What Have We Learned From Experimental Finance?

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Summary. This paper addresses five questions about how stock market works and what we have learned from experiments in this field. 1, Why do we need even more data on financial market? Don't we have enough already? 2. How could the data from such small scale simple markets help us gain insights into far more complex investment environments? 3. Is experimental finance a branch or variation of behavioral economics/behavioral finance? 4. What have we learned so far from assets market experiments? 5. What is next?

1 Why More Data?

This question is frequently asked. Of all branches of economics, financial economics probably has available the most detailed and up-to-the-minute observational data from stock exchanges around the world. This branch of economics is characterized by a strong empirical tradition. Why, then, do we need to spend time and money to conduct experiments with financial markets and gather even more data?

Data from the stock exchanges include bids, asks, transaction prices, volume, etc. In addition, data from information services includes information on actions and events that may influence markets. Theories of financial markets (and economics of uncertainty more generally) are built on investor expectations. We need data on investor beliefs and expectations to empirically distinguish among competing theories. Yet, neither of these two sources of data does, nor can, report on investor expectations.

In experimental markets, the researcher knows the underlying parameters, and either knows or can make reasonable conjectures about the investor expectations. Armed with this knowledge, the researcher knows the price and other predictions of alternative theories. Indeed, the experiments are designed so the alternative theories yield mutually distinct predictions for the market. This approach allows us to conduct powerful tests of theories which are not possible from the field data alone; we know little about the parameters and expectations that generate the field data from stock exchanges. We shall return to illustrative examples in a later section after addressing the five questions.

2 What Can We Learn From Such Simple Markets?

Experimental markets are typically conducted in simple laboratory or classroom settings with a small number of student subjects who may have little prior experience with trading and investment. On the other hand, security markets are complex, populated by experienced sophisticated professionals. Naturally, the second question frequently asked is: What could we possibly learn from such Mickey Mouse experiments about the far more complex "real" markets? Experimenter may pay, say, \$50 to each participant after a two or three hour session while traders in the security markets we are interested in often have millions if not billions of dollars at stake.

All science is aimed at finding simple principles that explain or predict a large part (rarely all) of the phenomenon of interest. Simple models, whether in mathematics or in laboratory, make many assumptions. These can be divided into core assumptions and assumptions of convenience. Core assumptions are essential features of the environment while the convenience assumptions are made for mathematical tractability (e.g., probability distributions and preference functions in most cases). The power of a theory depends on the robustness of its explanations and predictions as the environments from which we gather the data deviate from the assumptions of convenience (Sunder [12]). The experimenter can deliberately and progressively make the experimental environment deviate from the assumptions of convenience in the theory to measure this robustness. This robustness check is not possible in the field data generated by the environment prevailing in the market.

In economics and finance, as in other sciences, simple experiments are used to discover and verify general basic principles. We learn to count through analogies of images or physical objects. We learn to swim in knee-deep waters. We learn and verify the laws of electricity, not by using a computer or radio, but by simple instruments such as potentiometer or ammeter. Manipulation of simple controls and monitoring the results builds the fundamental knowledge of science. The noise generated by countless factors in complex environments makes it difficult to detect the fundamental principles that might underline the economics of environment in which we are interested. Simple math and lab models help us learn, before we immerse ourselves in the complexity of the real world phenomena. If the principal is general, it should be applicable not only to complex but also to simple environments of a laboratory. If it does not pass the test of simple environments, its claim to be applicable to more complex environments is weakened.

3 Experimental Vs. Behavioral Finance

The third question often raised is: Is experimental finance the same as behavioral economics or behavior finance? My answer is no. In experimental economics the emphasis is on the design of markets and other economic institutions to gather empirical data to examine the consequences of institutions and rules. We assume that people do what they think is best for them, given what they think they know. They may be inexperienced, but they are not dumb; they learn. In experimental finance, we design experiments to sort out the claims of competing theories. On occasion we might conjecture new theory from the data but then we don't use the data used to generate the conjecture to test it. Like engineers, experimentalists design test beds to examine the properties and performance of alternative market institutions. The focus in this literature is on equilibrium, efficiency, prices and allocations. This work complements mathematical modeling and empirical research with field data.

4 What Have We Learned?

The fourth question is: What have we learned from experiments? Within the last couple of decades, asset market experiments have revealed some important findings by exploiting the advantages of laboratory controls. These findings were not and could not have been reached from field data or mathematical modeling alone. However, in combination with field data and modeling, laboratory experiments have helped us make substantial advances in our understanding of security markets. Let us review some key findings.

Security markets can aggregate and disseminate information. In other words, markets can be informationally efficient. However, just because they can doesn't mean they always are. Information dissemination, when it occurs, is rarely instantaneous or perfect; learning takes time. Efficiency is a matter of degree, not a 0-1 issue.

Plott and Sunder [7] asked if markets can disseminate information from those who know to those who don't. A satisfactory answer to this question could not be established from analysis of field data because we don't know which investor has what information. Plott and Sunder [7] used a simple experiment to address the question. As Table 1 shows, they designed a simple, single-period, two-state (X or Y) security, with the probability of each state given. The market was populated with four traders each of three types for a total of 12 traders; Type I received dividend of 400 in State X and 100 in State Y while the other two types received dividends of 300-150 and 125-175 respectively. Each trader was endowed with two securities and 10,000 in "cash" at the beginning of each period. The last column of Table 1 shows the expected dividends from the security for each of the three types of traders, when they do not know whether State X or Y is realized. Under this no information condition, the equilibrium price of the security would be 220, the maximum of the three expected values (220, 210 and 155) and Type I traders should buy all the securities at this price from the other traders.

Table 1. Information Dissemination Equilibria in a Simple Asset Market (Source: Plott and Sunder [7]

	State X Prob. = 0.4	State Y Prob. = 0.6	
Trader Type			Expected Dividend
I	400	100	220
II	300	150	210
III	125	175	155
PI Eq. Price Asset Holder	400 Trader Type I Informed	220 Trader Type I Uninformed	
RE Eq. Price Asset Holder	400 Trader Type I	175 Trader Type III	

Suppose the realized state is X and two traders of each type are informed at the beginning of the period that the state is X, and the other two are not. The informed traders know that the value of the dividend from the security (if they decide to hold it) is given in Column X, while the uninformed traders (assuming they are risk-neutral) would value the securities at the expected values given in the last column of the table. The equilibrium price would be the maximum of these six numbers 400, and Type I informed traders would buy the security at that price. If the realized state were Y instead, by a similar argument, the equilibrium price would be 220, the maximum of the six numbers in the Y and the expected value columns, and the Type I uninformed traders should buy the security at that price. This equilibrium is labeled Prior Information (PI) equilibrium because it assumes that the traders rely entirely on the information they receive at the beginning of the period, and do not learn any additional information about the realized state from their participation in the market.

PI equilibrium is problematic because it assumes that traders would not learn from their failures. Whenever Type I uninformed traders pay a price of 220 to buy a security, they will discover that the state turns out to be Y with a dividend of only 100, leaving them with a loss. If we assume that one cannot fool some of the people all the time, these traders should learn not to buy the securities at that price, making the PI equilibrium unsupportable.

Under the rational expectations (RE) or efficient market hypothesis, information about the state would be disseminated from the informed to the uninformed traders through the market process. Under this assumption, in

State X, all traders would know the state is X, will yield an equilibrium price of 400 which is the maximum of the three dividends in the column for State X, and all traders of Type I would buy the securities from the others. Similarly, in State Y, the equilibrium price would be 175 which is the maximum of the three dividends in the column for State Y, and all traders of Type III would buy the securities. This market was designed so the PI and the RE hypotheses yielded mutually distinct predictions of the market outcomes in prices and allocations.

Figure 1 shows the results for one of these markets. In Periods 1 and 2, traders were not given any information and the prices were located in the vicinity of the no information prediction of 220. In Period 3, State Y was realized, and the prices were much closer to the RE prediction of 175 than to the PI prediction of 220. Similar results were repeated in the other periods (5, 6, 8 and 10) when State Y was realized. The observed allocative efficiency (shown in numbers above the x-axis), as well as prices, are much closer to the predictions of the RE model than PI model. This experiment provided direct empirical evidence that markets can disseminate information from the informed to the uninformed through the process of trading alone, without an exchange of verbal communication. Such markets can achieve high levels of efficiency by transferring securities to the hands of those who value those most.

Evidence on the ability of markets to disseminate information led to a more ambitious experiment: Can markets behave as if diverse information in the hands of the traders be aggregated so it is in the hands of all? To address this question, Plott and Sunder [8] designed a market with three states of the world (X, Y, and Z). When the realized state was, say, X, they informed some traders that it was "not Y" and informed the others that it was "not Z," Do markets aggregate the diverse information in the hands of individual traders and behave as if everyone learns that the realized state is X in such a case? They found that in markets such aggregation and dissemination of diverse information can take place, and markets can achieve high levels of information and allocative efficiency. The same happens when investors have homogenous preferences (which make it easier for traders to infer information from the actions of others).

Just because markets can aggregate and disseminate information does not mean that all markets do so under all conditions. Experiments show that market conditions must allow investors the opportunity to learn information from what they can observe. Even in these simple experimental markets, these conditions are not always satisfied for various reasons (e.g., too many states, too few observations and repetitions to facilitate learning). For example, in the information aggregation experiment mentioned above, a complete market for three Arrow-Debreu securities is efficient, but an incomplete market for a single security is not.

Even in the best of circumstances, equilibrium outcomes are not achieved instantaneously. Markets tend toward efficiency, but cannot achieve it imme-

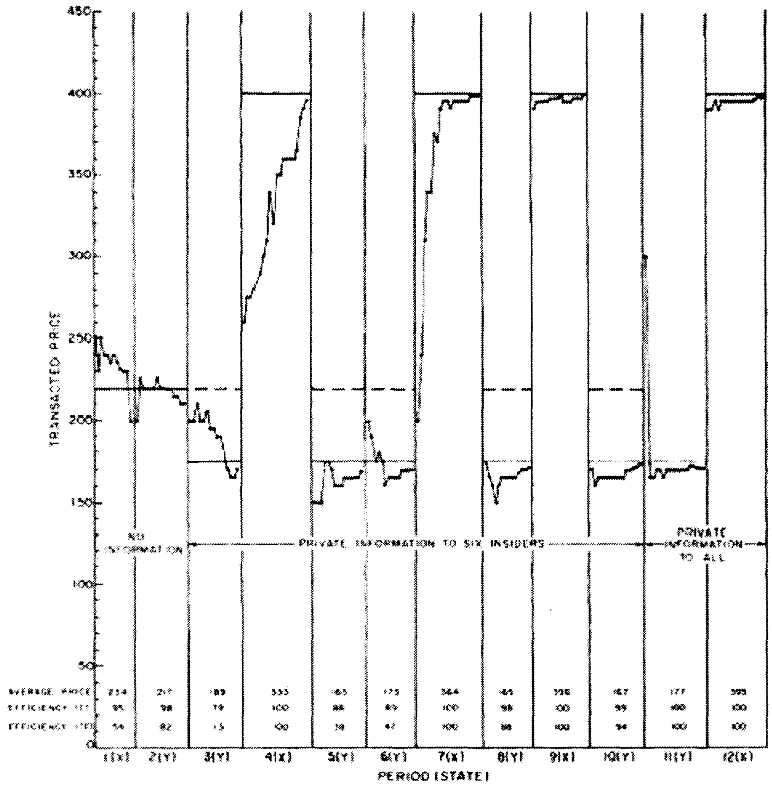

Fig. 4.—Market 3. Time series of contract prices

Fig. 1. Dissemination of Information in Security Markets (Source: Plott and Sunder, 1982, Figure 4)

diately. It takes time for investors to observe, form conjectures, test them, modify their strategies, etc. With repetition, investors get better at learning, but when the environment changes continually, including the behavior of other investors, the learning process may never reach a stationary point.

If markets are efficient in the sense of aggregating and disseminating information across traders, who would pay for costly research? Grossman and Stiglitz [3] and other authors have pointed out this problem. Experiments have helped us understand what actually goes on, and allowed us to better address this conundrum of the efficient market theory: Finite rate of learning makes it possible to support costly research, even in markets which tend toward efficient outcomes. Enough people would conduct research so the average returns to research equal the average cost. Research users have higher gross profits, but their net profits are the same as the profits of the others. As investors learn (in a fixed environment), their value of information decreases because they can ride free on others' information, and the market price of information drops. If the supply of information can be maintained at the lower price, the price drops to a level sustainable by learning frictions. If the supply of information also falls with its price, we get a noisy equilibrium.

After the exposure of misleading research distributed to clients from the research departments of investment bankers in recent years, regulators have sought to separate research and investment banking functions, and in some cases, required investment industry to fund free distribution of investment research to the public at large. The experimental research casts some light on the possible consequences of mandating the provision of free research to investors. It would be difficult, if not impossible, to assess the quality of such "free" research distributed to public. It is not clear if optimal investment in research can be maintained without private incentives to benefit from the results of the research. Mandated free distribution of research is likely to reduce its quality to a level where its price would be justified.

Economic theory tends to emphasize transaction prices as the main vehicle for the transmission of information in markets. Experimental markets show that other observables (bids, asks, volume, timing, etc.) also transmit information in markets. In deep markets, price can be the outcome of information transmitted through these other variables. In period 8 in Figure 1 for example, the first transaction occurs at the RE price. In order to arrive at the RE price, the traders need to learn information. This information transmission has already taken place through other variables before the first transaction of the period is executed.

Derivative markets help increase the efficiency of primary markets. Forsythe, Palfrey and Plott [1], in the first asset market experiment, showed that futures markets speed up convergence to equilibrium in the primary market (Friedman et al. [2]. Kluger and Wyatt [5] found that the option markets increase the informational efficiency of the equity market.

Traditionally, market efficiency has been defined statistically: if you can't make money from information (past data, public, or all information), the market is deemed to be efficient. Experiments have revealed that statistical efficiency is a necessary but not a sufficient condition for the informational efficiency of markets. The last four periods of the market depicted in Figure 2 from Plott and Sunder [8] are efficient by statistical criteria but are not informationally efficient. Just because you can't make money in the market does not mean that the price is right. Even when investors know that the price is not right, they may have no means of profiting from that knowledge.

5 What Is Next?

The above paragraphs give a highly selective summary of what we have learned from experimental asset markets. What is coming up next? The existence and causes of market bubbles is a perennial subject in financial economics. What might we learn about bubbles from experiments? Smith, Suchanek and Williams [9] showed that bubbles can arise in simple asset markets with inexperienced subjects, and tend to diminish with experience. Lei, Noussair and Plott [6] showed that bubbles can arise even when investors cannot engage in speculative trades. They suggest that bubbles can arise from errors in decision

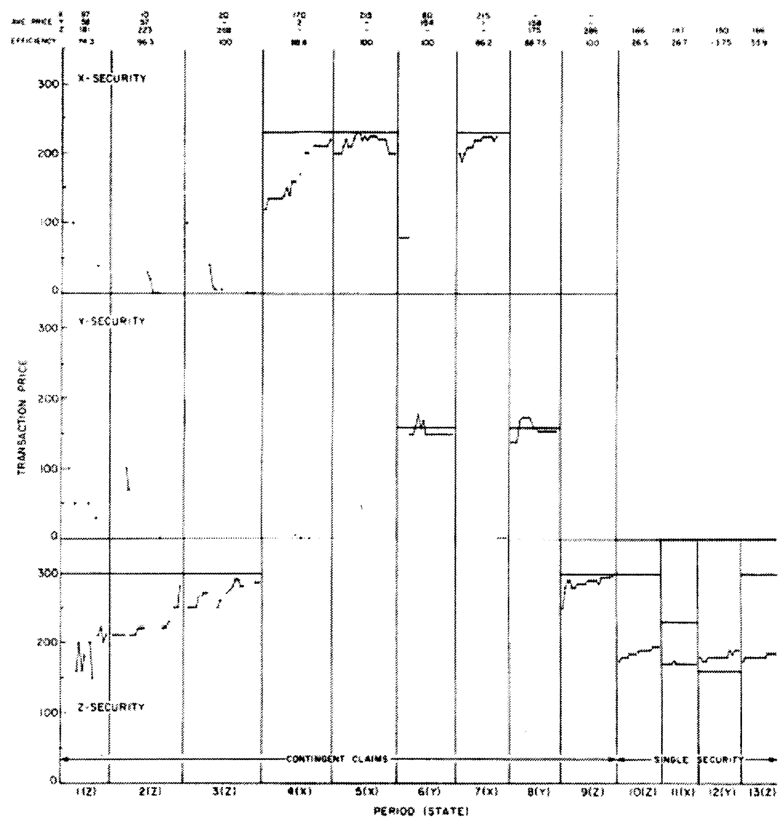

FIGURE 4.—Market 4-CC and 4-S transaction prices.

Fig. 2. Aggregation of Information in Security Markets (Source: Plott and Sunder [8], Figure 4)

making even in absence of a lack of common knowledge of rationality ("bigger fool" beliefs).

A recent experiment by Hirota and Sunder [4] explores the possibility that the fundamental economic model of valuation (DCF) may become difficult to apply in markets populated by short term traders. When a security matures beyond investment horizon, personal DCF includes the sale price at that horizon. The sale price depends on other investors' expectations of DCF beyond the investor's own horizon. Applying DCF involves backward induction from the maturity of the security through the expectations and valuations of the future "generations" of investors. Bubbles can arise, even with rational investors who make no errors, if they cannot backward induct the DCF. In their eleven experimental sessions, they found that bubbles arise consistently when the markets are populated with investors with short term investment horizons, and do not arise with long term investors.

DCF valuation model makes heroic assumptions about the knowledge necessary to do backward induction. Even if investors are rational and make no mistakes, it is unlikely that they can have the common knowledge necessary for the price to be equal to the fundamental valuation in a market populated by limited horizon investors. Not surprisingly, the pricing of new technology, high growth, and high risk equities are more susceptible to bubbles. In such circumstances, if we do not have common knowledge of higher order beliefs, testing theories of valuation becomes problematic.

This is only a thumbnail sketch of some experimental results on asset markets. We have not discussed many other important and interesting studies (for a more comprehensive survey, see Sunder 1995 in Kagel and Roth's Handbook of Experimental Economics). As the experimental camera focused on information processing in asset markets, the theoretical line drawing has been filled by details, shadows, color, and warts. This finer grain portrait of asset markets confirms the rough outline of the extant theory.But it is considerably more complex, and is providing guidance and challenges for further theoretical investigations of interplay of information in asset markets.

It is a unique experience to watch trading in an experimental asset market. You know all the information, parameters, and alternative theoretical predictions. Yet, what you see often surprises you, forcing you to rethink, and discover new insights into how these markets work. Experimental asset markets are our LEGO sets. Playing with them produces new ideas, and helps us sort out good ideas from the bad ones. I would have preferred to have you sit in my lab and experience all this yourself, instead of talking to you because students who participate in these markets gain a sophisticated understanding of the markets.

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