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Implied volatility and investor beliefs in experimental asset markets☆

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A B S T R A C T

Investor expectations move markets so the ability to measure beliefs is critical for market participants. Though the volatility implied by traded option prices is a popular gauge of beliefs, our understanding of its usefulness is incomplete. Our experimental markets feature a stock and a call option. The stock has two possible outcomes and the distance between the outcomes is our measure of volatility. The outcome range is not always announced. Regardless of whether it is announced and despite observed mispricing of the two assets, knowledge of the range implied by trading prices informs observers about subjects' beliefs concerning volatility.

"Bull-markets are born on pessimism, grow on skepticism, mature on optimism and die on euphoria." Sir John Templeton

1. Introduction

Prominent investor Sir John Templeton argued that markets are driven by investors' positive and negative expectations of the future. Because markets move with investor expectations, it is important to be able to gauge the investing public's beliefs (Barberis et al., 1998). One measure of forward-looking expectations is the Chicago Board Options Exchange's (CBOE's) volatility index (VIX), commonly referred to as the "investor fear gauge." The VIX reflects investors' expectations of future market volatility as expressed through trade (Whaley, 2000, 2009). In this paper, we examine how investors' views are related to implied volatility using an experimental method.

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Market volatility is of great concern to policymakers, academics, and practitioners alike. Volatility implied by traded option prices has become a standard measure of expectations of future uncertainty. Since the introduction of the VIX in 1993, researchers have examined how implied volatilities have changed over time and whether or not the fear gauge is informative about the future (e.g., Schwert, 2011; Völkert, 2014). Yet, at times skepticism surrounding the information content of the VIX is expressed. For example, a recent *Wall Street Journal* article warns investors not to "read too much into the fear gauge" (Jakab, 2014). We examine whether investor beliefs are related to implied volatility in experimental asset markets. To accomplish this, we design an experiment in which participants simultaneously trade in markets for the asset and a call option written on the asset.

The experimental market is simple, with only two possible outcomes in any period. We vary the range, that is, the distance between the possible outcomes. We consider two treatments. In the first treatment, we induce investor beliefs about the range, by publicly announcing the value. In the second treatment, we allow investors to form their own beliefs about the range. We do not provide either the value or the distribution of the range. In this treatment, we elicit participants' opinions concerning the unannounced spread parameter. Our experiments then test to see whether the implied range, calculated from the stock and call option prices revealed through trade, is related to the publicly announced range, and, when the range is unspecified, whether the implied range is related to participants' beliefs about the spread. In both cases, we find that the implied range is informative. The magnitude of the implied range informs an observer about market participants' beliefs concerning volatility. Forward-looking information regarding expectations is important to market participants because beliefs move markets.

Using experimental methodology provides a key advantage in studying how well implied volatility captures investors' beliefs because participants' beliefs can be directly measured. Beliefs about the range are induced in the treatment when participants are given the actual value. Further, in the treatment where the value of the range parameter is not announced, we are able to directly ask participants to report their beliefs. Outside the laboratory, investors' beliefs are usually measured indirectly using sentiment indicators, including the VIX. We find a significant, but not a perfect, link between directly measured investors' beliefs and the implied volatility.

The remainder of our paper is structured as follows. In Section 2, we provide a brief review of the literature. We describe the experimental method in Section 3. In Section 4, we provide a discussion of the results and, in Section 5, we offer concluding remarks.

2. Background and research questions

The VIX is designed to measure traders' expectations for the future. Using call and put options for a wide range of strike prices, Black-Scholes-Merton (Black and Scholes, 1973; Merton, 1973) option pricing formulas are used by the CBOE to back-out the volatility implied by current option prices. This so-called "fear gauge" is taken to be a barometer of investors' expectations. Some researchers have studied the properties of the VIX using data from naturally occurring markets and, though there have been a few asset market experiments featuring options, to our knowledge, no prior research has examined implied volatility using an experimental methodology. Next, we briefly discuss research on the VIX and experimental option markets.

2.1. Studies using the VIX

The VIX is widely regarded as a measure of market uncertainty by practitioners, and is a component of CNN's Index of Fear and Greed, a popular sentiment measure.[1] Academics use the VIX as an empirical measure of uncertainty and the market's expectation of volatility (e.g., Barinov, 2013). Empirical evidence supports the use of the VIX as a proxy for expectations. For example, Völkert (2014) provides evidence that the VIX is informative about changes in future volatility. In addition, Schwert (2011) examines market behavior surrounding the 2007–2009 financial crisis and concludes that the volatility expectations measured by the VIX were accurate. Furthermore, researchers report that expected equity returns respond to changes in investors' expectations of future uncertainty as measured by the VIX. For example, Durand et al. (2011) report that an increase in the VIX leads to flights to quality and higher required equity returns. In addition to pricing effects, uncertainty as measured by the VIX is shown to impact market quality, including liquidity (Chung and Chuwonganant, 2013).

A growing body of evidence supports the view that the VIX is informative about future stock market levels and volatility (e.g., Fleming et al., 1995; Hibbert et al., 2008; Chung et al., 2011). Implied volatilities are correlated with future market volatility and uncertainty measures based on the VIX exhibit return predictability (Dreschler and Yaron, 2011). If investors' beliefs are on average correct, these results can be interpreted as demonstrating that the implied volatility is capturing their beliefs. We study this proposition directly, using experimental methods. In the laboratory, we can specify the volatility of our experimental asset, and we can survey participants regarding their beliefs. Also, our experimental tests do not require investor beliefs to be correct on average.

[1] The VIX was originally calculated using implied volatilities from S&P 100 options. Later, the basis for calculation shifted to S&P 500 options as trading volume moved to these options. For details, see the Chicago Board Options Exchange publication (CBOE, 2014). On CNN's index see http://money.cnn.com/data/fear-and-greed/ (accessed January 30, 2019).

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2.2. Options in experimental asset markets

Only a handful of experimental studies feature options. Abbink and Rockenbach (2006) design a simple experiment in order to test whether options are priced according to the Binomial Option Pricing Model or BOPM (Cox et al., 1979). Their experimental participants did not interact in a market but instead made consecutive investment decisions across rounds. Participants are given the opportunity to invest in two risky assets, an underlying and its call option, where two possible states of the world are possible each round. While their laboratory setting is stark, it allows for clear tests of the BOPM and provides a starting point for subsequent research. With student participants, experimental prices diverged significantly from theoretical predictions. Interestingly, when the experiment was conducted again with professional traders, performance further deteriorated.

Other experiments focus on how option introduction affects the market for the underlying security. Both Kluger and Wyatt (1995) and de Jong et al. (2006) study the market quality of the underlying asset in the presence of asymmetric information. Kluger and Wyatt use a double auction market institution and report faster information aggregation in the presence of an option market. de Jong, Koedijk and Schnitzlein employ dealer markets with informed and liquidity traders. Unlike Kluger and Wyatt, de Jong et al.'s option and asset markets are open simultaneously, allowing for feedback between the markets. Nonetheless, the conclusions are similar. Both studies report that the introduction of an option can speed information dissemination and improve the efficiency of the market for the underlying security.

While we build upon this literature, our experiment is distinguished from previous work because we empirically measure the relation between the volatility implied by traded option prices and investors' beliefs. While a byproduct of our study, assessing an option-pricing model is not our main focus. As we detail below, our experimental market prices do not strongly conform to the values predicted by the BOPM (consistent with the results of Abbink and Rockenbach (2006)). However, testing an option pricing model is a byproduct of our examination, it is not our focus. Our experiment addresses a distinct question not tackled by previous research. Does the volatility implied by traded asset and option prices inform observers about traders' beliefs concerning volatility?

3. Experimental design

During each experimental session, student participants interacted in a series of experimental asset markets. The markets were conducted using a customized program written with the Fischbacher (2007) z-Tree (Zurich Toolbox for Readymade Economic Experiments) programming package. Each session consisted of ten 3-min trading periods, where eight participants traded two assets using a computerized double auction institution. In the following sections, we describe the traded assets and the market institution. We provide complete experimental instructions in Appendix A.

3.1. Experimental assets

Each experimental period has two possible states, high and low. The payoffs for each asset depend on the state, and the liquidating dividends are paid as shown in Fig. 1.

The payoffs for Asset 2 correspond to a call option with a strike price of $100 written on Asset 1. In the first twelve sessions (1–12), the payoff for Asset 2 is 0 or k, whereas in an additional five sessions (13–17) the payoff for Asset 2 is 0 or $4k$.[2] For exposition purposes, here we refer to Asset 1 as the “stock,” and Asset 2 as the “call.” However, both in the instructions and during the experiment, the assets are always referred to as Asset 1 and Asset 2 (see Appendix A). Typically, participants did not realize that the experiment pertains to options.

Two parameters varied across periods within a session. The probability parameter, *Prob*, represents the probability that the state is high, and took one of three possible values, 0.25, 0.50, and 0.75. The value is determined randomly, with 0.50 having a 50% chance of selection, and 0.25 and 0.75 each having a 25% chance of selection. The probability (*Prob*) was posted on the initial screen presented to participants at the beginning of each period. Thus, the probability of the state being high and low for the period was common knowledge to all participants.

The second parameter, k, determines the range of payoff for the underlying asset and is, thus, our measure of asset volatility. Participants are informed that k is an integer between 0 and 100, but are given no information concerning the likelihood associated with each outcome.

We have two within-participant treatments related to the k parameter. In the first treatment (periods 1, 2, 5, 6, and 9), the value of k is announced to all participants. In the second (periods 3, 4, 7, 8, and 10), no announcement is made concerning k. For the first treatment, we induce participants' beliefs about k to be correct by simply telling them the actual value. There is uncertainty about whether the high or low state will occur, but no uncertainty or disagreement among participants concerning the value of k.

In the second treatment, we no longer induce participants' beliefs, but allow them to form their own beliefs about k. Participants cannot use the moments of the distribution of k to form beliefs because they do not have the necessary

[2] As we will describe later, we conducted additional sessions with a higher payoff for Asset 2 in order to reduce the difference in expected payoffs for the two assets.

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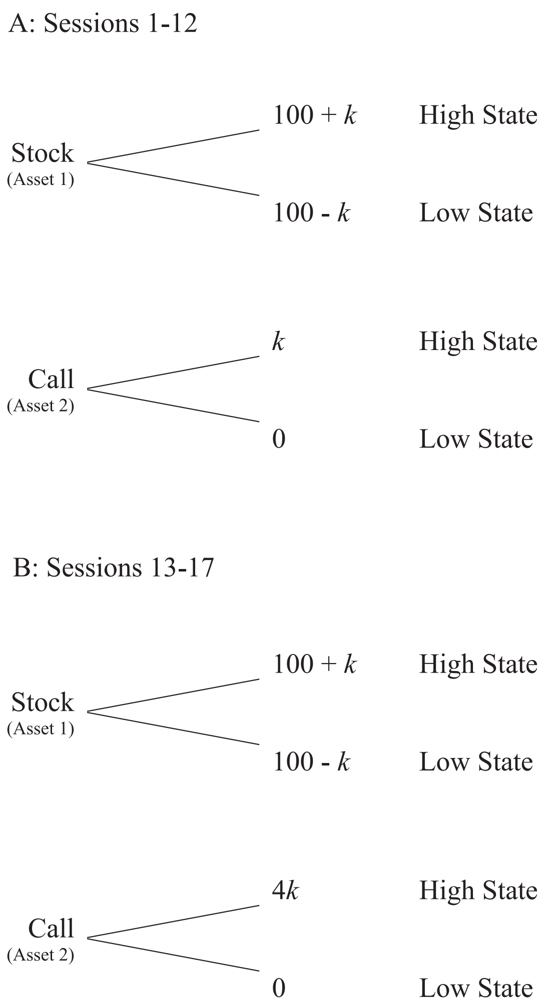

Fig. 1. Asset liquidation values. The liquidation value of each asset depends on the state, revealed at the end of the period. The probability that the state is high can be 0.25, 0.50, or 0.75. Each period, the probability is announced, prior to trading. The realized state is announced at the end of the period, after trading is finished. The parameter, k, ranges from zero to 100. In trading periods 1, 2, 5, 6, and 9, k was announced prior to trade. In the other periods, no information was given concerning k and both the value and the underlying distribution of k was unspecified. Fig. 1A: Sessions 1–12. Fig. 1B: Sessions 13-17.

information about the distribution. We do not try to explain participant beliefs here. Beliefs could be based on hunches, biases, decision errors, or confusion. In the second treatment, we retain the uncertainty about whether the high or low state will occur, but add the additional “risk” stemming from the feature that the value of k is vague.[3]

3.2. *Experimental markets*

At the beginning of each trading period, participants are awarded an initial cash balance of $1600 trading dollars.[4] However, half of this balance is a zero-interest loan and, at the end of the period, $800 is subtracted from each participant's cash balance. All participants are also endowed with five shares of the stock. Half of the participants are given three call options (that is, they are long shares of Asset 2) and the other half start with three written call options (that is, they are short shares of Asset 2). The participants with long and short positions are varied across periods so that over the entire session, all participants start long in calls half of the periods, and short in calls the other half of the periods.

[3] In this treatment, our participants are facing a situation analogous to ambiguity. In addition to possibly being risk-averse, participants may also prefer to avoid choices featuring parameters with unknown probability distributions. See Bossaerts et al. (2010) for an explanation of the effects of ambiguity on prices and allocations in an experimental asset market.

[4] In sessions 1–12, prior to the trading periods, participants answered a questionnaire containing instruments to measure both optimism and overconfidence. As we did not find any relation between these measures and implied volatility, we do not include these results in the paper. However, description of the instruments and the analysis using these measures is presented in Appendix B.

During a trading period, each trader could post and/or accept offers for one share of either security. Traders are free to post multiple orders for either asset and able to cancel outstanding orders at any time. Throughout each period, all outstanding offers are displayed. As trades occur, they are immediately displayed in a chronological list. However, the identity of traders posting or accepting offers is not shown on the trading screen.

While participants start each period with $1600 trading dollars, half of which is a zero-interest loan, they are not allowed to borrow additional funds. Participants are allowed to short sell, but only to a balance of negative ten shares of each asset. These constraints allowed participants to make purchases and sales as desired, but at the same time limited the losses they could suffer in a single period. If a participant lost money in a period, that loss is reflected in total earnings. However, regardless of performance, a participant's total payout is guaranteed to be at least $6.

After each trading period, z-Tree displays one or more additional screens. In periods where the k parameter is not specified, participants are asked to guess the value of k for the period. The guessed value of k, which for ease of exposition we refer to as "guess," is our elicited measure of participants' expectations of range. Next, the earnings summary screen is shown. Each participant's screen displays the values for the parameters, final state of the economy, payoffs for each of the assets, share and cash balances, and participant's earnings for the period. At the end of each trading period, all shares of the experimental assets are liquidated. Then, the next period commences until the final or 10th trading period.

Recall that in our design, the call option has a strike price of 100 so that in sessions 1–12, the possible payoffs are k in the high state and zero in the low. In sessions 13–17, the call pays $4k$ in the high state and zero in the low. The BOPM can be used to compute an implied k, or inferred range of payoffs. Using the standard BOPM formula applied to the asset and option payoffs in our experiment we can compute the implied range in payoffs or volatility for sessions 1–12 as:

$$k = 100 + (1 + r_f)(2C - S), \tag{1a}$$

and for sessions 13–17 as:

$$k = 100 + (1 + r_f)(C/2 - S), \tag{1b}$$

where r_f is the risk-free interest rate, C is the market price of the call option, and S is the market price of the stock or underlying asset. Using market data from the experiments, we compute the implied k and compare it with participants' beliefs about the range in possible payoffs. When the actual range is induced, comparison of the implied range (implied k) to the actual range (k) is a test of the BOPM. If the implied k does not equal actual k, the BOPM no-arbitrage condition is violated. When the actual range is unspecified, we examine whether the implied range is related to subjective beliefs about the range as reflected in participants' guesses.

Each session lasted approximately two-and-a-half hours, including both a software demonstration and a practice period. Participants were recruited from the student population of the University of Cincinnati. During the experiment, all prices and balances were denominated in "trading dollars" which were converted to dollars at the end of the session.

4. Results

Our results are drawn from 17 sessions, each containing 10 3-min markets.[5] There were eight participants per session, with 136 participants in total. Participants received a fixed fee of $6 U.S. dollars for participating, and typical total payouts ranged from $30 to $60 per participant.

4.1. Informational efficiency

Prices and volumes by period are presented in Tables 1 and 2. Table 1 reports median prices and volumes for the periods in which k is announced, and Table 2 contains the data for the periods in which k is unknown. Prices varied considerably across periods.[6] Some of this variability may have to do with risk-aversion and/or differences across sessions, but high variability in both stock and call prices is observed even within the same session. Volumes also fluctuate, with stocks trading more frequently in some periods, and calls trading more frequently in other periods. For periods where the range parameter is announced, expected values are also presented.

We first note that our markets sometimes displayed irrational pricing. The plus signs (+) in Table 1 denote irrational pricing in the corresponding periods. These cases represent prices that are either above the maximum possible payout, or below the minimum possible payout. The maximum and minimums are easily calculated because k is announced in this treatment. As our experiment is more complex than many experimental asset market designs, and our participants are inexperienced, perhaps the irrational prices are due to participant confusion and/or errors, as in Lei et al. (2001). They attribute irrationality at the start of their asset market experiments to participant confusion pertaining to the task and the

[5] There was a technical problem in one session where all the computers in the lab simultaneously shut down. As a result, session 5 has only 6 periods.

[6] Using averages instead of medians produce comparable results. Similarly, using the average of the periods' last five transactions for each asset does not greatly change the conclusions.

Table 1

Asset prices and volumes are presented by period, for the treatments where k is announced. Prob is the probability of the high state. Med S is the median price of the stock and Q_s is the number of shares traded for that period. Med C and Q_c are the call prices and volumes. Open is the number of call contracts outstanding at the end of the period. E is the expected value: $E_s = 100 - k\,(1{-}2(Prob))$ and $E_c = (Prob)k$ for Sessions 1–12, or $E_c = (Prob)4k$ for Sessions 13–17. A plus sign ($^+$) signifies that the median price was either greater than the asset's maximum possible liquidation value, or less than the minimum possible liquidation value.

Session	Period	k	*Prob*	*Med S*	Q_S	E_S	*Med C*	Q_C	*Open*	E_C
1	1	76	.75	145	18	138	50	31	24	57
1	2	18	.50	101	12	100	12	27	20	9
1	5	74	.25	65	22	63	20	21	17	18.5
1	6	58	.50	110	21	100	30	23	14	29
1	9	56	.25	75	15	72	25	20	17	14
2	1	79	.50	110	12	100	80^+	20	14	39.5
2	2	95	.25	75	21	52.5	34	12	12	23.75
2	5	82	.75	117.5	16	141	72.5	16	15	61.5
2	6	33	.50	95	12	100	50^+	16	11	16.5
2	9	48	.25	62	20	76	14	15	10	12
3	1	21	.75	113	9	110.5	20.5	14	17	15.75
3	2	44	.50	120	20	100	38.5	14	10	22
3	5	44	.75	129	18	122	45.5^+	33	9	33
3	6	7	.25	96	24	96.5	7.98^+	26	16	1.75
3	9	97	.75	165	22	148.5	60	21	14	72.75
4	1	3	.75	99	16	101.5	17^+	15	11	2.25
4	2	12	.50	100	19	100	10	18	19	6
4	5	55	.75	135	14	127.5	30	24	19	41.25
4	6	83	.75	163	19	141.5	45	29	14	62.25
4	9	56	.50	122.5	24	100	32.5	14	9	28
5	1	5	.50	64^+	18	100	30^+	13	12	2.5
5	2	67	.75	132	6	133.5	27	24	8	50.25
5	5	66	.50	87.5	8	100	35	11	10	33
5	6	33	.50	95	14	100	20	8	11	16.5
6	1	39	.25	65	14	80.5	12	16	19	9.75
6	2	55	.50	112.5	8	100	35	24	14	27.5
6	5	40	.50	95	33	100	30	24	8	20
6	6	18	.50	90	22	100	15	7	9	9
6	9	18	.50	105	25	100	12	14	8	9
7	1	95	.75	145	14	147.5	90	14	17	71.25
7	2	55	.25	50	15	72.5	18.5	14	14	13.75
7	5	5	.50	97	11	100	6^+	13	22	2.5
7	6	21	.50	90	11	100	10	9	12	10.5
7	9	15	.50	105	19	100	15	12	16	7.5
8	1	1	.75	20^+	32	100.5	20^+	33	23	0.75
8	2	74	.50	44	31	100	45	18	8	37
8	5	91	.50	80	28	100	30	21	10	45.5
8	6	9	.75	98.5	30	104.5	10.5^+	14	10	6.75
8	9	73	.25	40	21	63.5	25	16	7	18.25
9	1	69	.75	110	25	134.5	35	19	12	51.75
9	2	25	.25.	80	29	87.5	11	26	17	6.25
9	5	61	.50	95	44	100	35	32	22	30.5
9	6	18	.50	90	43	100	15	37	21	9
9	9	52	.75	100	49	126	40	40	14	39
10	1	20	.75	110	19	110	20	23	12	15
10	2	34	.50	105	17	100	16	7	8	17
10	5	84	.75	140	18	142	75	17	13	63
10	6	30	.75	105	18	115	45^+	29	16	22.5
10	9	71	.50	100	23	100	35	29	14	35.5
11	1	40	.50	130	17	100	33	18	12	20
11	2	35	.25	100	19	82.5	30	25	16	8.75
11	5	41	.75	140	19	120.5	52^+	16	7	30.75
11	6	66	.25	95	36	67	40	21	13	16.5
11	9	22	.50	110	21	100	15	17	7	11
12	1	11	.50	99	13	100	13^+	39	27	5.5
12	2	70	.75	100	17	135	48	15	8	52.5
12	5	36	.50	88	32	100	52.5^+	50	44	18
12	6	21	.75	100	21	110.5	39^+	20	19	15.75
12	9	60	.25	95	43	70	35	19	19	15
13	1	40	.50	70	17	100	50	23	21	80
13	2	93	.25	50	19	53.5	74.5	12	13	93
13	5	42	.50	109	15	100	100	16	11	84

Table 1 (*continued*)

Session	Period	*k*	*Prob*	*Med S*	Q_S	E_S	*Med C*	Q_C	*Open*	E_C
13	6	77	.25	95	19	61.5	105	16	14	77
13	9	55	.50	100	19	100	100	26	12	110
14	1	87	.25	80	19	56.5	70	11	11	87
14	2	15	.75	85	17	107.5	50	17	8	45
14	5	70	.50	90	13	100	140	20	14	140
14	6	89	.50	80	12	100	132.5	10	11	178
14	9	25	.50	78	25	100	65	20	11	50
15	1	27	.25	74.5	10	86.5	65	20	16	27
15	2	7	.25	91.5^{+}	12	96.5	125	7	10	7
15	5	16	.50	92.5	8	100	60	20	7	32
15	6	44	.50	110	5	100	140	14	7	88
15	9	31	.50	106	8	100	119	13	12	62
16	1	19	.75	100	15	109.5	87.5^{+}	8	17	57
16	2	24	.50	100	8	100	82	15	8	48
16	5	53	.50	110	10	100	132.5	20	22	106
16	6	61	.50	99	15	100	135	16	12	122
16	9	81	.50	100	11	100	200	19	14	162
17	1	39	.75	98	17	119.5	85	13	10	117
17	2	60	.75	120	17	130	192.5	10	14	180
17	5	41	.25	125	19	79.5	119	11	9	41
17	6	9	.50	100	14	100	50^{+}	24	20	18
17	9	39	.25	70	19	80.5	100	9	7	39

structure of their experimental asset. As their experiments progress, some participants recognize that other participants are prone to irrationality, and may speculate, causing a price bubble. However, after more experience, decision errors decline. As participants become more rational and come to realize that the other participants are rational, the market crashes. Although our asset market design differs from theirs, our participants may well be confused, particularly at the start of the session. For the underlying asset, we observe three unambiguous violations of rationality, and all occurred in the first two periods. For the call, we report 16 violations, with six in the first period of the session.

Table 1 also contains the expected value of each asset. For the underlying asset, the median price varies considerably, sometimes being above the expected value and sometimes below. The null hypothesis that the price of the underlying asset is equal to the expected value cannot be rejected using either a paired *t*-test ($p = .18$, two-tailed) or a Wilcoxon signed rank test ($p = .16$, two-tailed). However, corresponding hypothesis tests comparing the call median price to its expected value do reject the null using both the paired *t* ($p < .0001$, two-tailed) and the Wilcoxon ($p < .0001$, two-tailed) tests. Averaging over all markets in the treatment where *k* is announced, the median call price is greater than the expected value by 10.05.

4.2. *Allocational efficiency*

Tables 1 and 2 also report the number of call option contracts outstanding at period end (*Open*). In our setting, the market portfolio is simply the portfolio of stocks because in aggregate there are zero options. Recall that half of the participants begin with a long position in three call options and the other half begin short three call options. Since there are eight participants, there are 12 contracts outstanding at the beginning of the period.

If the market is allocationally efficient, we expect *Open* to equal zero by the end of the period because fund separation implies that all participants hold the market portfolio. Averaging across all periods and both treatments, the average *Open* is 13.0. The minimum *Open* is four and the maximum is 44. If the magnitude of *Open* can be interpreted as a measure of allocational efficiency, we observe little evidence that our markets are any more efficient at the end of the period than at the beginning.

In their experimental examination of pricing and portfolio holding in large-scale asset markets, Bossaerts et al. (2007) also report that portfolio allocations are inefficient. They find evidence that although asset prices are consistent with the CAPM, their participants' allocations are not. Our understanding of the relation between pricing and allocational efficiencies in markets deserves further attention by researchers.

4.3. *Arbitrage opportunities*

Because we have redundant assets in our markets, we can also check prices for arbitrage opportunities. To this end, we calculated the prices of Arrow-Debreu securities, or state-contingent claims (SCC) prices, for the first treatment in which *k* is announced. In periods where the sum of the SCC prices does not equal one, there is an arbitrage opportunity. This occurs in most periods, as shown in Table 3. No-arbitrage implies that the implied *k* will be equal to the actual *k*, so rejecting the null that implied *k* equals actual *k* is just another way of saying that there is an arbitrage opportunity.

Table 2
Asset prices and volumes are presented by period, for the treatments where *k* is not announced. *Med S* is the median price of the stock and Q_s is the number of shares traded for that period. *Med C* is the median price of the call and Q_c is the number of calls traded for that period. *Open* is the number of call contracts outstanding at the end of the period, and Prob is the probability of the High state.

Session	Period	*Prob*	*Med S*	Q_S	*Med C*	Q_C	*Open*
1	3	0.25	90	30	17	9	11
1	4	0.75	130	26	40	19	7
1	7	0.50	105	25	40	18	9
1	8	0.25	87	19	17	17	15
1	10	0.50	102	23	35	20	14
2	3	0.25	70	17	44.5	24	12
2	4	0.50	92.5	12	52.5	14	15
2	7	0.75	115	19	49.5	12	13
2	8	0.25	69	19	19.5	14	16
2	10	0.75	127	21	50	17	22
3	3	0.25	100	15	26	15	11
3	4	0.50	109	27	29	14	11
3	7	0.50	105	15	30.5	18	8
3	8	0.50	120	39	29	11	12
3	10	0.50	119	23	32	23	9
4	3	0.25	91	18	11	17	12
4	4	0.25	96	14	12	24	9
4	7	0.75	140	21	40	11	6
4	8	0.50	132	20	30	23	9
4	10	0.75	140	20	50	20	12
5	3	0.25	112.5	8	26	13	11
5	4	0.75	125	7	50	21	6
6	3	0.25	90	32	20	21	14
6	4	0.25	70	31	15	19	16
6	7	0.50	100	28	27.5	10	7
6	8	0.75	125	36	27	15	12
6	10	0.25	94	26	15	26	13
7	3	0.50	100	4	25	5	10
7	4	0.75	140	14	40	7	12
7	7	0.50	134	18	31.5	20	20
7	8	0.75	110	13	50	9	11
7	10	0.50	90	21	19	13	14
8	3	0.50	45	19	49.5	16	12
8	4	0.25	23	50	32	23	11
8	7	0.25	45	35	30	15	5
8	8	0.50	49	26	26	30	10
8	10	0.50	55	21	27	11	11
9	3	0.25	70	32	25	36	20
9	4	0.75	87.5	20	40	30	19
9	7	0.75	100	34	42.5	44	19
9	8	0.5	100	45	37	38	27
9	10	0.5	120	51	32.5	20	19
10	3	0.25	100	18	19	11	7
10	4	0.50	105	17	27.5	28	16
10	7	0.50	100	18	30	22	15
10	8	0.50	100	21	30	21	16
10	10	0.50	100	19	40	27	18
11	3	0.75	120	17	42.5	14	12
11	4	0.50	122.5	26	42	16	4
11	7	0.50	140	15	50	17	10
11	8	0.50	120	21	40	19	10
11	10	0.25	110	32	20	22	21
12	3	0.50	127	8	50	34	14
12	4	0.25	84	60	30	22	17
12	7	0.25	90	67	20	24	22
12	8	0.50	105	21	54	14	9
12	10	0.50	100	36	45	23	18
13	3	0.50	95	18	75	18	15
13	4	0.75	102.5	12	110	16	8
13	7	0.50	120	11	140	12	8
13	8	0.25	80	19	100	17	9
13	10	0.50	105	16	140	21	8
14	3	0.50	90	17	90	9	7

Table 2 (*continued*)

Session	Period	*Prob*	*Med S*	Q_S	*Med C*	Q_C	*Open*
14	4	0.25	70	13	60	14	14
14	7	0.50	72.5	18	80	15	14
14	8	0.25	53	17	65	11	7
14	10	0.50	67.5	14	62.5	20	14
15	3	0.50	117.5	12	125	7	10
15	4	0.75	135	13	150	11	10
15	7	0.50	115	8	140	11	6
15	8	0.75	120	5	230	12	6
15	10	0.75	129.5	12	169	11	5
16	3	0.50	100	12	97	10	14
16	7	0.25	89	27	120	17	12
16	8	0.25	95	15	110	29	15
16	10	0.50	100	13	105.5	22	11
17	3	0.50	97	20	220	11	9
17	4	0.50	120	18	165	12	11
17	7	0.50	100	28	150	11	11
17	8	0.25	95	13	200	8	9
17	10	0.50	80	16	130	14	11

Other experimental studies with options (Kluger and Wyatt, 1995; Abbink and Rockenbach, 2006) also report violations of no-arbitrage conditions. They conjecture that the BOPM does not work because it is difficult for participants to detect and then to take advantage of arbitrage opportunities in the experimental environment. This explanation likely applies in our markets as well. However, even though direct comparison across studies is difficult because of differences in design, violations of the no-arbitrage condition in our sessions 1–12 appear to be more egregious. In some sessions, the sum of the SCC prices exceeds 10, and in one case the sum is over 100.[7]

When analyzing the no-arbitrage violations for sessions 1–12, we notice that the problem appears to be worse when the expected values of C and S are distant. Thus, we conduct five additional sessions (13–17) in which we change the payoff of C from $(k, 0)$ to $(4k, 0)$. This change reduces the difference in expected payoffs for the two assets. Pricing in sessions 13–17 improves in the sense that the no-arbitrage condition is violated less severely. As the results reported in Table 3 suggest, the sum of the SCC prices is closer to one.[8] Thus, we conjecture that a large gap in the expected values of C and S acts as an arbitrage hurdle because of our trading institution, which restricts all orders to one unit. Further research is called for to clarify this issue.

4.4. *Implied k: when k is announced*

In half of the periods, k is publicly announced. Participants' beliefs about the value of k are therefore induced to be the correct values. For these periods, we study the relation between the implied k and the announced k. Each period, we calculate the implied k from the median transaction prices during the double auctions.

Table 4 presents the results of several OLS models with announced k as the independent variable and implied k as one of the explanatory variables. In addition to the full sample, we exclude periods based on several, arbitrarily chosen cutoff values for the ratio of $E(C)/E(S)$, as indicated in Panels B, C, and D. Removing the outliers pushes the sum of the SCC prices closer to one.

Table 4 also presents the results of F-tests with the null hypothesis that $\alpha = 0$, $\beta = 1$, (and $\delta = 0$, $\gamma = 0$ if applicable), and the alternative that one or more of the equalities are violated. Notice that this null hypothesis is equivalent to the null that the implied k equals the announced k. As indicated by the p-values, the null is strongly rejected in each case. This result is really the same result discussed in the previous section, because the no-arbitrage condition is the reason why the implied k would equal the announced k. When the Arrow-Debreu prices do not sum to one, the implied k will not equal the announced k. In line with the results reported by Abbink and Rockenbach (2006), our experimental markets' options prices are not consistent with the BOPM.

[7] We also look at allocational efficiency and violation of the no-arbitrage relation. We regress *Open* (the number of outstanding option contracts at the end of the period) against the absolute difference between the SCC prices and one to see whether no-arbitrage violations are more severe when allocations are further from the efficient allocation of *Open* equal to zero. We identify no correlation. Regression coefficients for *Open* are not significantly different from zero.

[8] The details of our computerized double auction may explain why. Our computerized markets have an order size of one share. Traders can make as many offers as desired, up to a short sale limit. But, they have to click on the "place bid" or "place ask" button once for each share offered. In this environment, it makes sense for traders to pay more attention to the shares with a $100 expected value, rather than the shares with a relatively low $2.50 expected value. Even a high percentage deviation in the price of C may not be as important as a smaller deviation in the more expensive share. And, it takes a lot of clicking to actually trade a block of C shares. This feature might plausibly make it more difficult to exploit an arbitrage opportunity. The minor modification, changing the payoff of Asset 2 to $4k$ in the high state, makes an extreme disparity between the expected values of the two assets less common.

Table 3

Implied k and the prices of state contingent claims are presented by period, for the treatments where k is announced. For sessions 1–12: Implied $k = 100 + 2C - S$, the price of the High Claim is C/k, and the price of the Low Claim is $(C+100-S)/k$. For sessions 13–17: Implied $k = 100 + (C/2) - S$, the price of the High Claim is $C/4k$, and the price of the Low Claim is $((C/4))+100-S)/k$. When the state contingent claim prices sum to one, the implied k will equal the announced k. If the state contingent claim prices do not sum to one, the implied k will not equal the announced k, and there will be an arbitrage opportunity. *Open* is the number of call contracts outstanding at the end of the period, and Prob is the probability of the High state.

Session	Period	*Open*	*Prob*	*k*	Implied *k*	Price High Claim	Price Low Claim	Sum
1	1	24	.75	76	55	0.66	0.07	0.73
1	2	20	.50	18	23	0.67	0.61	1.28
1	5	17	.25	74	75	0.27	0.74	1.01
1	6	14	.50	58	50	0.51	0.34	0.86
1	9	17	.25	56	75	0.45	0.89	1.34
2	1	14	.50	79	150	1.01	0.89	1.90
2	2	12	.25	95	93	0.36	0.62	0.98
2	5	15	.75	82	128	0.88	0.67	1.55
2	6	11	.50	33	105	1.51	1.67	3.18
2	9	10	.25	48	66	0.29	1.08	1.37
3	1	17	.75	21	28	0.98	0.36	1.34
3	2	10	.50	44	57	0.88	0.42	1.30
3	5	9	.75	44	62	1.03	0.38	1.41
3	6	16	.25	7	20	1.14	1.71	2.85
3	9	14	.75	97	55	0.62	−0.05	0.57
4	1	11	.75	3	35	5.67	6.00	11.67
4	2	19	.50	12	20	0.83	0.83	1.67
4	5	19	.75	55	25	0.55	−0.09	0.46
4	6	14	.75	83	27	0.54	−0.21	0.33
4	9	9	.50	56	43	0.58	0.18	0.76
5	1	12	.50	5	96	6.00	13.20	19.20
5	2	8	.75	67	22	0.40	−0.07	0.33
5	5	10	.50	66	83	0.53	0.72	1.25
5	6	11	.50	33	45	0.61	0.76	1.36
6	1	19	.25	39	59	0.31	1.21	1.51
6	2	14	.50	55	58	0.64	0.41	1.05
6	5	8	.50	40	65	0.75	0.88	1.63
6	6	9	.50	18	40	0.83	1.39	2.22
6	9	8	.50	18	19	0.67	0.39	1.06
7	1	17	.75	95	135	0.95	0.47	1.42
7	2	14	.25	55	87	0.34	1.25	1.58
7	5	22	.50	5	15	1.20	1.80	3.00
7	6	12	.50	21	30	0.48	0.95	1.43
7	9	16	.50	15	25	1.00	0.67	1.67
8	1	23	.75	1	120	20.0	100.0	120.0
8	2	8	.50	74	146	0.61	1.36	1.97
8	5	10	.50	91	80	0.33	0.55	0.88
8	6	10	.75	9	23	1.17	1.33	2.50
8	9	7	.25	73	11O	0.34	1.16	1.50
9	1	12	.75	69	60	0.51	0.36	0.87
9	2	17	.25.	25	42	0.44	1.24	1.68
9	5	22	.50	61	75	0.57	0.66	1.23
9	6	21	.50	18	40	0.83	1.39	2.22
9	9	14	.75	52	80	0.77	0.77	1.54
10	1	12	.75	20	30	1.00	0.50	1.50
10	2	8	.50	34	27	0.47	0.32	0.79
10	5	13	.75	84	110	0.89	0.42	1.31
10	6	16	.75	30	85	1.50	1.33	2.83
10	9	14	.50	71	70	0.49	0.49	0.98
11	1	12	.50	40	36	0.83	0.08	0.90
11	2	16	.25	35	60	0.86	0.86	1.72
11	5	7	.75	41	64	1.27	0.29	1.56
11	6	13	.25	66	85	0.61	0.68	1.29
11	9	7	.50	22	20	0.68	0.23	0.91
12	1	27	.50	11	27	1.18	1.27	2.45
12	2	8	.75	70	96	0.69	0.69	1.38
12	5	44	.50	36	117	1.46	1.79	3.25
12	6	19	.75	21	78	1.86	1.86	3.72
12	9	19	.25	60	75	0.58	0.67	1.25
13	1	21	.50	40	55	0.31	1.06	1.37
13	2	13	.25	93	87	0.20	0.74	0.94

Table 3 (*continued*)

Session	Period	*Open*	*Prob*	*k*	Implied *k*	Price High Claim	Price Low Claim	Sum
13	5	11	.50	42	41	0.60	0.38	0.98
13	6	14	.25	77	58	0.34	0.41	0.75
13	9	12	.50	55	50	0.45	0.45	0.90
14	1	11	.25	87	55	0.20	0.43	0.63
14	2	8	.75	15	40	0.83	1.83	2.67
14	5	14	.50	70	80	0.50	0.64	1.14
14	6	11	.50	89	86	0.37	0.60	0.97
14	9	11	.50	25	55	0.65	1.53	2.18
15	1	16	.25	27	56	0.56	1.50	2.06
15	2	10	.25	7	19	0.71	1.93	2.64
15	5	7	.50	16	38	0.94	1.41	2.35
15	6	7	.50	44	60	0.80	0.57	1.37
15	9	12	.50	31	54	0.96	0.77	1.73
16	1	17	.75	19	44	1.15	1.15	2.30
16	2	8	.50	24	41	0.85	0.85	1.71
16	5	22	.50	53	56	0.63	0.44	1.07
16	6	12	.50	61	69	0.55	0.57	1.12
16	9	14	.50	81	100	0.62	0.62	1.23
17	1	10	.75	39	45	0.54	0.60	1.14
17	2	14	.75	60	76	0.80	0.47	1.27
17	5	9	.25	41	34	0.73	0.12	0.85
17	6	20	.50	9	25	1.39	1.39	2.78
17	9	7	.25	39	80	0.64	1.41	2.05

Table 4

For each period where the k parameter is announced, the implied k is calculated using median prices of the two assets. Panels A through D present OLS regressions predicting announced k, using implied k as an explanatory variable. The parameters *p25* and *p75* are dummy variables representing the observations where the probability treatment is 25% and 75% respectively. Standard errors are below parameter estimates, with p-values below the standard errors. The final column reports the F-statistic for a test with the null that $\alpha = 0$ and $\beta = 1$ (and other explanatory variables = 0 if applicable), along with the associated p-value. The adjusted R^2 is also reported in the last column.

Model (n = 84)	α *Std Error p*	β *Std Error p*	γ *Std Error p*	δ *Std Error p*	*F-Statistic p* *Adj* R^2
Panel A: Is the Implied k Informative? (All Periods)					
$k = \alpha + \beta(\text{Implied } k) + e$	17.105	0.467			30.94
	5.371	0.078			<0.0001
	0.002	<0.0001			0.30
$k = \alpha + \beta(\text{Implied } k) + \gamma(p25^*\text{Implied } k)$	16.710	0.432	0.152	0.016	23.56
$+ \delta(p75^*\text{Implied } k) + e$	5.354	0.088	0.091	0.083	<0.0001
	0.003	<0.0001	0.09	0.85	0.33
Model (n = 62)	α *Std Error p*	β *Std Error p*	γ *Std Error p*	δ *Std Error p*	*F– Statistic p* *Adj* R^2
Panel B: Is the Implied k Informative? (Excluding periods where $E(S)/E(C) < 0.15$ or $E(S)/E(C) > 6.67$)					
$k = \alpha + \beta(\text{Implied } k) + e$	30.648	0.371			44.95
	6.489	0.087			<0.0001
	<0.0001	<0.0001			0.23
$k = \alpha + \beta(\text{Implied } k) + \gamma(p25^*\text{Implied } k)$	30.487	0.314	0.134	0.095	31.75
$+ \delta(p75^*\text{Implied } k) + e$	6.445	0.093	0.085	0.079	<0.0001
	<0.0001	0.001	0.12	0.24	0.27
Model (n = 53)	α *Std Error p*	β *Std Error p*	γ *Std Error p*	δ *Std Error p*	*F-Statistic p* *Adj* R^2
Panel C: Is the Implied k Informative? (Excluding periods where $E(S)/E(C) < 0.20$ or $E(S)/E(C) > 5$)					
$k = \alpha + \beta(\text{Implied } k) + e$	31.004	0.414			47.17
	6.654	0.090			<0.0001
	<0.0001	<0.0001			0.30
$k = \alpha + \beta(\text{Implied } k) + \gamma(p25^*\text{Implied } k)$	31.037	0.368	0.115	0.067	32.31
$+ \delta(p75^*\text{Implied } k) + e$	6.676	0.098	0.091	0.080	<0.0001
	<0.0001	0.0005	0.21	0.41	0.32
Model (n = 48)	α *Std Error p*	β *Std Error p*	γ *Std Error p*	δ *Std Error p*	*F-Statistic p* *Adj* R^2

(*continued on next page*)

Table 4 (*continued*)

Model (n = 48)	α *Std Error p*	β *Std Error p*	γ *Std Error p*	δ *Std Error p*	*F-Statistic p* *Adj R^2*
Panel D: Is the Implied k Informative? (Excluding periods where $E(S)/E(C) < 0.25$ or $E(S)/E(C) > 4$)					
$k = \alpha + \beta(\text{Implied } k) + e$	32.378	0.406			43.76
	7.109	0.095			<0.0001
	<0.0001	<0.0001			0.29
$k = \alpha + \beta(\text{Implied } k) + \gamma(p25^*\text{Implied } k)$	32.081	0.367	0.123	0.054	30.28
$+ \delta(p75^*\text{Implied } k) + e$	7.157	0.103	0.103	0.085	<0.0001
	<0.0001	0.0009	0.24	0.52	0.31

However, the models in Panels A—D also show that a market observer (who does not know k) can use the implied k as an instrument to measure k, even though the no-arbitrage condition does not generally hold. The regressions to predict announced k with the implied k provide some explanatory power. As seen in Panel A, the coefficient on implied k is strongly significant, and the adjusted R^2 is about 30%.

We repeat the analysis with filters based on the ratio of the expected values of the call and the underlying asset. If the ratio of the expected values is indeed related to extreme mispricing, we can see how pricing outliers affect the overall informativeness of the implied k. OLS regression results in Panels B, C, and D suggest that the implied and announced k are positively correlated. The coefficient on the implied k is strongly significant in all regressions, and the variables controlling for the probability treatment are not significant.

We conclude that, although implied k and announced k are not equal, a market observer can infer at least some useful information about investors' beliefs about k from the implied k. The observer does not need to know the parameter values available to the participants. Simply tracking the implied range provides a measure of participants' beliefs. The standard errors, reported in Table 4, provide insight into the informativeness of the estimated relationship. While we reject that the estimated slope coefficient for the reported implied k regressions is equal to one, a market observer can gain insight into the value of k using the implied value. For example, the estimate of the slope reported in Panel A is 0.467, with a 95% confidence interval of (0.314, 0.620). Across the various specifications reported in Table 4, the estimates are relatively stable and range from 0.314 to 0.467.

4.5. *Implied k, when k is not announced*

In half of the periods, participants are not told the value of k, the volatility parameter. Information about k is unspecified, as participants only know the maximum and minimum possible values. While participants knew that k is an integer between zero and 100, they had no information about the probability distribution governing k. Participants are also told that no other participant has any additional information about k. Therefore, there was no information available to help a participant infer the value of k. Instead of inducing beliefs about k, we allow participants to form their own beliefs.

In the periods where k is not announced, we collect participants' guesses as to the value of k.[9] Descriptive information about these guesses is presented in Table 5.

If a participant has diffuse priors about k, then he or she should guess 50. Table 5 shows that only 12 participants guessed k at 50 every period. The majority of participants varied their guesses from period to period. Further, most participants' average guess does not equal 50. Participants' beliefs concerning k may be affected by confusion, decision biases and/or probability judgment errors. However, our purpose is not to explain how participants' beliefs are formed. Our focus here is to see whether investors' beliefs are captured by implied volatilities.

In Table 6 we compare the implied k, calculated for each period using the median trading prices of the stock and the call, to the average of the participants' guesses for k for the same period. We summarize OLS model results predicting guesses with the implied k as an explanatory variable in the table. The hypothesis that the implied k is equal to the average guess is tested via F-tests. The F-statistics are based on the null that $\alpha = 0$, $\beta = 1$, (and $\delta = 0$, $\gamma = 0$ if applicable), and the alternative that one or more of the equalities are violated. Given the model specification, this null is the same as the null that the implied k equals the average guess. In both models, the null is rejected. However, in both models the coefficient of implied k is positive and statistically significant. The adjusted R^2 and the standard errors indicate that the predictive ability of this model is less than that of the corresponding model estimated for Treatment 1 in which k is announced.

As in the earlier regressions where the observations are periods, the strength of the results may be overstated because the observations may not be independent. Table 7 presents estimates for a comparable regression model where the observations are session averages. In this model the coefficient for implied k is still positive and statistically significant.

Observing the implied volatility provides information about participants' beliefs about the value of k, even when the sources of those beliefs are not likely based on rational factors. When k is not announced, we do not really know why participants are varying their guesses. Guesses may be affected by confusion, decision biases or hunches. Our design does not allow us to determine how participants' beliefs are formed, and this is not the purpose of our experiment. We are interested in

[9] These guesses were not incentivized in that participants' responses did not directly affect their payoffs.

Table 5
For each period in which *k* was not announced, subjects were asked to provide an estimate or guess of *k*. The guess was made after the double auction was completed, just before the liquidation values were revealed. *Avg g*, *Min g*, and *Max g* are the average, the minimum and the maximum guesses by the each subject.

Session	Subject	*Avg g*	*Min g*	*Max g*
1	1	50	50	50
1	2	38	11	99
1	3	50	50	50
1	4	54	20	70
1	5	39	21	60
1	6	57	25	100
1	7	22	10	35
1	8	50	50	50
2	1	50	50	50
2	2	57	35	87
2	3	51	30	70
2	4	45	2	90
2	5	30	20	40
2	6	49	30	70
2	7	39	30	50
2	8	56	50	80
3	1	35	25	50
3	2	50	50	50
3	3	61	30	80
3	4	27	15	40
3	5	39	15	52
3	6	100	100	100
3	7	30	30	30
3	8	26	4	50
4	1	24	15	30
4	2	25	15	45
4	3	38	25	50
4	4	52	45	65
4	5	21	10	60
4	6	28	8	46
4	7	26	20	35
4	8	34	15	60
5	1	35	25	45
5	2	30	20	40
5	3	11	1	20
5	4	30	25	35
5	5	50	50	50
5	6	55	45	65
5	7	60	45	75
5	8	50	50	50
6	1	35	25	75
6	2	39	30	50
6	3	66	50	80
6	4	22	10	25
6	5	32	20	50
6	6	25	25	25
6	7	46	30	50
6	8	20	10	35
7	1	45	25	60
7	2	33	20	50
7	3	20	20	20
7	4	36	10	50
7	5	28	20	35
7	6	50	25	85
7	7	50	25	75
7	8	37	15	50
8	1	39	20	50
8	2	45	25	75
8	3	40	30	50
8	4	50	35	60
8	5	66	50	80
8	6	47	35	50
8	7	33	20	50
8	8	45	20	80

(*continued on next page*)

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Table 5 (*continued*)

Session	Subject	*Avg g*	*Min g*	*Max g*
9	1	24	10	30
9	2	32	10	75
9	3	50	50	50
9	4	50	50	50
9	5	40	30	45
9	6	40	25	50
9	7	52	30	60
9	8	33	1	80
10	1	65	30	99
10	2	34	20	40
10	3	58	45	80
10	4	31	5	50
10	5	24	3	50
10	6	36	20	70
10	7	50	50	50
10	8	28	20	40
11	1	48	30	60
11	2	39	20	50
11	3	17	0	30
11	4	43	25	60
11	5	27	5	50
11	6	50	50	50
11	7	58	15	100
11	8	30	10	50
12	1	37	20	55
12	2	73	0	100
12	3	50	20	95
12	4	49	25	85
12	5	51	50	55
12	6	36	30	50
12	7	48	40	50
12	8	41	25	85
13	1	64	45	85
13	2	41	7	60
13	3	60	50	70
13	4	40	20	75
13	5	52	20	80
13	6	48	16	65
13	7	46	0	80
13	8	51	25	90
14	1	52	30	65
14	2	46	30	70
14	3	49	11	68
14	4	25	15	30
14	5	44	35	60
14	6	38	30	50
14	7	55	36	69
14	8	17	15	20
15	1	55	30	80
15	2	29	5	50
15	3	69	69	69
15	4	50	50	50
15	5	36	26	56
15	6	59	15	90
15	7	30	20	57
15	8	53	40	75
16	1	39	25	60
16	2	49	13	77
16	3	35	10	76
16	4	45	30	50
16	5	43	30	55
16	6	29	25	30
16	7	39	25	50
16	8	73	50	80
17	1	49	40	65
17	2	34	15	55
17	3	68	45	90
17	4	38	20	50

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Table 5 (*continued*)

Session	Subject	*Avg g*	*Min g*	*Max g*
17	5	36	25	50
17	6	22	0	52
17	7	72	40	100
17	8	45	10	90

Table 6
For each period in which k is not announced, subjects provided an estimate or guess of k. Guesses are averaged, and compared to the implied k, which is calculated using median trading prices for the call and stock. The OLS regressions predict guessed k, using implied k as an explanatory variable. The parameters *p25* and *p75* are dummy variables representing the observations where the probability treatment is 25% and 75% respectively. Standard errors are below parameter estimates, with p-values below the standard errors. The final column reports the F-statistic for a test of $\alpha = 0$ and $\beta = 1$ (and other explanatory variables = 0 if applicable), along with the associated p-values. The adjusted R^2 for the corresponding model is also reported in the last column.

Model (n = 81)	α *Std Error p*	β *Std Error p*	γ *Std Error p*	δ *Std Error p*	*F-Statistic p* *Adj* R^2
$Guess = \alpha + \beta(\text{Implied } k) + e$	36.961	0.0875	–	–	817.33
	2.261	0.033			<0.0001
	<0.0001	.009			0.10
$Guess = \alpha + \beta(\text{Implied } k) + \gamma(p25^*\text{Implied } k)$	36.679	0.093	−0.216	0.028	420.68
$+ \delta(p75^*\text{Implied } k) + e$	2.146	0.035	0.026	0.028	<0.0001
	<0.0001	0.010	0.405	0.315	0.12

Table 7
For each period in which k is not announced, subjects provided an estimate or guess of k. Each period, guesses are averaged across subjects, and the implied k is calculated using median trading prices for the call and stock. To obtain session averages, both are then averaged over the relevant periods. All periods where k is not announced are used. OLS estimates predicting session guessed k with implied k as an explanatory variable are reported. Standard errors are below parameter estimates, with p-values below the standard errors. The final column reports the F-statistic for a test with the null $\alpha = 0$ and $\beta = 1$, along with the associated p-value. The last column also contains the adjusted R^2.

Model (n = 17)	α *Std Error p*	β *Std Error p*	*F-Statistic p* *Adj* R^2
$Guess = \alpha + \beta(\text{Implied } k) + e$	35.031	0.117	591.09
	0.117	0.056	0.000
	<0.0001	.0535	0.23

whether the implied k measures participants' beliefs regardless of the belief formation process. In our experiments, the implied range is correlated with participants' beliefs as reflected by their guesses.

5. Conclusion

Implied volatility is used to measure investors' expectations by both academics and practitioners. We study the relationship between implied volatility and investor beliefs in simplified experimental asset markets. The range (k), or distance between possible outcomes, is our measure of dispersion or volatility. Our design includes two treatments.

In the first treatment, we induce investor beliefs about k by publicly announcing the range parameter. We find that the implied volatility does not equal the actual range, which suggests that the BOPM does not describe pricing in our markets. Detecting mispricing during the experimental double auctions is cognitively difficult. And even if mispricing is spotted, arbitrage is challenging because it is difficult to simultaneously execute trades for both assets. In addition, we find evidence of participant confusion in the form of asset prices that are either higher than the maximum or lower than the minimum possible payouts when k is announced. Participant confusion may be an important factor in explaining why prices are irrational in our markets.

Although we conclude that the BOPM does not hold, we also find a statistically significant positive relation between the implied and actual volatility. A market observer can learn something about actual volatility from seeing the implied value. Thus, implied volatility is partially informative even though the prices and allocations are often irrational and no-arbitrage conditions are violated. This finding is important in that it demonstrates that implied volatility can be informative regardless of possible impediments to rational option pricing.

When the actual range is not announced, we do not test the BOPM because the actual volatility is ambiguous. Instead, we test whether the implied range can inform an outside observer about traders' beliefs. Individual participants are asked to guess the range, and these guesses are compared to the implied range. We find a statistically significant link between the average of participants' guesses as to the value of the range, and the implied range. Importantly, an observer can use the implied range to roughly gauge investor beliefs about the range even when the observer does not know the range, its probability distribution, or even the probabilities associated with the high and low states.

Finally, the implied range is partially informative even when participants' beliefs are likely not based on fundamental information about asset values. The no-arbitrage condition that drives the BOPM is violated in our sessions. In addition, many of the trading prices in our experiment are quite far from expected values, and sometimes even irrational in the sense that they are either higher than the maximum asset liquidation value, or lower than the minimum liquidation value. Asset holdings at period end are also inconsistent with equilibrium predictions. Yet, in our laboratory markets, the implied range is useful as a measure of investor beliefs even though the no-arbitrage condition is violated and we frequently observe prices that are perceptibly different from fundamental values.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.finmar.2019.02.001.

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