Identifying winning new product concepts can be a challenging process that requires insight into private consumer preferences. To measure consumer preferences for new product concepts, the authors apply a “securities trading of concepts,” or STOC, approach, in which new product concepts are traded as financial securities. The authors apply this method because market prices are known to efficiently collect and aggregate private information regarding the economic value of goods, services, and firms, particularly when trading financial securities. This research compares the STOC approach against stated-choice, conjoint, constant-sum, and longitudinal revealed-preference data. The authors also place STOC in the context of previous research on prediction markets and experimental economics. Across multiple product categories, the authors test whether STOC (1) is more cost efficient than other methods, (2) passes validity tests, (3) measures expectations of others, and (4) reveals individual preferences, not just those of the crowd. The results show that traders exhibit a self-preference bias when trading. Ultimately, STOC offers two key advantages over traditional market research methods: cost efficiency and scalability. For new product development teams deciding how to invest resources, this scalability may be especially important in the Web 2.0 world.

Keywords: marketing research, new product development, behavioral economics, consumer behavior, wisdom of crowds

Securities Trading of Concepts (STOC)

New product innovation depends on a firm’s ability to both generate many potentially winning concepts and accurately distinguish between winners and losers. Preferences for some new product categories are primarily attribute based and, therefore, are most amenable to decompositional methods such as conjoint analysis. However, in the so-called Web 2.0 world, which encourages interaction and collaboration between firms and their customers and between customers themselves, myriad potential product concepts and design possibilities are put forward, creating the need for more accurate and scalable filtering methods for identifying the most promising integrated product concepts.

We propose that securities trading of concepts (STOC), in which new product concepts are traded as financial securities,
can potentially serve as this filter and help identify winning new product concepts, such as those with market appeal, during the early and lower investment phases of new product development. The reason that STOC may work well is that securities markets are well known to efficiently collect and aggregate diverse information about value using the simple summary statistic of price (Hayek 1945). Rather than summarizing economic value, the security prices in STOC measure intensity of preference among the traders for competing new product concepts because traders receive multiple votes and can show the strength of their votes with the number of their shares that they allocate. Compared with existing preference measurement research methods such as surveys, voice-of-the-customer methods, conjoint analysis, concept tests, and focus groups, STOC has potential cost and scale advantages because of its attractiveness to respondents and the way it collects multiple answers from each respondent. Despite similarities in outward appearance and implementation to prediction markets, STOC differs significantly in that it measures preferences for concepts that may never be realized rather than observable outcomes and controls for the effects of outside news, both of which we discuss in more detail subsequently.

The current research proposes that (1) STOC compares favorably to extant methods, (2) STOC passes validity tests, (3) STOC measures expectations of others, and (4) STOC also may reveal individual preferences if traders make buying and selling decisions partially on the basis of their personal preferences and use them to form expectations of others’ preferences. We attempt to achieve these results empirically through a series of experiments in multiple product categories. In each experiment, STOC is tested against traditional market research methods applicable to new product concepts.

This research illuminates the relative strengths and weaknesses of STOC with the hope of better informing the market about preference measurement techniques. The article proceeds as follows: We begin by providing a brief overview of the STOC concept and methodology. Then, we compare STOC with existing methods. We go on to test the STOC methodology and highlight the empirical results. Finally, we discuss the results, offer some managerial implications, acknowledge the deficiencies, and provide some conclusions.

**THE STOC CONCEPT AND METHODOLOGY**

The STOC methodology centers on hypothetical consumers trading hypothetical securities (each associated with a product or service concept) in virtual stock markets. In Table 1, we summarize the five key steps in designing a STOC game.

Each participant receives an initial portfolio of cash (virtual or real) and virtual stocks. Participants are also provided with detailed information on the product concepts, including specifications, images, and multimedia illustrations. A typical objective of the STOC game might be for each participant to maximize the value of his or her portfolio, which is evaluated at the closing stock prices or the volume-weighted-average prices (VWAPs). Markets are typically open for 20 to 30 minutes and end at random times. STOC’s high speed derives from the lack of outside news, which allows prices to converge quickly. If participants play with real money, they will have the opportunity to profit from trading and, conversely, will bear the risk of losing money. The financial stakes in the game provide incentives for participants to reveal true preferences, process information, and conduct research. If fictitious money is used, prizes can be awarded according to the participants’ performances. All participants can also be rewarded simply for their service.

As in real financial markets, stock prices are determined by supply and demand, which depend on participants’ evaluation of their own and others’ preferences for the underlying products. Thus, at the market equilibrium, prices should fully reflect all participants’ aggregate preferences for the products being tested. Traders make trading decisions just as they would in a financial stock market: They assess the values of the stocks, sell overvalued ones, and buy undervalued ones, essentially voting on the worth of the underlying products. In this way, a stock’s price becomes a convenient index of a product’s consumer value. In our STOC tests, all trades require a specific buyer to purchase shares from a specific seller, both of whom have placed a limit order (i.e., we use a double auction with no market makers, as employed by Smith [1976], but we use computerized rather than verbal bidding); one could also use market-making software that enables one-sided trades in “thin” markets with few traders, as Hanson (2003, 2007).

**Table 1**

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
<th>Challenges</th>
<th>Key Considerations</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Choose STOC concepts</td>
<td>Narrowing from many options</td>
<td>Stocks should clearly and concisely depict multiple product concepts that differ from each other. Not every trader has to see every stock.</td>
</tr>
<tr>
<td>2</td>
<td>Define STOC prices</td>
<td>Open-ended vs. precise definition</td>
<td>Traders need to understand the definition of each stock (e.g., “the % of people who prefer this concept,” “market share of this product”).</td>
</tr>
<tr>
<td>3</td>
<td>Define and teach trading method</td>
<td>Programming and user interface</td>
<td>The user interface should be easy to use and informative about the trading activity for each security and trader performance.</td>
</tr>
<tr>
<td>4</td>
<td>Trading and data collection</td>
<td>Need simultaneous trading; trader errors</td>
<td>Transaction details between any two traders needs to be recorded: security name, volume, price, and timing. Traders should be able to review, edit, and cancel open orders that have not cleared.</td>
</tr>
<tr>
<td>5</td>
<td>Data analysis</td>
<td>Choosing a metric; what is measured?</td>
<td>The metric should include all information such as the number of shares traded and at which price (not just closing prices).</td>
</tr>
</tbody>
</table>

**STOC VERSUS EXISTING CONSUMER PREFERENCE MEASUREMENT METHODS**

Potential Benefits Versus Other Market Research Methods

We can compare STOC against existing, well-established methods for estimating consumer preferences—for example, (1) surveys (see Burchill and Brodie 1997), (2) voice-of-the-customer methods (see Griffin and Hauser 1993), (3) conjoint analysis (see Green and Srinivasan 1990; Green and Wind 1981; Srinivasan and Shocker 1973), (4) concept tests (see Dahan and Hauser 2002; Dahan and Srinivasan 2000; Urban, Hauser, and Roberts 1990), and (5) focus groups (see Calder Dahan and Hauser 2002; Dahan and Srinivasan 2000; Urban, Hauser, and Roberts 1990), and (5) focus groups (see Calder 1977; Fern 1982).

STOC offers five potential benefits over most preference measurement methods:

1. **Accuracy resulting from incentive compatibility:** STOC traders have the incentive to trade on the basis of their most accurate perceptions of others’ preferences because they are more likely to perform well in the game by doing so. This is distinct from incentive-aligned conjoint analysis (Ding, Green, and Srinivasan 1990) in that traders have the incentive to reveal their expectations of others rather than their own individual preferences. Specifically, STOC overcomes certain social biases because the method does not directly reveal potentially sensitive private information or preferences, as might happen with traditional methods of individual data collection, including incentive-aligned conjoint methods. STOC also continuously captures the intensity and degree of preference in ways that surveys typically do not (e.g., by weighting multiple trades of varying volume on the basis of the total amount of capital committed). STOC’s validity and accuracy can be tested empirically by comparing its preference measurement results against those of the traditional methods.

2. **Interactive learning:** STOC traders learn from each other through the price mechanism. Because participants observe one another’s valuations of the product concepts, they can update and adjust their own valuations dynamically in the market environment. Learning may reduce response error, especially as STOC prices converge. Learning may be especially useful for fashion goods, for which individual preference may depend at least partially on the opinions of others. A downside of learning is that STOC’s revelation of prices (at least to the group of traders) hurts the firm’s ability to keep the results private. STOC’s learning effects can be measured by asking traders the same preference questions immediately before and after trading and calculating which responses better capture actual preferences and which have lower variance.

3. **Scalability:** Unlike surveys, in which the number of questions asked is limited by the capacity of each respondent to answer, securities markets are intrinsically scalable because each trader only needs evaluate a small subset of the universe of securities. Dahan, Soukhorooukova, and Spann (2010) specifically demonstrate scalability limited only by the total number of traders and outline experimental designs that group any number of traders into subgroups. The efficiency of the market, and therefore the quality of data collected, improves with the number of participants. This scalability benefit extends to the number of product concepts that may be evaluated; because there is no requirement for each respondent to trade every security, the bounded rationality of the traders does not limit the number of concepts that can be evaluated in a STOC market. Limiting the number of securities that each trader sees to a small subset of the full gamut of ideas being tested also mitigates the aforementioned risk of public revelation.

4. **Integrated product concepts:** Like Dahan and Srinivasan’s (2000) virtual concept testing (VCT), the STOC method is particularly useful relative to conjoint methods when a product cannot be easily quantified, delineated, or represented by a set of attributes (e.g., a movie script, a fashion item, a car body style, a piece of art). Market participants evaluate the integrated product concepts directly, and market prices effectively reflect the overall viability of the concepts, including the ability of a concept to fulfill unarticulated needs. All that is required is a thorough physical depiction of each concept. Although STOC could also be used to measure preferences for product attributes and their levels, as Dahan, Soukhorooukova, and Spann (2010) demonstrate, such an approach might make more sense as a complement to conjoint analysis rather than a substitute (e.g., as a way of filtering from a larger set of possible attributes to a smaller one more manageable in conjoint). STOC may also outperform conjoint analysis in predicting choice share for highly integrated, aesthetic product concepts such as Wii video games because their attributes are harder to define.

5. **Economics of recruiting and compensating respondents:** STOC is potentially more cost efficient than other consumer-preference testing methods if respondents prefer trading to answering surveys and if more data are collected per respondent. The economics of any concept-testing method depend largely on the costs of recruiting and then compensating a sample of respondents willing to accurately share their preferences about M concepts. The firm must recruit more than N respondents because response rates are likely to be below 100% and the costs per person for recruiting and compensation may vary on the basis of the “attractiveness” of the preference measurement method being used. The total respondent-related costs can be summarized as follows (derived in Appendix A):

\[
TC = M \times \frac{N_{\text{sample}}}{\text{recruit} / \text{respondent}} \times \left( \frac{1}{r\%} + \frac{1}{\text{respondent}} \right).
\]

We summarize the five key factors influencing the total respondent cost of measuring preferences for M given concepts, and the challenge underlying each of these factors, in Table 2.

**Result 1**

We propose that STOC improves all five cost factors simultaneously by being more attractive to respondents (lowing crecruit and improving r%) and, by virtue of being a competition rather than a straight survey, more motivating (improving qrespondent) and engaging (lowing crespondent). The sample size required should be smaller because respondents learn from one another and respond with expectations about the population mean, thus reducing error and variance, and each provide multiple data points (reducing Nsample) in the form of trades. These effects are testable, as in the following two potential results:

**Result 1a:** STOC will be more attractive to respondents. Respondents will prefer trading in STOC games over answering constant-sum point-allocation survey questions covering an equal number of product concepts.

**Result 1b:** STOC will be more cost efficient than other consumer-preference testing methods. The economics of any concept-testing method depend largely on the costs of recruiting and then compensating a sample of respondents willing to accurately share their preferences about M concepts. The firm must recruit more than N respondents because response rates are likely to be below 100% and the costs per person for recruiting and compensation may vary on the basis of the “attractiveness” of the preference measurement method being used. The total respondent-related costs can be summarized as follows (derived in Appendix A):
markets are small-scale, real-money futures markets in which contract payoffs depend on economic and political events such as elections, meaning that traders receive incentives based on how they predict future events. The IEM features real-money futures markets in which contract payoffs depend on the outcome of political and economic events. The IEM predictions have outperformed most national polls (BusinessWeek 1996). Similarly, the Hollywood Stock Exchange (HSX.com) has provided accurate predictions of movie box office results (Spann and Skiera 2003). The Foresight Exchange (see http://www.ideosphere.com) predicts the probability of future events occurring, such as changes in the environment, scientific breakthroughs, the collapse of companies, or political and news outcomes. Companies such as Hewlett-Packard, Microsoft, Best Buy, and Google have used internal prediction markets to forecast printer sales, software release dates, consumer electronics sales, and software take-up rates.

Such prediction markets share with STOC the benefits of information aggregation, the joy of competitive play, the ability to learn from others, and the incentive to be accurate. Prediction markets focus on actual outcomes; operate for weeks, months, and sometimes years; and incorporate private information and news as it happens. In contrast, STOC markets focus on concepts that may never come into existence and, therefore, may never have actual outcomes, run for a much shorter time period (10–60 minutes typically), and are not influenced or complicated by outside news. Indeed, the only information available to STOC traders is the personal preferences they hold, their expectations of others’ preferences, and whatever they learn by observing price movements during trading.

Rational Expectations (RE) Models and Experimental Markets

STOC is also closely related to the literature streams in rational expectations (RE) models with asymmetric information and experimental markets. Rational expectations is an economic result that states that agents’ predictions of the future value of economically relevant variables is not systematically incorrect because all the errors are random. Many contemporary macroeconomic models, game theory, and other applications of rational choice theory use RE. In a standard asymmetric information RE model (Grossman 1981), heterogeneous agents with diverse information trade with one another, and under certain conditions, the market

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**Table 2**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Challenge</th>
<th>To Lower Cost</th>
<th>STOC’s Potential Benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td>(N_{\text{sample}})</td>
<td>Number of required respondents</td>
<td>Statistical power</td>
<td>Reduce (N_{\text{sample}})</td>
<td>Lower because of interactions with others and multiple answers per respondent</td>
</tr>
<tr>
<td>(q_{\text{respondent}})</td>
<td>Question capacity per respondent</td>
<td>Bounded rationality</td>
<td>Increase (q_{\text{respondent}})</td>
<td>Higher because of motivation and ability to self-select questions to be traded</td>
</tr>
<tr>
<td>(c_{\text{recruit}})</td>
<td>Cost to recruit people</td>
<td>People avoid surveys</td>
<td>Reduce (c_{\text{recruit}})</td>
<td>Lower because recruits are attracted to playing the game, even multiple times</td>
</tr>
<tr>
<td>(c_{\text{respondent}})</td>
<td>Compensation for respondents</td>
<td>People value their time</td>
<td>Reduce (c_{\text{respondent}})</td>
<td>Lower because of the intrinsic pleasure of playing the game itself</td>
</tr>
<tr>
<td>(r%)</td>
<td>Response rate</td>
<td>Many people opt out</td>
<td>Increase (r%)</td>
<td>Higher because of the intrinsic pleasure of game, desire to play again, and competitiveness</td>
</tr>
</tbody>
</table>

**Result 1b: STOC will require smaller sample sizes for an equal amount of information.**

We confirmed both results on the basis of simple observations and surveys. We observed Result 1a through surveys of 63 real-world executives and engineers at a telecommunications firm and 113 MBA students, each of whom completed market research surveys and played STOC games for the same product concepts on the same day. Both groups expressed strong preferences for STOC over the surveys (90% and 85%, respectively).

Result 1b is demonstrated by virtue of the small sample sizes in each of 11 STOC experiments; trader groups ranged in size from 18 to 56, with a median size of 38 traders. The traditional market research methods against which we compared the STOC results involved much larger respondent samples, typically 100–300 respondents, yet the results from both approaches are comparable in quality, as the data will show.

That STOC would require smaller sample sizes makes intuitive sense. Traditional market research typically requires respondent sample sizes of 50–300, or more, to allow for heterogeneity in preference, and most concept tests measure preferences for 5–12 concepts at a time because of cognitive constraints, so a total of 4–50 respondents per concept tested is typical. Conversely, our STOC experiments reveal that 1–2 traders per concept stock are sufficient to produce stable results. The amount required to recruit potential respondents and compensate those completing the exercise can typically be reduced by half or more because of their preference for playing the game. Thus, by cutting the sample size in half and the recruiting costs per respondent by a similar amount, STOC could potentially reduce the total respondent costs of a concept preference study by 75% or more. Because the infrastructure costs of running the STOC trading system are essentially fixed, we anticipate long-term variable cost savings from STOC testing.

**Prediction Markets**

Beyond the other well-established methods for estimating consumer preferences discussed previously, there are nonfinancial “prediction markets” used to forecast political elections, movie box office data, and other real-world outcomes. The Iowa Electronic Markets (IEM; see http://www.biz.uiowa.edu/iem) pioneered prediction markets for the purpose of forecasting election results (Forsythe et al. 1993). The IEM is operated by the University of Iowa College of Business for research and teaching. These
will converge to an equilibrium in which prices fully reveal all relevant information. The most important criterion for convergence is that agents condition their beliefs on market information. In particular, agents make inferences from market prices and quantities about other agents’ private information.

The RE model has received considerable attention in the study of experimental markets (Davis and Holt 1993; Forsythe and Lundholm 1990; Plott and Sunder 1982, 1988). Studies of the informational efficiency of a market relative to the RE benchmark fall into two categories: markets with fully informed agents (“insiders”) and uninformed agents and markets with many partially informed agents. In various experimental markets with human subjects, the results for both market structures are the same: markets eventually converge to the RE equilibrium (i.e., information aggregation and dissemination occur successfully).

STOC trading shares some characteristics with such experimental economics markets, and information aggregation and dissemination provide a compelling explanation for the success of our experiments. For example, traders who possess superior information about the products or have high confidence in their beliefs can be considered insiders. Conversely, traders who have little knowledge or opinion of the products can be regarded as the “uninformed.” The interaction between the insider and the uninformed constitutes information dissemination. What is intriguing about this scenario is that even when a subset of traders ignores the underlying product information and focuses only on market information, the market still converges to efficient prices that aggregate all the relevant information and beliefs. A striking example of just how informationally efficient financial markets can be is provided by Maloney and Mulherin (2003), who document that in the wake of the Space Shuttle Challenger’s explosion in 1986, the stock price of Morton Thiokol (the vendor that was ultimately held responsible for the infamous failed O-ring in the booster rocket) dropped precipitously within minutes after the explosion and much more so than any other vendors’ stock prices during the same period. In our own experiments, post-STOC-trading surveys of the traders (Figure 1) reveal that the majority base their trades more on what is happening during the game than on their underlying preferences for the product concepts and that their expectations of others changed significantly while trading.

Alternatively, individual traders may form their own beliefs about the products, acknowledging that market prices will depend on aggregate beliefs. This is similar to the information aggregation scenario in which there are no insiders but all traders are partially informed. Even in this case, when no single trader has full information, an RE equilibrium will be reached under general conditions (Davis and Holt 1993, Chap. 7; Grossman 1981).

However, there is one important difference between STOC markets and the other exchanges in the experimental markets literature. In a typical experimental market, participants’ preferences and information sets are fixed and assigned by the researchers. Therefore, even before trading begins, it is possible to calculate theoretical equilibrium prices. In contrast, in a STOC market, neither the participants’ preferences nor their information sets are known; these are what STOC market trading experiments are meant to discover. This distinction suggests an important practical consideration in implementing STOC markets: The composition of traders should match the population of target consumers as closely as possible, or at least include traders with insight into the preferences of these consumers. For example, if the target population for a particular product is teenaged female consumers, a STOC market consisting of middle-aged men may not yield particularly useful preference rankings for that product. However, if the cross-section of traders in a STOC market is representative of the target population, the force of market rationality will ensure that the prices discovered provide an accurate measure of aggregate preferences. We demonstrate the importance of selecting representative traders in our experiments on Wii video games by having two groups of traders with distinct preferences trade eight identical video game concepts; the outcomes differ dramatically.

Some Possible Challenges Related to STOC and Markets in General

It is important to note some of the possible downsides related to STOC and to markets in general. For example, STOC requires simultaneous participation by a group of people, the size of which grows linearly with the number of concepts being tested. It also requires specialized trading system software and communications infrastructure. We lay out the methodology in detail in the Web Appendix (http://www.marketingpower.com/jmrrune11). Despite the proven accuracy of prediction markets forecasting election outcomes, movie box office receipts, and sporting events, just to name a few, healthy skepticism about securities markets remains. This skepticism has only been reinforced by the perceived market failures of the last few years, all of which suggests an uphill battle for the diffusion of market-based methods in general and STOC in particular.

Of course, in general, market-based methods for eliciting information also have certain limitations. Unlike typical marketing research techniques in which information is
of stated-choice and revealed-preference results but less so of longitudinal sales data.

More specifically, we began our experiments in 2000 by conducting two STOC tests of Dahan and Srinivasan’s (2000) bike pump concepts, depicted as static images that resemble the physical prototypes examined by their respondents (Figure 3). We use their physical prototype, conjoint analysis, and static web VCT results for bike pumps to validate the STOC method. We ran both bike pump STOC experiments on opposite coasts of the United States several years after the original data were collected, using the same group of traders as a method of measuring test-to-test repeatability.

Beginning in 2000, we also tested eight crossover vehicles (Dahan and Hauser 2002) in four STOC experiments (see Figure 4). Three crossover vehicles had already been released (Lexus, Mercedes, and BMW), and five were yet to be released (Pontiac, Acura, Buick, Audi, and Toyota) at the time of the STOC experiments. In the six following years, we collected unit sales data for each of the eight vehicles from Ward’s Automotive News. We used these data as a test of external validity and the predictive power of the STOC method, but we find that the lack of price sensitivity for vehicles during STOC trading hurts predictive validity.

Toubia et al.’s (2003) study using laptop PC messenger bags offers an excellent data set for validating STOC because their data set consists of customizable laptop PC messenger bags sold for real money through a simulated store to 330 MBA students. We focus on eight randomly chosen bags, representing a range of popularity (choice share), that were actually “sold” to 43% of the respondents in their research. To test whether STOC could predict the simulated store choice shares, we ran two STOC tests to measure preferences for the same eight bags but using two different forms of stimuli: the table shown in Figure 5 and the individual images shown in Figure 6.

Finally, in 2009, we conducted three STOC experiments using 19 Wii video game concepts developed by student teams competing with one another in two MBA courses at the University of California, Los Angeles. Each video game concept included game play software and at least one piece of original hardware (i.e., a peripheral device that would enhance game play and work with the Wii console’s motion-detecting, force-sensing, and/or WiFi features).

Each Wii video game concept was also defined by its feature levels for six conjoint attributes (see Figure 2) in a study completed by each of the 90 students as well as 160 outside respondents.

Figure 7 depicts the concepts proposed by the 35 students, competing on 8 teams, in an elective course on new product. Figure 8 show the concepts proposed by 55 executive MBA students, competing on 11 teams, in a core marketing course.

After presenting their concepts to one another at the final session of their respective courses, the students used constant-sum voting to complete three surveys: (1) self-preferences for all concepts except their own (which determined project grades), (2) expectations of others’ preferences for all eight concepts (with recognition for the “best guessers”), and (3) expectations of the eight average STOC prices just before trading. After trading was completed, the students completed a fourth, constant-sum “post-STOC” survey using what they
### Table 3
DATA COLLECTED FOR EACH OF FOUR PRODUCT CATEGORIES

<table>
<thead>
<tr>
<th>Method Product Type</th>
<th>Experiment</th>
<th>STOC Method</th>
<th>Conjoint Analysis</th>
<th>VCT</th>
<th>Self-Stated Choices</th>
<th>Simulated Store</th>
<th>Longitudinal Sales Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bike pump concepts</td>
<td>Tests 1 and 2, n = 28</td>
<td>9 pumps; same traders tested twice</td>
<td>Rank 18 full profiles, estimated 10 parameters with LINMAP, n = 141</td>
<td>Dahan and Srinivasan 2000</td>
<td>VCT physical, VCT web, n = 102 and 87</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual laptop bags</td>
<td>Test 1, n = 50</td>
<td>Table of 8 laptop bags</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Toubia et al. 2003 unit shares for 8 bags sold in the simulated store, n = 143</td>
</tr>
<tr>
<td>Actual laptop bags</td>
<td>Test 2, n = 62</td>
<td>Images of 8 laptop bags</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual crossover vehicles</td>
<td>Test 1, n = 49</td>
<td>8 vehicles, no prices</td>
<td>VCT with and without prices</td>
<td>Top 3 of 8 with prices</td>
<td></td>
<td></td>
<td>Cumulative units sold for each of 8 vehicles from 2001 to 2006 per Ward’s Automotive News</td>
</tr>
<tr>
<td>Actual crossover vehicles</td>
<td>Test 2, n = 43</td>
<td>8 vehicles, no prices</td>
<td>VCT with and without prices</td>
<td>Top 3 of 8 with prices</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual crossover vehicles</td>
<td>Test 3, n = 42</td>
<td>8 vehicles, with prices</td>
<td>VCT with and without prices</td>
<td>Top 3 of 8 with prices</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual crossover vehicles</td>
<td>Test 4, n = 16</td>
<td>8 vehicles, no prices</td>
<td>VCT with and without prices</td>
<td>Top 3 of 8 with prices</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wii video game concepts</td>
<td>Test 1, n = 35</td>
<td>8 own Wii video games</td>
<td>Rank 16 full profiles, estimated 10 parameters with LINMAP, n = 35 and 65</td>
<td>Constant-sum allocation of 100 points across 8 or 11 Wii games in 4 surveys: self-preferences E[Others’ Preferences] E[STOC Prices] E[Actual Share] after STOC game</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wii video game concepts</td>
<td>Test 2, n = 55</td>
<td>8 others’ Wii video games</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wii video game concepts</td>
<td>Test 3, n = 58</td>
<td>11 own Wii video games</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
had learned from trading to reestimate the mean preferences for all eight Wii video game concepts.

Test 2 of the Wii video game was identical to Test 1, except that the 55 executive education students completing the four surveys and playing the STOC game judged the eight concepts from the other class; that is, they had no involvement in the development of those eight concepts. In Test 3, the executive MBA students evaluated the 11 game concepts that their own teams had developed.

We are grateful for the cooperation of the aforementioned researchers who enabled us to use the identical product concept illustrations in our STOC tests. Thus, we are able to compare results for identical market research problems using STOC versus previous methods.

For the first eight STOC experiments, traders were told that their final portfolio valuations would be based on the closing prices of each stock plus the cash they had left on hand. For the final three experiments testing Wii video game concepts, traders were told that final portfolio valuations would be based not on closing prices but rather on mean prices throughout the trading period (i.e., using VWAPs). Traders first learned about the concepts by viewing detailed product information (see Figure 9). After priming traders with the product concepts, we used a common user interface (see Figure 10) for the 11 STOC
Figure 4
EIGHT CROSSOVER VEHICLES

<table>
<thead>
<tr>
<th></th>
<th>Pontiac Aztek</th>
<th>Mercedes-Benz ML320</th>
<th>Acura MD-X</th>
<th>Buick Rendezvous</th>
<th>Lexus RX-300</th>
<th>BMW X-5</th>
<th>Audi All-Road</th>
<th>Toyota Highlander</th>
</tr>
</thead>
<tbody>
<tr>
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<td>7</td>
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<td>5 (7 opt.)</td>
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<td>●</td>
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<td>●</td>
<td>●</td>
<td>●</td>
</tr>
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</table>

Figure 5
EIGHT LAPTOP PC MESSENGER BAGS IN A TABULAR FORMAT

<table>
<thead>
<tr>
<th>Bag 3</th>
<th>Bag 4</th>
<th>Bag 8</th>
<th>Bag 9</th>
<th>Bag 10</th>
<th>Bag 13</th>
<th>Bag 15</th>
<th>Bag 16</th>
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<tr>
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<td>$89</td>
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<td>$95</td>
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<td>$78</td>
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<td>Large</td>
<td>Medium</td>
<td>Large</td>
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<tr>
<td>Appearance</td>
<td>Black</td>
<td>Red &amp; Black</td>
<td>Black</td>
<td>Black</td>
<td>Red &amp; Black</td>
<td>Red &amp; Black</td>
<td>Red &amp; Black</td>
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<tr>
<td>Logo</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
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<td>Yes</td>
<td>Yes</td>
<td>No</td>
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<td>No</td>
</tr>
<tr>
<td>PDA Holder</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
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<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
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<td>No</td>
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<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
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<td>Full Flap</td>
<td>Velcro Tab</td>
<td>Velcro Tab</td>
<td>Velcro Tab</td>
<td>Full Flap</td>
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<td>Boot</td>
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<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

Figure 6
LAPTOP PC MESSENGER BAGS DEPICTED VISUALLY WITHOUT A TABULAR FORMAT
Figure 7
Wii VIDEO GAME CONCEPTS DEVELOPED BY 35 STUDENTS ON EIGHT COMPETING TEAMS

(8) Eight Student-Developed Wii Video Games

**Strike-a-Pose**
- $69.99
- 2 Players
- Perform Challenges
- Broom and balance peripheral
- Bundle of gamer including:
  - Flying
  - Mind Control
  - Wand dueling
- Rated E

**Yoga Your Way**
- $69.99
- Your home, your time
- Your Godis
- Virtual Yoga Instructor
- Audio & Visual Feedback
- Progress Tracking
- Customizable
- $149.99

**MUSICXPLOSION**
- Strike a Po, like you've always wanted
- Hear me song you love while creating an amazing visual display
- Perform it your way, four players
- Play alone or with your friends Avatar
- Hanole your business
- $179.00

**Wii Wiitches**
- $79.00
- A heart-pumping fantasy game for the thinking man
- Leve your world behind!
- $79.00

**Wii Witches**
- $89.99
- Mature Rating
- Experience the world's most exclusive bars & nightclubs
- Feel the excitement of performing flair tricks in front of huge crowds
- Learn how to make real cocktails
- 2 Player Co-op (Local, Online)
- Up to 4 player Social Interactive Drinking Games (Local, Online)
- Flip Cup, Beer Pong, Quarters, and more
- $199.00

**INDIANA JOLIE**
- $179.00
- Personalize your night - Ignite your inner & outer passions, or style only Facebook & Instagram
- New Telephone Kickers
- You pick the style of the night
- Includes 2 Kickers
- $99.90

Figure 8
Wii VIDEO GAME CONCEPTS DEVELOPED BY 55 STUDENTS ON 11 COMPETING TEAMS

(11) Eleven Student-Developed Wii Video Games

**Wii Got Game**
- $89.99
- Bring the bar to you - an exclusive social drinking, dancing, and debauchery
- The ONLY game with an actual breathalyzer to change your “confidence level” and “virtual state of mind”
- Work on your game while you pre game
- Rush the sorority or crush the sorority?
- $199.00

**Wii Excercise**
- $199.00
- Celebrity vs. Paparazzi
- Experience the life of celebrities or paparazzi
- Move up to the A-list
- Battle other hot celeb!
- Lend Dream Roles
- $99.99

**Wii Timbersports World Championship**
- $119.99
- Who said action sports were only for men?
- Battle for honor, battle for pride, battle for real
- $63.99

**Shall WII Dance**
- $89.99
- Shall WII Dance is an exciting, dance, and party game for anyone, everywhere, anytime
- $89.00

**DAREDEVIL**
- One game, three extreme sports!
- Strap it on - wireless sensors
- $99

**MO-CON**
- $129.99
- $89.99

**Language Quest**
- $89.99
- mo-con
tests, each of which ran in less than 60 minutes, including initial instructions and postrading wrap-up.

The STOC tests enable us to generate results regarding (1) the validity of STOC’s preference measurements, (2) whether STOC prices measure individual preferences or traders’ expectations about others’ preferences, and (3) whether STOC reveals individual preferences even when traders focus on other people. There are six potential results from STOC’s validity testing:

Result 2a: Convergent validity with VCT: Web-based VCT and constant-sum voting will be highly correlated with STOC prices.

Result 2b: Convergent validity with conjoint analysis: Conjoint analysis and STOC results will be highly correlated.

Result 2c: Test-to-test repeatability: Repeated STOC test results will be highly correlated when run with the same traders or two groups of traders with similar preferences but uncorrelated when run with groups of traders with distinct preferences.
Result 2d: Simulated store predictive validity: STOC results will accurately predict simulated store sales.

Result 2e: Actual market share predictive validity: STOC results will accurately predict actual market shares.

Result 2f: Product price insensitivity: STOC results will correlate more highly with VCT results when product prices and price sensitivity are not included.

The final three Wii video game experiments also enable us to test whether STOC prices more completely reflect individual self-preferences or participants’ expectations of others, as summarized in the following two potential results:

Result 3a: STOC prices reflect E[Others]: STOC prices will correlate more closely with traders’ expectations of others (and with their previous expectations of STOC prices) than with traders’ self-preferences.

Result 3b: Learning: Traders’ estimates will improve and converge after STOC trading.

Finally, even though STOC prices capture traders’ consensus preferences, we can still test whether trading reveals individual preferences because individual traders are subject to false-consensus effects and may bias their beliefs about other people on the basis of self-preferences. In such a case, biases are a good thing because they may reveal preferences, which is STOC’s primary goal. Thus:

Result 4: Individual trading bias: Traders will exhibit bias based on self-preferences when trading; therefore, individual trading will reveal individual self-preference.

**EMPIRICAL RESULTS OF STOC TESTS**

Before reporting the STOC test results, we try to identify a metric that summarizes the trading data, which consist of a series of price–volume pairs for each trade of each stock, as in the example in Figure 11 for the bike pump called “AirStik.”

Volume-weighted-average prices, which capture all of the trades from start to finish during a trading game, weighting each trade price by the number of shares traded, correlate to the validation data better and more consistently than the five alternative metrics shown in Figure 12 (median, low price, mean, closing price, and high price). Therefore, in subsequent reporting we use VWAPs, normalized to sum to 100, when analyzing STOC results.

The VWAP’s observed superiority is consistent with the results of Shin and Dahan (2011), who model whether STOC market prices conform to a stationary or nonstationary process and also model movements on the basis of central tendencies of stock prices, “momentum” effects, and regression to the mean. They analyze the same trading data as we do in the current research and use unit-root tests to verify the stationarity, or lack thereof, of the mean prices for each security; they find that STOC security prices are stationary. Their model is as follows:

\[
P_{t+1} = \alpha + \gamma \times \text{DIFF}_{t-1} + e_{t,1} \quad e_{t,1} = \rho \times e_{t-1} + \nu_{t,1} \quad \sim \text{w.n.}
\]

where \(\alpha\) is an intercept term for each stock; \(\text{DIFF}\) is the difference between the current stock price, \(P\), and that stock’s VWAP up to time \(t\); and the errors, the \(e\) values, are autoregressive and follow a white-noise process (w.n.) (i.e., a sequence with zero mean, constant variance, and no serial correlation [Enders 2004]).

In Shin and Dahan’s (2011) empirical analysis, the \(\alpha\) values for each stock are highly correlated to our VWAP values, and their results support the conclusion that an ideal STOC metric should include all trades. It is important to note that when applying Shin and Dahan’s test of stationarity to all of our STOC data, we find that all of our trading experiments pass the stationarity test at the 95% confidence level. That is, they do not follow a random walk in which the next trade is equally likely to be above the current stock price or below it. Their model correctly predicts whether the price of each stock will rise or fall in the next trade 72.1% of the time versus a 50–50 guess. This stationarity occurs

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We thank Hyun Shin for his assistance with these analyses.
because there is no outside information entering the market during a STOC game, only the individual preferences and beliefs about others that exist at the time trading begins and what is revealed through the price mechanism as the game unfolds. One way of interpreting this result is that STOC works like traditional market research in which trades represent a representative sample drawn from the population. We will use this important stationarity result when analyzing data at the individual trader level for Result 4 by comparing each trade made against these stationary VWAPs.

Table 4 summarizes the testing on the basis of results from all 11 STOC experiments. Of the 11 results, 10 are confirmed with remarkably strong results.

**Result 2 Confirmed with One Exception**

In the majority of cases, STOC correlates well with VCT and constant-sum voting (Result 2a is confirmed), self-stated preferences, and conjoint analysis (Result 2b is confirmed). Most of the experiments showed good test-to-test reliability (Result 2c confirmed), especially with similar or identical groups of traders, but there were two notable exceptions. The fourth crossover-vehicle test, with only 16 global executives trading, did not correlate well with the other three STOC tests. Similarly, the second Wii video game STOC test had virtually no correlation with the first Wii video game test, even though both tested the same eight products. The most likely explanation is that the two groups of traders had wildly different preferences (as evidence of the difference between the two groups, we note that they had a correlation of only .02 between their average self-preferences). Thus, although Result 2c is confirmed and we believe that STOC is reliable and repeatable, we caution that STOC measures consensus preferences of that particular group of traders, so as with other market research methods, a representative sample is required.

For Result 2d, that STOC correlates with simulated store sales, the findings seem equivocal because, as Table 5 shows, the first test depicting laptop bags in a tabular format failed, whereas the second test depicting the same bags in simpler images succeeded remarkably well. The only difference between the two tests was in the stimuli used, not the underlying product concepts. Simply put, the tabular format for the eight laptop PC bags failed miserably, whereas the simple images of each bag and its features were much better understood. Thus, Result 2d is confirmed, given effective stimuli. The lesson is that stimuli matter in STOC, as in other market research methods, and pretesting of stimuli is advised.

Although the success of STOC in predicting market shares in a simulated store suggests that the method could be used in forecasting potential real-world sales of product concepts, we urge caution. Simulated stores control for many marketing-mix variables, such as advertising, brand equity, and product availability, that are not controlled in actual product markets. The next result highlights the risks of using STOC to predict actual sales.

We did not achieve Result 2e (i.e., that STOC predicts actual market shares); indeed, it is convincingly rejected on the basis of all four crossover-vehicle experiments. The failure of STOC to predict actual vehicle market share makes intuitive sense considering that STOC measures vehicle preferences without respect to vehicle price, not what respondents would actually buy given budget and product availability constraints. This result highlights the earlier distinction between prediction markets, which measure expectations about future observable outcomes, versus STOC, which measures preferences for product concepts.

Confirming Results 2a, 2b, and 2c, the findings from the two bike pump experiments show a remarkable agreement with those of Dahan and Srinivasan (2000), despite fundamental differences between the two methods and wide separation in time and location. The detailed results in Table 6 reveal a high degree of correlation between both STOC tests and Dahan and Srinivasan’s original bike pump validation data. Table 7 calculates the mean absolute errors between any two sets of choice share predictions and shows that STOC fared well in measuring preferences based on the static web images.

Differences include those in the data collection mechanism (a virtual security market in the STOC case vs. a virtual shopping experience in Dahan and Srinivasan’s [2000] study), the modeling of the predicted market share (the use of relative security prices with STOC vs. individual-level conjoint analysis in the other study), the questions asked (what
Table 4
SUMMARY OF 11 EXPERIMENTS AND RESULTS 1–4

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<td>❌</td>
<td>❌</td>
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</tr>
</tbody>
</table>
Cited previously, “STOC” represents the normalized market shares based on the VWAPs of each of the eight securities.

As we did not factor in vehicle prices and respondent price sensitivity, the correlations between STOC and VCT disappear (correlations of -.10 to .31). STOC traders focus on vehicle preferences, not on willingness to pay. Thus, Result 2f is confirmed: STOC traders reveal their product concept preferences but not necessarily their intent to buy or their price sensitivity.

### Result 3 Confirmed

The results for the first two Wii video game tests appear in Table 9. The high correlations between aggregate individual preferences and E[Others] (.94, .94, and .88) and between E[STOC Prices] and STOC VWAP (.93, .94, and .63) confirm a strong wisdom-of-crowds effects. Although many individual respondents and traders do not accurately estimate others’ preferences, aggregating their individual beliefs produces an accurate estimate of aggregate preferences because most of the participants’ errors cancel out.

Although the results for the individual tests are remarkably good, the correlations between Tests 1 and 2 for the same eight Wii video game concepts are virtually nonexistent, highlighting our previous point that differences in trader populations will be reflected in STOC results.

The tests also confirm Result 3a, that STOC measures expectations of others more so than self-preferences. In all three tests, the correlations between E[Others] and VWAPs are significant and higher than those between VWAPs and self-preferences (e.g., .91 vs. .89 in Test 1, .79 vs. .69 in Test 2, and .66 vs. .32 in Test 3). Traders rely more heavily on their beliefs about other traders than on their personal preferences when trading, which is especially evident in Test 3 (see Table 10).

Traders learn from each other, confirming Result 3b, as evidenced by post-STOC trading results outperforming E[STOC Prices] measured just before trading in all three tests.

Comparisons to conjoint analysis for the three Wii video game tests are shown in Table 11 and indicate that the competition between STOC and conjoint analysis is essentially a draw. STOC outperforms conjoint analysis in estimating self-preferences for two of the three Wii video game tests; the values in the lower row of Table 11 exceed those in the upper row for Tests 1 and 2. Conjoint analysis outperforms STOC in Test 3, though neither method does particularly well in that test. Overall, having the information from both methods would be superior to depending on either one alone, and STOC trading of attributes and levels could act as an input to conjoint analysis when trying to narrow from many possible attributes to a manageable few.

In addition, STOC may prove more useful in measuring preferences for attributes such as product aesthetics and ease of use that are difficult to measure by using conjoint analysis.

### Table 5

<table>
<thead>
<tr>
<th>Test 2: STOC</th>
<th>Simulated Store Sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image Format</td>
<td>Store Sales</td>
</tr>
<tr>
<td>Test 1: STOC table format</td>
<td>-.14</td>
</tr>
<tr>
<td>Test 2: STOC image format</td>
<td>-.80</td>
</tr>
</tbody>
</table>

*p < .05.

### Table 6

<table>
<thead>
<tr>
<th>Conjoint Analysis</th>
<th>Web Static Images</th>
<th>Test 1: STOC</th>
<th>Test 2: STOC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical prototypes</td>
<td>.99***</td>
<td>.98***</td>
<td>.75*</td>
</tr>
<tr>
<td>Conjoint analysis</td>
<td>.99***</td>
<td>.75*</td>
<td>.83**</td>
</tr>
<tr>
<td>Web static images</td>
<td>.81**</td>
<td>.89**</td>
<td>.86**</td>
</tr>
</tbody>
</table>

Result 2e is not achieved: STOC failed to predict actual vehicle sales: The first row of Table 8, in which correlations to actual 2001–2006 unit sales of the eight vehicles were calculated for each method, reveals that all four STOC tests did not predict actual sales, so Result 2e is rejected. This result confirms our point that STOC markets are not prediction markets but rather measure underlying preferences among the traders, not intent to purchase. Conversely, self-stated choices and VCT with pricing did predict actual unit sales (correlations in the .42–.63 range), although the results are not statistically significant. The superiority of VCT and self-stated choice over STOC derives from the distinction between what people prefer and what they are willing to pay. STOC zeroes in on preference rather than willingness to pay. In addition, vehicle prices were not highlighted in STOC Tests 1, 2, and 4 and were emphasized to traders only in Test 3, which was the only STOC test with at least some predictive value (.52, but again not significant).

2. **STOC captures preferences well, but not price sensitivity:** All four crossover-vehicle tests reveal that STOC accurately measured vehicle preferences without considering vehicle pricing. Consider the crossover-vehicle STOC results in Table 8. When we leave vehicle prices out of the analysis, STOC correlates remarkably well with the VCT results (correlations of .80, .97, .72, and .83, respectively, for Tests 1–4). However, when we do factor in vehicle prices and respondent price sensitivity, the correlations between STOC and VCT disappear (correlations of -.10 to .31). STOC traders focus on vehicle preferences, not on willingness to pay. Thus, Result 2f is confirmed: STOC traders reveal their product concept preferences but not necessarily their intent to buy or their price sensitivity.

### Table 7

<table>
<thead>
<tr>
<th>Mean Absolute Error (MAE) Between Two Bike Pump STOC Tests and Validation Data from Dahan and Srinivasan (2000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conjoint Analysis</td>
</tr>
<tr>
<td>-------------------</td>
</tr>
<tr>
<td>Physical prototypes</td>
</tr>
<tr>
<td>Conjoint analysis</td>
</tr>
<tr>
<td>Web static images</td>
</tr>
<tr>
<td>Test 1 STOC</td>
</tr>
</tbody>
</table>

*p < .05.

**p < .01.

***p < .001.

The group prefers in STOC vs. what you prefer in the others study, and the participant population (Stanford students of all types in Dahan and Srinivasan’s study and Massachusetts Institute of Technology MBA students in the STOC study).

The crossover test results in Table 8 also confirm Results 2a and 2c. “Self-stated” survey data represent the normalized market shares for vehicles ranked according to each participant in the top three of eight choices. “VCT with Prices” represents vehicle market shares based on scoring in the top three of eight vehicles using Dahan and Srinivasan’s (2000) methodology and accounting for the price of each vehicle when calculating utility. “VCT No Prices” is the same calculation, but based on vehicle preferences without accounting for vehicle prices in the utility calculations. As we discussed previously, “STOC” represents the normalized market shares based on the VWAPs of each of the eight securities.

Two notable results follow from this analysis:

1. Result 2e is not achieved: STOC failed to predict actual vehicle sales: The first row of Table 8, in which correlations to actual 2001–2006 unit sales of the eight vehicles were calculated for each method, reveals that all four STOC tests did not predict actual sales, so Result 2e is rejected. This result confirms our point that STOC markets are not prediction markets but rather measure underlying preferences among the traders, not intent to purchase. Conversely, self-stated choices and VCT with pricing did predict actual unit sales (correlations in the .42–.63 range), although the results are not statistically significant. The superiority of VCT and self-stated choice over STOC derives from the distinction between what people prefer and what they are willing to pay. STOC zeroes in on preference rather than willingness to pay. In addition, vehicle prices were not highlighted in STOC Tests 1, 2, and 4 and were emphasized to traders only in Test 3, which was the only STOC test with at least some predictive value (.52, but again not significant).

2. **STOC captures preferences well, but not price sensitivity:** All four crossover-vehicle tests reveal that STOC accurately measured vehicle preferences without considering vehicle pricing. Consider the crossover-vehicle STOC results in Table 8. When we leave vehicle prices out of the analysis, STOC correlates remarkably well with the VCT results (correlations of .80, .97, .72, and .83, respectively, for Tests 1–4). However, when we do factor in vehicle prices and respondent price sensitivity, the correlations between STOC and VCT disappear (correlations of -.10 to .31). STOC traders focus on vehicle preferences, not on willingness to pay. Thus, Result 2f is confirmed: STOC traders reveal their product concept preferences but not necessarily their intent to buy or their price sensitivity.
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<tr>
<td>Actual units sold</td>
<td>2001–2006</td>
<td></td>
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</tr>
<tr>
<td>.44</td>
<td>.58</td>
<td>–.2</td>
<td>.22</td>
<td>.42</td>
<td>.63†</td>
<td>–.1</td>
<td>.03</td>
<td>.62†</td>
<td>.48</td>
<td>–.0</td>
<td>.52</td>
</tr>
<tr>
<td>Test 1: Self-Stated</td>
<td>.54</td>
<td>.54</td>
<td>.62†</td>
<td>.89**</td>
<td>.79*</td>
<td>.55</td>
<td>.64†</td>
<td>.91**</td>
<td>.37</td>
<td>.63†</td>
<td>.90**</td>
</tr>
<tr>
<td>Test 1: VCT with Prices</td>
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<td>–.1</td>
<td>32</td>
<td>.91**</td>
<td>–.2</td>
<td>–.1</td>
<td>55</td>
<td>.97***</td>
<td>–.0</td>
<td>.50</td>
<td>.94***</td>
</tr>
<tr>
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<td>Test 2: Self-Stated</td>
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<td>Test 2: VCT with Prices</td>
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<td>Test 2: VCT No Prices</td>
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<tr>
<td>Test 3: Self-Stated</td>
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<tr>
<td>Test 3: VCT with Prices</td>
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<tr>
<td>Test 3: VCT No Prices</td>
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<tr>
<td>Test 4: VCT with Prices</td>
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<td></td>
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<td></td>
<td></td>
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<tr>
<td>Test 4: VCT No Prices</td>
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<td></td>
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<tr>
<td>Test 4: STOC</td>
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</tbody>
</table>

All four STOC tests correlate highly with VCT when vehicle pricing is ignored, confirming Result 2f.

Notes: Result 2e is not achieved based on STOC’s failure to predict actual sales in top row.
below the VWAP might indicate an “abnormal” dislike for a particular stock, and buying a stock above the VWAP might reveal a strong preference for the concept associated with that stock. Next, we test these results empirically by examining the 50% of transactions in the off-diagonal white cells. The goal is to detect individual preferences in the trading data.

In Appendix B, we develop a metric measuring trader n’s bias for stock m:

$$\frac{\text{VWAP}_m + (\xi_{m,n} \times \sigma_m)}{\sum_{m=1}^{N} \text{VWAP}_m + (\xi_{m,n} \times \sigma_m)}$$

where the \(\xi_{m,n}\) measures trader n’s relative bias for stock m using the volume-weighted trades made by that person for that stock in the off-diagonal cells of Table 11 and \(\sigma_m\) measures the volume-weighted variance of stock m’s price relative to its volume-weighted mean (VWAP). We note that each trader’s biases for all m stocks sum to 100% and, therefore, can be compared with the constant-sum survey results. We can compare the individual trader’s bias against known preferences from the individual-level survey data. The key result, depicted in Figure 13, is that trading reveals preferences at the individual level.

Two primary findings regarding individual-level preferences confirm Result 4:

1. Respondents are subject to false-consensus biases: There are strong positive correlations between the survey of self-preference and each respondent’s expectation of others. This implies that most respondents’ expectations of others are strongly biased by self-preference, which is consistent with the false-consensus bias. Note that we observe a similar effect at the aggregate level for the Wii game concepts (see Tables 9 and 10), in which the correlations between mean self-preferences and mean expectations of others were extremely high and significant (94, 94, and .88, respectively).

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**Table 9**

<table>
<thead>
<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>SELF Preferences</td>
<td>.94***</td>
<td>.92**</td>
<td>.90**</td>
</tr>
<tr>
<td>Test 1: E[Mean (Others)]</td>
<td>.98***</td>
<td>.90**</td>
<td>.91**</td>
</tr>
<tr>
<td>Test 1: E[STOC Prices]</td>
<td>.92***</td>
<td>.93***</td>
<td>.29</td>
</tr>
<tr>
<td>Test 1: STOC VWAP</td>
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<td>.00</td>
<td>.14</td>
</tr>
<tr>
<td>Test 2: E[Others]</td>
<td>.02</td>
<td>.09</td>
<td>.24</td>
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<td>Test 2: E[STOC Prices]</td>
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<td>.35</td>
<td>.47</td>
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<td>Test 2: STOC VWAP</td>
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<td>.59</td>
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</table>

<table>
<thead>
<tr>
<th>Test 2: Post-STOC</th>
<th>Test 2: Post</th>
<th>Test 2: Post STOC</th>
</tr>
</thead>
<tbody>
<tr>
<td>SELF Preferences</td>
<td>.94***</td>
<td>.84**</td>
</tr>
<tr>
<td>Test 2: E[Mean (Others)]</td>
<td>.93***</td>
<td>.81*</td>
</tr>
<tr>
<td>Test 2: E[STOC Prices]</td>
<td>.95***</td>
<td>.94***</td>
</tr>
</tbody>
</table>

\(\ddagger p < .10.\)
\(* p < .05.\)
\(** p < .01.\)
\(*** p < .001.\)

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**Table 10**

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>SELF Preferences</td>
<td>.88***</td>
<td>.92***</td>
<td>.47</td>
</tr>
<tr>
<td>Test 3: E[Mean (Others)]</td>
<td>.97***</td>
<td>.75**</td>
<td>.66*</td>
</tr>
<tr>
<td>Test 3: E[STOC Prices]</td>
<td>.74**</td>
<td>.63*</td>
<td></td>
</tr>
<tr>
<td>Test 3: Post-STOC</td>
<td>.96***</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(+ p < .05.\)
\(** p < .01.\)
\(*** p < .001.\)
Table 11
PREDICTING AGGREGATE SELF-PREFERENCES: STOC VERSUS CONJOINT ANALYSIS R-SQUARE AND RANK CORRELATION FOR THREE TESTS (WINNERS IN BOLD)

<table>
<thead>
<tr>
<th>Test</th>
<th></th>
<th>r²</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (M = 8, N = 35)</td>
<td></td>
<td>.60</td>
<td>.69</td>
</tr>
<tr>
<td>2 (M = 8, N = 55)</td>
<td></td>
<td>.06</td>
<td>.14</td>
</tr>
<tr>
<td>3 (M = 11, N = 58)</td>
<td></td>
<td>.30</td>
<td>.61</td>
</tr>
</tbody>
</table>

Conjoint analysis
STOC VWAP

Table 12
TRADES BETWEEN PEOPLE ARE PROFITABLE FOR ONE PERSON AND UNPROFITABLE FOR THE OTHER, AND UNPROFITABLE TRADES REVEAL INDIVIDUAL PREFERENCES AND TRADING BIASES

<table>
<thead>
<tr>
<th>Trade</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy a Stock</td>
<td>Below VWAP</td>
</tr>
<tr>
<td>Sell a Stock</td>
<td>Above VWAM</td>
</tr>
</tbody>
</table>

Figure 13
PARTICIPANTS' TRADE BASED ON THEIR OWN EXPECTATIONS OF OTHERS, WHICH DEPEND ON SELF-PREFERENCES DUE TO FALSE CONSENSUS

2. People trade on the basis of their biases: It is particularly noteworthy that individual trader preferences measured with the trading-bias metric are positively correlated with the survey of self-preference data (mean p = .25) and even more so with the participants' E[Others] values (mean p = .46), which in turn are highly correlated with self-preferences (mean p = .61). Although STOC was not primarily designed to measure preferences at the individual level, the method reveals traders' personal biases for and against the product concepts being tested. As in conjoint analysis, STOC measures implicit preferences rather than requiring explicitly stated preferences.

Figure 14 compares participants' ability to estimate others' preferences with the extent to which they rely on those estimates when trading, revealing that those who estimated others' preferences better relied more on their own preferences when trading, whereas traders who predicted others' preferences poorly followed the market rather than trading on the basis of their own beliefs. One explanation for this remarkable result is that market prices tend to confirm the beliefs of those who start trading with accurate estimates, whereas those whose estimates are far off the mark adjust their trading after learning market prices. That is, they learn from the STOC market, providing further confirmation of Result 3b.

DISCUSSION AND CONCLUSIONS
We study a novel application of the market mechanism: the use of securities markets to aggregate and infer diverse consumer preferences. We implement this idea in the specific context of 11 product concept-testing studies that aim to predict potential market share for between 8 and 11 product prototypes. In this research, we confirm four STOC results: (1) Games are more popular and cost efficient than surveys, (2) STOC passes validity tests but is not a prediction market, (3) the method measures consensus expectations of others, and (4) the method also uncovers individual preferences, not just those of the crowd.

We observe that, unlike financial and prediction markets, STOC prices regress toward stationary means as a result of the absence of outside information. Of the 11 STOC experiments, 10 are remarkably consistent with several common preference measurement techniques. However, stimuli must be clear and salient, and traders need to be trained and properly primed before trading. STOC reveals individual heterogeneity through trading biases.

We caution that the STOC methodology was not designed to measure individual preferences. Conjoint analysis is likely to be more effective in that context, especially in measuring price sensitivity and attribute trade-offs. However, STOC reveals individual preferences indirectly. Nevertheless, STOC requires simultaneity and technical infrastructure that other methods would not need, thus posing challenges to its widespread adoption. To improve STOC's reliability in some marketing applications, it may be necessary to anchor the values of the securities to some objective fundamental variables of the corresponding product concepts.
To test market share predictions, for example, security values might be compared with the realized market shares of the subset of products that already exist or, barring the existence of real market share data, with the outcomes of external customer choice surveys. We hope to refine STOC market methods along these and other lines in further research. Finally, confidentiality needs to be considered when using STOC because product concept information is revealed to a group of traders in the process, as are group preferences. Experimental design mitigates this issue to an extent by using STOC's scalability by making each trader aware of only a subset of potential new concepts.

Despite the challenges, STOC offers two primary advantages relative to traditional market research methods:

1. **Cost efficiency**: The finding that respondents prefer competing in the STOC game to providing self-stated preferences, combined with the efficiency of STOC’s market pricing mechanism in aggregating preferences, reduces recruiting and respondent compensation costs by as much as 75% for any given number of concepts.

2. **Scalability**: The ability to conduct a large number of concept tests quickly and simultaneously, limited only by the number of respondents, is particularly beneficial. STOC serves as an early phase screening mechanism for concepts flowing from Web 2.0’s crowd-sourcing and open innovation or from particularly prolific product innovation within the firm during new product development.

The efficacy of STOC markets at identifying winning concepts may not surprise economists. After all, Keynes (1936, p. 140) commented on the similarities between stock selection and a beauty contest more than 74 years ago: “Professional investment may be likened to those newspaper competitions in which the competitors have to pick out the six prettiest faces from a hundred photographs, the prize being awarded to the competitor whose choice most nearly corresponds to the average preferences of the competitors as a whole.” The analogy is perhaps more accurate for describing what happens in financial markets and STOC games in the short run. After all, over the long run, financial stock prices depend not only on investors’ subjective beliefs and expectations of others but also on other objective information such as companies’ earning potentials and valuations of assets. Conversely, the trading experiments presented in this article are precisely “beauty contests” because values of the virtual securities are derived endogenously from the preferences of the market participants and their expectations of others’ preferences, both of which are largely subjective.

**APPENDIX A: DERIVATION OF EQUATION 1**

We can derive Equation 1 by considering the two primary, people-related costs of running a market research study: (1) those associated with recruiting potential respondents and (2) those for compensating people who actually participate.
Respondent Costs

\[
\text{Total Cost} = \left( \frac{\text{Number of Respondents Needed}}{\text{Response Rate}} \times \frac{\text{Cost per Respondent}}{\text{Recruit}} \right) \times \text{Recruits} \times \text{Cost per Recruit}
\]

Respondent Compensation

\[
\text{Response Rate} \times \frac{\text{Compensation per Respondent}}{\text{Recruit}} \times \text{Number of Respondents Needed} \times \frac{\text{Compensation per Respondent}}{\text{Recruit}}
\]

Number of Respondents Needed

\[
= \frac{\text{Number of Concepts Being Tested} \times \text{Sample Size Required}}{\text{Question Capacity per Respondent}}
\]

Average Cost per Respondent

\[
\times \frac{\text{Cost per Recruit}}{\text{Response Rate}} + \frac{\text{Compensation per Respondent}}{\text{Recruit}}
\]

which we summarize with the following notation:

\[
\text{Total Cost} = \left( \frac{\text{Number of Respondents Needed}}{\text{Response Rate}} \times \frac{\text{Cost per Respondent}}{\text{Recruit}} \right) \times \text{Recruits} \times \text{Cost per Recruit}
\]

\[
= \frac{\text{Number of Concepts Being Tested} \times \text{Sample Size Required}}{\text{Question Capacity per Respondent}} \times \frac{\text{Cost per Recruit}}{\text{Response Rate}} + \frac{\text{Compensation per Respondent}}{\text{Recruit}}
\]

where \( N_{\text{sample}} \) is the number of required respondents, \( q_{\text{respondent}} \) is the question capacity per respondent, \( c_{\text{recruit}} \) is the cost to recruit each person, \( c_{\text{respondent}} \) is the compensation for each respondent, and \( r\% \) is the response rate.

**APPENDIX B: THE TRADING-BIAS METRIC**

Here, we develop a trading-based metric to measure individual biases and the preferences those biases imply.

- We denote stocks using \( m = 1, ..., M \) and individual traders using \( n = 1, ..., N \).
- Let \( P_{m,n} \) be the price of the \( n \)th trade of stock \( m \) for trader \( n \).
- \( \text{VWAP}_m \) is the volume-weighted average price for stock \( m \).
- \( V_{m,n} \) is the volume (number of shares) of the \( n \)th of \( K_{m,n} \) trades of stock \( m \) for trader \( n \).
- \( s_{m,n} \) is the side of the \( n \)th trade (buy or sell) of stock \( m \) for trader \( n \).
- \( I(\text{VWAP}_m, P_{m,n}, s_{m,n}) \) is an indicator function, which returns 1 if trader \( n \) bought shares above the \( \text{VWAP}_m \) or sold shares below the \( \text{VWAP}_m \) and 0 if otherwise:

\[
I(\text{VWAP}_m, P_{m,n}, s_{m,n})
\]

\[
\begin{align*}
1: & \quad s_{m,n} = \text{buy, } P_{m,n} > \text{VWAP}_m, \\
0: & \quad \text{otherwise}
\end{align*}
\]

\[
\sigma_m = \text{volume-weighted standard deviation of stock } m,
\]

which equals

\[
\sum_{i=1}^{K_{m,n}} \left( P_{m,n} - \text{VWAP}_m \right) \times I(\text{VWAP}_m, P_{m,n}, s_{m,n})
\]

\[
\sum_{i=1}^{K_{m,n}} \text{V}_{m,n} \times I(\text{VWAP}_m, P_{m,n}, s_{m,n})
\]

\[
\sum_{i=1}^{K_{m,n}} \text{V}_{m,n} \times I(\text{VWAP}_m, P_{m,n}, s_{m,n})
\]

\[
\sum_{i=1}^{K_{m,n}} \text{V}_{m,n} \times I(\text{VWAP}_m, P_{m,n}, s_{m,n})
\]

We now define trader \( n \)'s bias for stock \( m \) as the following standardized metric:

\[
\left( \frac{\text{VWAP}_m + \left( \hat{z}_{m,n} \times \sigma_m \right)}{\sum_{m=1}^{M} \text{VWAP}_m + \left( \hat{z}_{m,n} \times \sigma_m \right)} \right)
\]

Note that each trader’s biases for all \( m \) stocks sum to 100% and therefore can be compared with the constant-sum survey results.

**REFERENCES**


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In order to conduct market experiments, we developed software, which replicates the mechanisms of real-world market. The STOC Web Market is software implemented in Java, which provides a platform for different types of electronic markets on the World Wide Web. We designed the software to use it as control laboratory for software and/or human traders based simulations and experiments.

1.1 Technical Description

As shown in Figure 1, an abstract level design of the system defines roles of electronic market. The main roles are broken down into pieces as the following: order routing, match/execution, clearance/settlement, information dissemination, market administration, and market surveillance.

When orders are received from traders, the market is responsible for routing the order to an appropriate internal order book, where market makers (or auctioneers) can match them with
other orders. When multiple securities are traded, each order needs to be routed to an appropriate market maker who handles the same security. After orders are matched and executed by market makers, they are cleared and settled. The clearing/settling refers to updating the market information such as last traded price, and traders' portfolio information. Once orders are settled, traders are notified of updated market information and their portfolio holdings, which is the role defined as information dissemination. Throughout this process, appropriate market surveillances are taken place. The market surveillance is to monitor the orders to make sure that they are not violating the predefined market rules. Lastly, the system needs to be capable of administrating the rules of the market in terms of order matching, executing, clearing, and settling.

The STOC Web Market is designed into several modules to fulfill such roles. The software is implemented in Java with database connectivity to store all trade related information in a database for further analysis. The market participants access the market via Java applet, which gets downloaded into their Web browser. The Java language provides several advantages such as portability, dynamic loading, multi-threading, and object serialization, which make it a convenient platform for implementing the inherent complexity of the market simulator. These factors are especially advantageous to our system since it uses Web technology. They made it possible for all users to interact with the system from any platforms and trade securities concurrently in the market. Also they have made possible to build a robust system with relatively limited time. The Figure 2 represents the Java modules we built for the simulator. In the rest of this section, we describe each module in more detail.
Figure 2: Components of STOC Web Market

*Market Server Module*

The market server module serves six major functions: order match/execution, information dissemination, order routing, clearance/settlement, market administration, and brokerage service.

- **Order Match/Execution**: The order match/execution plays a central role in handling and executing the orders. One of the principal advantages of object-oriented programming is that we can easily incorporate different types of order match/execution schemes into the system.

- **Information Dissemination**: The information dissemination is to provide market information to traders. The market server disseminates information in two ways: one is to disseminate information to all traders participating in the market, and the other is to disseminate information to a specific trader. In order to disseminate public information to all traders, the market server uses an object called a ‘Ticker Tape’, which all traders have direct access to. For example, security information is placed on the ‘Ticker Tape’ when it is traded, or when the bid/ask prices are altered by newly placed orders. It also provides other general market information – whether market is open or closed, opening time of market,
duration of sessions, and other market news. In order to disseminate information to a specific trader, market server directly sends information to the trader using private channel. Each client maintains the channel for direct communication with the market server. The private information such as trade confirmation and portfolio holdings are sent through this channel.

- **Order Routing**: When orders are received, the market server routes them to an appropriate order book, which consolidates all orders of the same security.

- **Clearance/Settlement**: After the trade has taken place, the market server clears the transaction between two counter parties by transferring cash and securities between buyer and seller. The role of market server as a clearinghouse is to update trader’s portfolio in the database. After the update, the market server provides updated portfolio information to the owner of that portfolio. The clearance/settlement can be implemented with different settlement rules and clearing procedures that may apply to different securities. For example, futures market has different settlement rules from those of the options market.

- **Market Administration**: In order to administer the market, the software provides a console window for market administrator as depicted in Figure 3. The console window is to serve five major roles: opening and closing of the market, monitoring traders who are participating in the market, monitoring the market makers, configuring duration of sessions, and disseminating general market information to market participants.

- **Brokerage Service**: The essence of the brokerage service is the maintenance of accounts. Traders open accounts through simple registration process. When a new trader opens up an account, the market server accesses the information stored in the database on how the
initial portfolio shall be created. Based on this information, the market server assigns predefined amount of fictitious money and shares of securities to the newly created account.

Figure 3: A Console for Market Server

Market Maker Module

The STOC Web Market is a highly configurable market in two aspects, the market institutional structures (trading mechanisms) and the types of securities to be traded. The market structure is abstracted in the model of market makers. For each security traded in the market, different types of market makers can be integrated into the market in a “plug-and-play” manner.

In the current STOC Web Market system, the market maker is not responsible for checking general market rules, but may wish to impose additional rules on its own clients for transactions
placed through the market maker itself. If so, the market maker should give appropriate error message of the rules that are violated to the trader. If no rules are violated, the market maker must note the order to market server module. In addition, if this order allows some sales to proceed, the market maker notes to market server module to consummate the sales. Each market maker should strive to fulfill orders eventually, of course; however, there is no requirement that it be done immediately. Also, multiple market makers can handle the same security.

Figure 5: Client User Interface

![Client User Interface Image]

*Client User Interface*

The traders can access the market using GUI interface developed in Java applet. The applet consists of two parts: signup/login and trading interface (Figure 5). In signup/login screen, trader can either register herself as a new user or login to the market with pre-existing user ID and password. After logging in, the client side protocol allows trader to do the followings using
trading interface: place and cancel orders, obtain updates on ongoing market activity, and obtain information on its own portfolio.

Database Module

The database is divided into two groups of tables; tables for defining the market, and tables for storing trading information.

- **Defining the Market**: There are four entities that define the market; security information, users, initial value of portfolios, and market session. In order to setup a market, all of these information need to be provided. When trader registers as a new user, the trader’s information is stored in the ‘users’ table. At the same time, the trader’s initial portfolio is created in the ‘portfolios’ table based on the initial value, which are predefined in the database.

- **Storing Trading Information**: There are mainly two types of trading information. One is order information and the other is sales information. The order information consists of type of security, side (buy or sell), price, and quantity. After the execution, the sales information is stored in ‘sale log‘ table. It is important to separate the two in the database since the first one is needed to show quote information, and the second one is used to determine the price of securities.

1.2 Summary

In summary, the main features of the STOC Web Market Simulator are: (1) automating trading, (2) modular design for market structure, and (3) an environment that allows effective interactions between traders.
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