95	-0.07	-0.09	0.68**	251
	(4.39)	(6.23)	(1.96)	(11.01)	0.74	(0.61)	(-0.26)	(-0.34)	(5.68)	0.46
dCB_t	0.50**	1.53**	0.50**	0.75**	251	0.00	-0.03	-0.04	0.68**	251
	(3.13)	(6.80)	(2.35)	(10.60)	0.73	(0.01)	(-0.11)	(-0.17)	(5.71)	0.45
$dMich_t$	0.64**	1.61**	0.59**	0.75**	251	0.01	-0.03	-0.04	0.68**	251
	(2.34)	(6.70)	(2.81)	(10.45)	0.72	(0.03)	(-0.12	(-0.17)	(5.65)	0.45
Panel B dependent:			$\boldsymbol{dPDS_t}$					***dPDI***		
$dAAII_t$	36.46**	1.36**	0.40	-0.14**	250	6.94	-0.08	-0.02	-0.36**	250
	(4.78)	(5.16)	(1.78)	(-2.63)	0.28	(0.68)	(-0.35)	(-0.07)	(-5.26)	0.11
dCB_t	0.41**	1.49**	0.59**	-0.18**	250	-0.04	-0.02	0.05	-0.36**	250
	(2.61)	(5.45)	(2.45)	(-3.45)	0.23	(-0.19)	(-0.09)	(0.20)	(-5.28)	0.11
$dMich_t$	0.69**	1.57**	0.67**	-0.18**	250	0.01	-0.04	0.04	-0.36**	250
	(2.45)	(5.64)	(2.79)	(-3.51)	0.21	(0.02)	(-0.16)	(0.15)	(-5.28)	0.11
Panel C dependent:			$\boldsymbol{dPDS\_P_t}$					$\boldsymbol{dPDI\_P_t}$		
$dAAII_t$	16.34**	0.48**	0.42**	-0.25**	250	8.38	0.07	-0.23	-0.44**	250
	(2.70)	(2.57)	(2.52)	(-3.20)	0.14	(1.39)	(0.49)	(-1.37)	(-4.93)	0.19
dCB_t	0.33**	0.46**	0.46**	-0.25**	250	0.05	0.11	-0.18	-0.43**	250
	(2.85)	(2.72)	(2.75)	(-3.20)	0.13	(0.42)	(0.66)	(-1.16)	(-4.83)	0.18
$dMich_t$	0.48**	0.53**	0.51**	-0.26**	250	0.13	0.09	-0.18	-0.43**	250
	(2.22)	(2.83)	(3.04)	(-3.26)	0.12	(0.70)	(0.62)	(-1.15)	(-4.87)	0.18
Panel D dependent:			$\boldsymbol{dPDS\_C_t}$					$\boldsymbol{dPDI\_C_t}$		
$dAAII_t$	16.93**	1.01**	0.03	-0.30**	250	-1.53	-0.16	0.23	-0.43**	250
	(2.95)	(6.67)	(0.22)	(-3.61)	0.27	(-0.24)	(-0.96)	(1.33)	(-4.27)	0.17
dCB_t	0.08	1.10**	0.15	-0.33**	250	-0.09	-0.13	0.24	-0.43**	250
	(0.68)	(6.72)	(0.98)	(-4.44)	0.25	(-0.75)	(-0.83)	(1.43)	(-4.20)	0.18
$dMich_t$	0.36	1.12**	0.17	-0.33**	250	-0.12	-0.14	0.23	-0.43**	250
	(1.42)	(7.09)	(1.13)	(-4.37)	0.24	(-0.64)	(-0.85)	(1.42)	(-4.21)	0.18

PDS_t is the sum of public investor open buy call and sell put logarithm volumes minus the sum of open buy put and sell call logarithm volumes across all individual stock options. $dPDS_t$ is its monthly changes. $dPDS\_P_t$ or $dPDS\_C_t$ is the $dPDS_t$ exclusively from stock calls or puts. PDI_t, $dPDI_t$, $dPDI\_P_t$ and $dPDI\_C_t$ are similar variables for S&P500 index options. Sentiment is the monthly change of individual investor sentiments adjusted for macro factors, and is measured as $dAAII_t$, dCB_t or $dMich_t$. Rm_{t-1} and Rm_t are the pre and contemporaneous market premia, respectively. The parentheses contain Newey West (1987) t-statistics that correct for serial correlation and heteroscedasticity. Variables are monthly from January 1990 to December 2010.

**: significant at the 1% level. *: significant at the 5% level.

Table 3 *PDS* from different types of investors, trades or contracts

	Sentiment	Rm_{t-1}	Sentiment	Rm_{t-1}	Sentiment	Rm_{t-1}	Sentiment	Rm_{t-1}
Panel A: 1990 – 2001								
	Discount		Full Service		Other		Firm Proprietary	
$dAAII_t$	62.78^{**}	3.69^{**}	34.64^{**}	0.45	48.77^{**}	2.02^{**}	-14.23	-1.07^{**}
	(3.68)	(6.74)	(2.36)	(1.21)	(2.68)	(2.25)	(-0.81)	(-2.13)
dCB_t	0.82^{**}	4.33^{**}	0.94^{**}	0.37	0.40	1.97^{*}	-0.62	-1.08^{**}
	(3.26)	(6.87)	(3.06)	(1.02)	(1.01)	(2.06)	(-1.32)	(-2.19)
$dMich_t$	2.29^{**}	3.78^{**}	1.23	0.19	0.49	1.26	-0.36	-2.77^{**}
	(2.91)	(5.78)	(1.32)	(0.31)	(0.81)	(1.60)	(-0.59)	(-2.01)
Panel B: 2002-2011								
	Small Trades		Medium Trades		Large Trades		Firm Proprietary	
$dAAII_t$	71.24^{**}	2.15^{**}	59.58^{**}	1.69^{**}	18.9	0.84	-2.91	-1.17^{**}
	(6.33)	(5.31)	(5.62)	(3.03)	(1.69)	(1.76)	(-0.24)	(-3.89)
dCB_t	0.52^{**}	2.03^{**}	0.39^{*}	1.56^{**}	0.22	0.73	0.03	-1.17^{**}
	(2.28)	(4.65)	(1.92)	(3.19)	(0.98)	(1.53)	(0.12)	(-3.75)
$dMich_t$	1.36^{**}	2.10^{**}	1.57^{**}	1.62^{**}	-0.62	0.83	-0.13	-1.14^{**}
	(2.01)	(4.77)	(2.42)	(2.37)	(-0.97)	(1.75)	(-0.48)	(-3.82)
Panel C: Different Moneyness Options and Closing Trades								
	OTM		ATM		ITM		Close Trades	
$dAAII$	43.40^{**}	2.33^{**}	32.64^{**}	2.52^{**}	7.38	1.54^{**}	-19.97	0.98^{**}
	(4.32)	(5.84)	(2.66)	(5.51)	(0.55)	(3.31)	(-1.71)	(2.01)
dCB	0.94^{**}	2.61^{**}	0.70^{**}	2.63^{**}	0.40	1.33^{**}	-0.50^{**}	0.84
	(3.22)	(6.49)	(2.52)	(6.07)	(1.76)	(3.25)	(-2.21)	(1.76)
$dMich$	0.97^{**}	2.60^{**}	0.66	2.67^{**}	0.46	1.38^{**}	-0.62^{*}	0.82
	(2.23)	(6.33)	(1.75)	(5.83)	(1.34)	(3.13)	(-1.91)	(1.66)

The dependent is $dPDS_t$ calculated as the monthly change of PDS_t. PDS_t is the sum of the various investors/trades open buy call and sell put logarithm volumes minus the sum of open buy put and sell call logarithm volumes across all individual stock options. Sentiment is the monthly change of individual investor sentiments adjusted for macro factors, and is measured as $dAAII_t$, dCB_t or $dMich_t$. Rm_{t-1} is previous month market excess returns. Control variables include contemporaneous market excess returns and the lagged dependent. Coefficient estimates on control variables are omitted. The parentheses contain t-statistics computed from Newey West (1987) standard errors correcting for heteroscedasticity and serial correlation. Variables are monthly from January 1990 to December 2010.

**: significant at the 1% level.

*: significant at the 5% level.

Table 4 Slope of implied volatility smile for stock and index options

	Sentiment	Rm_{t-1}	Rm_t	*BBt*	$\Delta\sigma_t^S$ or $\Delta\sigma_t^I$	*IVRV*	lag	Obs/R^2
			Panel A	**Dependent: $SlopeS_t$**				
$dAAII_t$	370.15**	9.11**	3.02	1.63	-0.12**	-0.53	0.30**	251
	(3.61)	(3.44)	(0.74)	(1.42)	(-2.61)	(-1.02)	(8.02)	0.46
dCB_t	6.42**	12.08**	7.81**	1.48	-0.11**	-0.46	0.28**	251
	(2.50)	(4.39)	(2.05)	(1.23)	(-2.25)	(-1.04)	(8.43)	0.45
$dMich_t$	10.72**	12.20**	7.63**	1.51	-0.11**	-0.41	0.27**	261
	(2.69)	(4.33)	(2.02)	(1.25)	(-2.25)	(-0.90)	(8.37)	0.45
			Panel B	**Dependent $SlopeI_t$**				
$dAAII_t$	-7.79	5.97	-4.08	2.68*	-0.41**	-1.07*	0.39**	251
	(-0.06)	(1.13	(-0.61)	(1.89)	(-7.30)	(-1.90)	(5.88)	0.41
dCB_t	-3.22	6.93	-3.67	2.57*	-0.42**	-0.98*	0.39**	251
	(-1.26)	(1.30)	(-0.61)	(1.82)	(-7.73)	(-1.90)	(5.92)	0.42
$dMich_t$	-3.67	6.75	-4.16	2.72*	-0.42**	-0.91	0.39**	251
	(-0.82)	(1.25)	(-0.68)	(1.93)	(-7.74)	(-1.78)	(5.98)	0.41

	Sentiment	PDS_t	Rm_{t-1}	Rm_t	BB_t	$\Delta\sigma_t^S$	$IVRV_t$	Lag
		Panel C	**Dependent: $SlopeS_t$, control for PDS**					
$dAAII_t$	269**	2.16**	4.22	-2.04	1.15	-0.14**	-0.53	0.23**
	(2.79)	(3.93)	(1.78)	(-0.33)	(0.89)	(-2.13)	(-1.02)	(7.80)
dCB_t	5.13**	2.17**	4.79*	-3.36	1.07	-0.11**	-0.46	0.25**
	(2.06)	(4.02)	(1.89)	(-1.03)	(0.97)	(-2.05)	(-1.04)	(7.91)
$dMich_t$	8.76**	2.36**	4.26	-3.76	1.13	-0.16**	-0.41	0.26**
	(2.82)	(4.25)	(1.83)	(-0.85)	(0.87)	(-2.04)	(-0.90)	(7.23)

$SlopeS_t$ is the cross sectional average the difference between the implied volatilities of OTM stock calls and the implied volatilities of OTM stock puts. $SlopeI_t$ is the slope of the implied volatility of S&P500 index options. Sentiment is the monthly change of individual investor sentiments adjusted for macro factors, and is measured as $dAAII_t$, dCB_t or $dMich_t$. Rm_{t-1} and *Rm* are previous and contemporaneous market excess returns, respectively. BB_t is the bull-bear spread. Lag is the lagged dependent. $\Delta\sigma_t^S$ or $\Delta\sigma_t^S$ is the monthly change of implied volatility of stocks or index. $IVRV_t$ is the volatility premium. *PDS* is the positive exposure demand for stock options. The parentheses contain t-statistics computed from Newey West (1987) standard errors that correct for serial correlation and heteroscedasticity. The time period is from 1990 to 2010.
**: significant at the 1% level. *: significant at the 5% level.

Table 5 Returns of trading strategy on stock options (%)

	buy/sell mid	Buy ask sell bid	No of Months / obs	$dAAII_t^{Raw}$ > 0 buy/sell mid	Rm_{t-1} -0.5 > 0 Buy ask sell bid	$dAAII_t^{Raw}$ < 0 buy/sell mid	Rm_{t-1} -0.5 < 0 Buy ask sell bid
No Delta Hedge							
$\lvert dAAII_t^{Raw}\rvert$>0.05	7.36	2.22	110	-9.68**	-14.83**	28.05**	22.92**
$\lvert Rm_{t-1}$-0.5$\rvert$>1%	(1.74)	(0.52)	58,471	(-3.42)	(-4.31)	(6.14)	(5.31)
$\lvert dAAII_t^{Raw}\rvert$>0.05	11.49**	6.39	98	-2.60**	-7.69**	26.77**	21.66**
$\lvert Rm_{t-1}$-0.5$\rvert$>2%	(2.50)	(1.39)	55,966	(-1.98)	(-2.79)	(5.63)	(4.85)
$\lvert dAAII_t^{Raw}\rvert$>0.15	16.14**	10.87**	59	17.08**	11.94**	14.99**	9.87**
$\lvert Rm_{t-1}$-0.5$\rvert$>1%	(5.86)	(3.96)	36,374	(4.44)	(3.10)	(3.89)	(2.56)
$\lvert dAAII_t^{Raw}\rvert$>0.15	21.50**	16.42**	53	27.00**	21.92**	16.40**	11.32**
$\lvert Rm_{t-1}$-0.5$\rvert$>2%	(7.32)	(5.59)	32,358	(6.44)	(5.23)	(4.08)	(2.82)
Delta Hedge							
$\lvert dAAII_t^{Raw}\rvert$>0.05	4.96**	-0.05	110	5.13	0.11	4.76	-0.22
$\lvert Rm_{t-1}$-0.5$\rvert$>1%	(2.19)	(-0.02)	58,471	(1.59)	(0.03)	(1.51)	(-0.07)
$\lvert dAAII_t^{Raw}\rvert$>0.05	5.91**	0.95	98	8.54**	3.57	3.08	-1.88
$\lvert Rm_{t-1}$-0.5$\rvert$>2%	(2.45)	(0.39)	55,966	(2.46)	(1.03)	(0.93)	(-0.56)
$\lvert dAAII_t^{Raw}\rvert$>0.15	7.23**	2.94**	59	20.60**	15.30**	-4.76**	-9.04**
$\lvert Rm_{-1}$-0.5$\rvert$>1%	(3.87)	(2.11)	36,374	(7.61)	(6.39)	(-2.25)	(-3.53)
$\lvert dAAII_t^{Raw}\rvert$>0.15	9.17**	4.91**	53	24.90**	19.63**	-4.35**	-8.60**
$\lvert Rm_{t-1}$-0.5$\rvert$>2%	(4.66)	(3.01)	32,358	(8.67)	(7.53)	(-1.99)	(-3.21)

We sell OTM calls and buy OTM puts at the end of the month if $dAAII_t^{Raw}$ >0.05 or 0.15 and Rm_{t-1}-0.5 > 1% or 2%. We buy OTM calls and sell OTM puts if $dAAII_t^{Raw}$< -0.05 or –0.15 and Rm_{t-1}-0.5< -1% or -2%. $dAAII^{Raw}$ is the monthly change of raw AAII sentiment measures. $Rm_{t-1}$is the pre month market risk premium. 'Buy/sell mid', 'Buy ask' and 'Sell bid' refer to the prices of the options at which we buy or sell. The time period is from January 1990 to December 210. *T*-stats adjusted for cross-correlation are in parentheses. **: significant at the 1% level. *: significant at the 5% level.

Table 6 Cross sectional stock portfolio analysis

$dAAII_t$	Rm_{it-1}	$dAAII_t$* $Ratio_{it}$	dAAII$_t$* σ_{it}	dAAII* $\sigma\sigma_{it}$	Rm_{it-1}* $Ratio_{it}$	Rm_{it-1}* σ_{it}	Rm_{it-1}* $\sigma\sigma_{it}$	Controls	Obs /R^2
Panel A Dependent $dPDS_{it}$									
33.21**	1.27**	86.33**			1.65**				242,487
(3.97)	(5.20)	(3.04)			(2.46)			....	0.06
45.35**	1.63**		-16.26			-0.51			242,487
(6.64)	(8.42)		(1.26)			(-1.73)		…	0.06
48.88**	1.57**			-27.02			-0.76		242,487
(6.41)	(8.52)			(-1.47)			(-1.59)		0.06
Panel B Dependent: $SlopeS_{it}$									
87.38**	7.58**	345.09**			2.39*				147,266
(2.13)	(2.64)	(3.43)			(1.96)			…	0.16
69.77**	6.73**		336.54**			15.41**			147,266
(2.09)	(2.02)		(4.24)			(5.56)		…	0.16
70.68**	6.92**			407.93**			14.54**		147,266
(2.12)	(1.98)			(3.53)			(6.03)		0.16

$Ratio_{it}$ is the ratio between the volumes from discount customers or small trades and the volumes from all non market maker investors. σ_{it} is the annualized volatility of stock daily returns in month *t*. $\sigma\sigma_{it}$ is the annualized volatility of volatility in month *t*. $dPDS_{it}$ is the monthly change of PDS_{it}. PDS_{it} is computed as the sum of the public investor open buy call and sell put logarithm volumes minus the sum of open buy put and sell call logarithm volumes on stocks *i*. $SlopeS_{it}$ is the slope of the IVF for options on stock *i*, computed as the difference between the implied volatilities of OTM calls and the implied volatilities of OTM puts. $dAAII_t$ is the monthly changes in $AAII_t$ individual investor sentiment adjusted for the changes in macro-economic factors. Rm_{it-1} is the previous month stock returns. Variables are monthly and from 1990 to 2010.

**: significant at the 1% level.

*: significant at the 5% level.

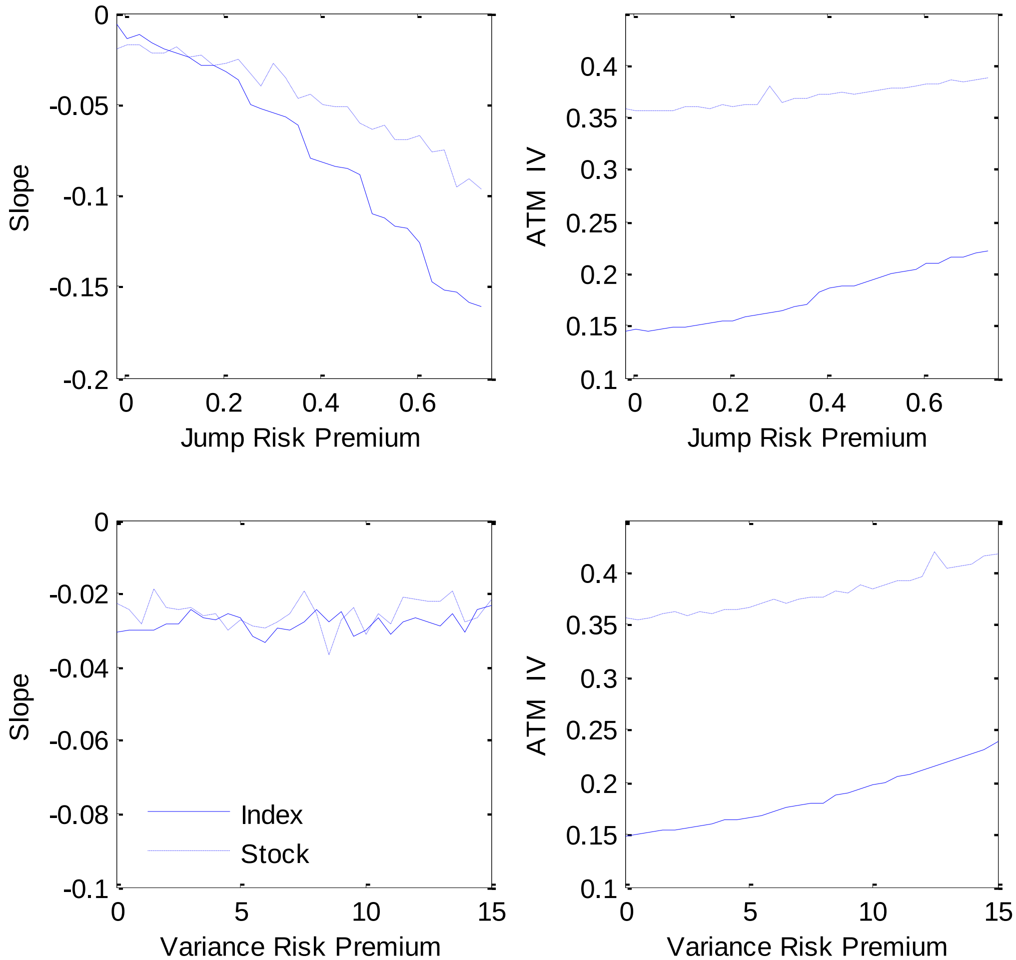

Figure 1 Implied volatility function (IVF) of index and stock options with jump and variance risk premia. The slope of the IVF is the average IV of 30-day OTM calls minus the average IV of 30-day OTM puts. Options are OTM if $0.125 \leq \Delta_C \leq 0.375$ or $-0.375 \leq \Delta_P \leq -0.125$ and ATM if $0.375 < \Delta_C < 0.626$ or $-0.625 < \Delta_P < -0.375$. IV and delta are computed from the Black-Scholes model.

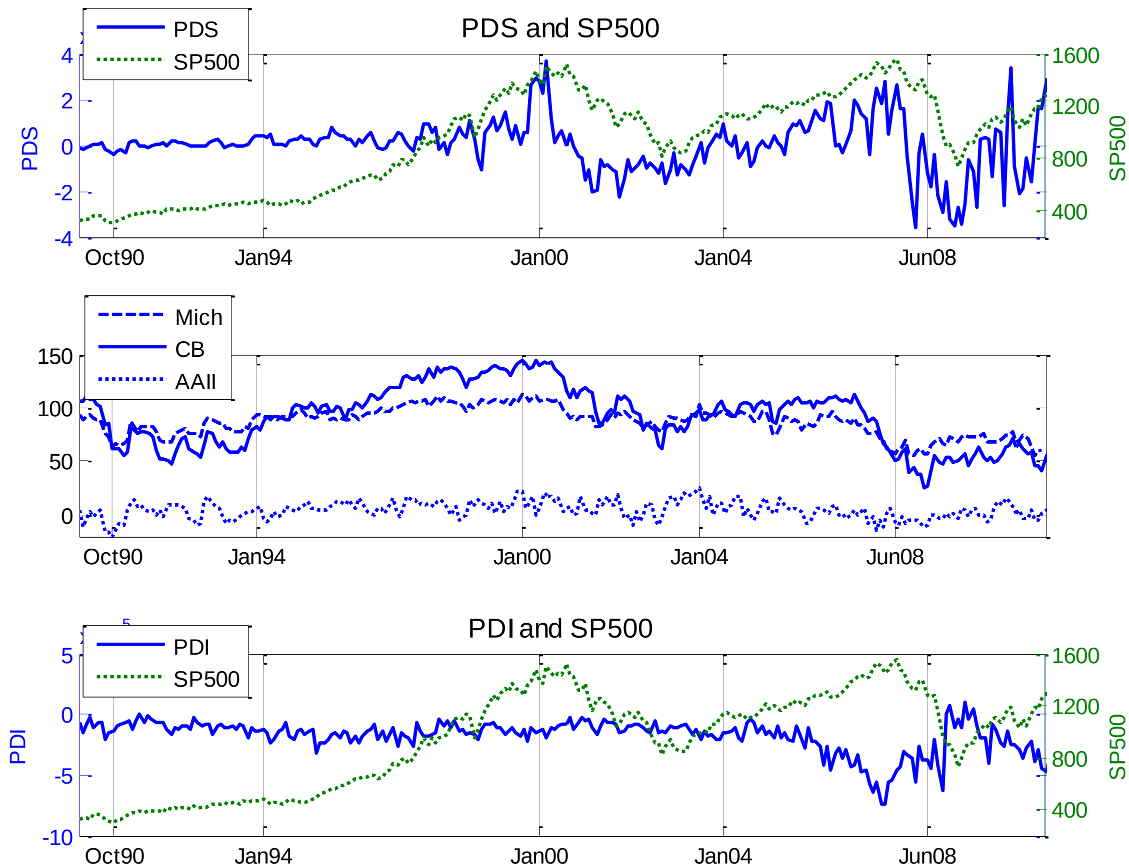

Figure 2 S&P500 Index Level, *PDS*, *PDI* and Individual Sentiments *PDS* is the positive exposure demand for stock options, calculated as the sum of the public investor open buy call and sell put volumes minus the sum of open sell call and buy put volumes across all stock options. *PDI* is the positive exposure demand for S&P500 index options. The numbers are in monthly frequency and from 1990 to 2010.

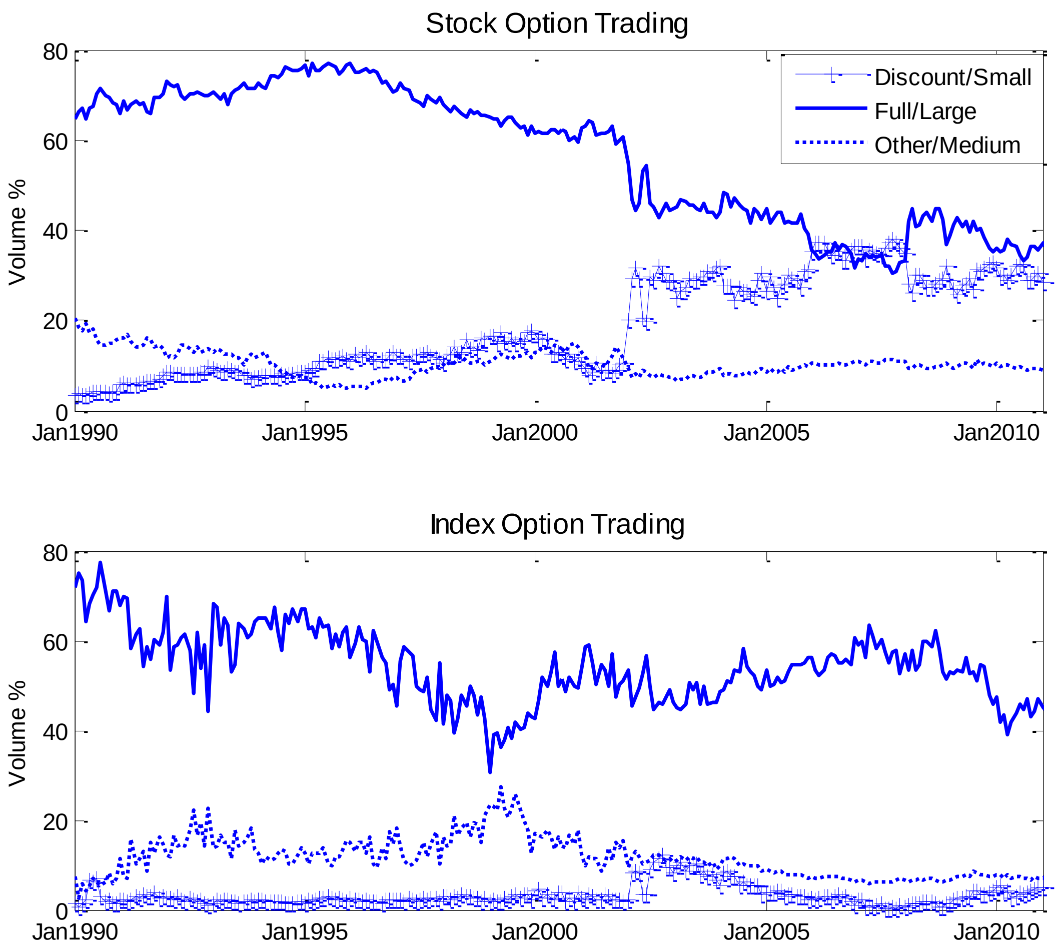

Figure 3 Stock and S&P500 index option trading of different types of investors or trade sizes The percentage trading volume of discount brokerage customers, full-service customers, and the other public customers before 2002 and the percentage trading volume of small, large and medium trades from 2002 onwards. Percentage trading volume is measured as the volume originating from specific investors or trade groups divided by total non-market maker volume. The percentage trading volume of firm proprietary traders is omitted.