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Advice and Fictive Learning: The Pricing of Assets in the Laboratory

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Advice and Fictive Learning:
The Pricing of Assets in the Laboratory

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Abstract: A burgeoning literature in the neurosciences suggests that individuals modify their behavior not only in response to their own experiences, but also from what they learn about the experiences of others engaged in similar tasks. Importantly, these different forms of learning are associated with common neurological processes. We explore whether others' advice provides a fictive learning signal that substitutes for one's own experience. We examine this question in an environment where inexperienced traders frequently perform poorly – an experimental asset market. Prices in sessions with advice tend towards fundamentals mitigating the severity of price bubbles. Further, advice allays behaviors shown to yield bubbles in prior studies. Taken jointly, our data suggest that advice triggers fictive learning which helps agents avoid the "mistakes" made by naïve counterparts.

Keywords: asset markets, laboratory experiments, advice, fictive learning

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There is substantial evidence that the decisions of experienced agents in a marketplace differ systematically from those of their inexperienced counterparts. For example, Genesove and Mayer (2001) find that evidence of loss aversion in real estate markets is attenuated when examining the behavior of agents handling their own property. In financial markets, costly errors made by retail traders are often reduced or eliminated amongst market professionals (Odean, 1998; Grinblatt and Keloharju, 2001; Locke and Mann, 2005). Similar results have been obtained in a variety of experimental settings (Knez et al., 1985; Smith, Suchanek, and Williams, 1988; Myagkov and Plott, 1997; List, 2003 and 2004; Alevy, Haigh, and List, 2007).

Yet direct experience in the marketplace is not the only means through which individuals can learn to avoid potentially "costly" behaviors. In this study, we make use of experimental methods to investigate the causal impact of others' advice on individual behavior and aggregate market outcomes. We frame our question in the context of asset pricing in financial markets since prior work highlights that both observation of others' behavior and information obtained from outside sources – i.e., others in our social network, electronic and print media, paid advisors – can affect individual trader behavior and overall market outcomes (see, e.g., Shiller and Pound, 1989; Bjerring et al., 1993; Desai and Jain, 1995; Antweiler and Frank, 2004; Hong, Kubik, and Stein, 2005; Mizrach and Weerts, 2009).

Cumulatively, these studies emphasize that market participants make use of a plethora of information to assist decision-making. Some of this information takes the form of public announcements designed to reach as many market participants as possible (see, e.g., Antweiler and Frank, 2004; Bjerring et al., 1993; Mizrach and Weerts, 2009). Yet, many "advisors" target their advice more carefully, for example, identifying and suggesting strategies within a proprietary trading firm. We focus on the latter case in which an advisor has a proprietary interest in the trading outcomes of the advisee.

Although much can be gleaned from the extant literature, the causal impact of others' advice on individual behavior and overall market performance remains an open question. Existing studies lack the data needed to identify causal links between the content of outside information, its use by individual agents, and subsequent market outcomes. We overcome these difficulties through exogenous variation in the availability of advice in a controlled setting. As asset values are induced (and hence known), we are able to test the hypotheses of interest without the need to assume and specify a particular pricing model.

Our study implements the intergenerational advice framework of Schotter and Sopher (2003) in an environment where naïve (inexperienced) traders frequently make costly mistakes – an asset market modeled on the seminal study of Smith, Suchanek, and Williams (1988; SSW hereafter).[2] In this framework, a sequence of non-overlapping "generations" of players participate in a stage game for a finite number of periods and are replaced by other agents who continue the game in the same role for an identical length of time. Players in generation t can "communicate" with their successor in generation $t + 1$ by leaving them written advice. Compensation is a function of both own performance and the performance of the successor in generation $t + 1$, creating an incentive to leave valuable advice.[3]

[2] SSW (1988) demonstrate that when such markets are populated by inexperienced agents, prices frequently deviate from fundamental values and follow a path that can be construed as a price "bubble" followed by a "crash". However, with repeated experience amongst a common cohort of traders, bubbles are mitigated and prices approach fundamentals. The robustness of this result is highlighted in Porter and Smith (2003) who review more than 70 treatments and note that, "…to date, only common group experience provide minimal conditions…for trading at fundamental value." Explorations of this result continue today with recent work showing that bubbles may be mitigated by providing instruction or information on the nature of the dividend process (Lei and Vesely, 2009; Huber and Kirchler, 2012; Sutter et al., 2012), subject to concerns about common knowledge of the instruction process (Cheung et al. 2012).

[3] In many regards, our framework shares similarity with programs within proprietary trading firms whereby senior traders have the opportunity to advise, mentor, and coach a new trader (or group of traders) for a share of the profits

We implement treatments in which the stage game is a trading session in the SSW asset market, and create links connecting up to three generations of traders. We include a number of sessions in which only a subset of agents in period $t + 1$ receive advice from a predecessor yielding mixed markets of advised and unadvised traders. Our treatments also vary the information provided to the subsequent generations of traders. In some sessions, traders observe ***both*** the written advice and detailed information on the market activity of their predecessor – including a graphical depiction of prices for all transactions in the session from which the advice came. In other sessions, traders observe ***only*** the written advice.

The implementation of mixed markets enables a comparison with the work of Dufwenberg, Lindqvist, and Moore (2005; DLM hereafter) who show that prices in markets that have converged to fundamentals remain close to such benchmark when a subset of experienced traders is replaced by naïve counterparts. Heterogeneity in the information provided allows us to draw conclusions about the relative importance to advisees of advice versus advice that is paired with market history.

Several insights emerge from our experiment. First, others' advice influences market outcomes in a manner similar to the acquisition of own experience: deviations from fundamental values diminish rapidly from generation to generation. Between the first and second generation of play, bubble measures fall by approximately 40 to 80 percent whether traders received both advice and history or advice only. Moreover, we find no discernable differences across markets where only a portion of traders receive advice and those where all nine traders are advised – a result consonant with the mixed experience markets from DLM (2005). However, our data

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earned by their advisees. For a more detailed description of such a program, we refer the interested reader to http://www.kershnertrading.com/shared_success/coaching.shtml advance this literature by demonstrating that mixed markets can *generate* convergence towards pricing at market fundamentals, not merely sustain it once has been achieved.

Second, we find that advice is largely reflective outlining trading strategies that are profitable in markets where prices follow the pattern of a bubble and subsequent crash. As successors follow this advice, they avoid the types of momentum trading strategies that have been shown to yield bubbles in prior studies (see, e.g., SSW, 1988; Lei, Noussair, and Plott, 2001). Moreover, agents in successor markets are more responsive to deviations from fundamentals and the resulting arbitrage possibilities.

Taken jointly, these data suggest the underlying mechanism by which advice influences market behavior – it triggers counterfactual (or fictive) learning. Under fictive learning, subjects evaluate actions based on the difference between actual returns and those which could have been experienced if another action had been taken. Importantly, a growing body of literature in the neuro-sciences highlights that individuals learn not only from their own experienced rewards but also from the rewards obtained by others engaged in similar tasks (Canessa et al, 2009, 2011; Burke et al., 2010). Hence on a neural basis, the actions of others are a close (if not perfect) substitute for one's own experience. They provide fictive learning signals that trigger activity in areas of the brain known to process experienced rewards and guide subsequent decisions (see, e.g., Lohrenz et al., 2007; Hayden et al., 2009; Canessa et al., 2011).[4]

In our setting, others' advice provides a fictive learning signal. Observed messages condition traders to expect the pricing dynamics of a bubble and draw their attention to strategies that are profitable in such markets – i.e., buy shares in early periods when prices are low and sell

[4] Lohrenz et al. (2007) use a sequential investment game and show that both realized earnings and those that could have been realized if the subject had changed their investment decision (a fictive learning signal) are important drivers of investment levels. Canessa et al. (2011) use a simple gambling task and show that observed choices (and hence risk-tolerance) depend critically on both experienced and fictive learning signals.

shares in the middle periods before prices crash. As such strategies are akin to those followed by a fundamentalist – buy (sell) whenever prices are less than (greater than) expected value – prices converge towards fundamentals and the severity of bubbles diminish.[5]

Finally, our data suggest that the returns to advice accrue at the market rather than at the individual level. While advised and unadvised agents earn statistically similar amounts, we observe a significant reduction in the variance of payoffs across agents in sessions with advice. In this regard, our data are at odds with the existing literature on the returns to experience in constant sum games such as asset markets (DLM, 2005) and p-beauty contests (Slonim, 2005). However, our results are consonant with insights from List and Price (2005) who find that while buyer experience is a catalyst to thwart anticompetitive pricing, the returns to such experience accrue at the market level in the form of lower prices for all traders.

I. Experimental Design

Since our interest is in studying whether advice influences market outcomes, we use a market structure that has reliably yielded pricing "anomalies" (bubbles) in previous experiments; parameters that are consistent with Design 4 found in SSW. Table I details the initial endowments, dividend payouts and other aspects of this particular market structure. Each market consists of nine traders all of whom are endowed with both cash and assets. The endowments are equal in expected value, but are heterogeneous across traders in that some receive more cash and others more assets.[6] Initial allocations are private information and traders are not told the underlying distribution from which the allocations are drawn. Final payments to the

[5] This underlying mechanism is similar to that observed in Haruvy, Lahav, and Noussair (2007) who examine the role of expectations on market behavior. In their study, traders are shown to base expectations on prior history and thus overestimate the timing of market peaks. However, individuals would best-respond to these beliefs by reducing the number of purchases and increasing the number of sales prior to anticipated price peaks. As expectations were adaptive across replications of the stage-game, prices and expectations ultimately converge towards fundamentals.

[6] Heterogeneous endowments is one element of asset market design that been shown to reliably yield price bubbles in previous experiments.

experimental subjects are based on a conversion to US dollars at the rate of 1.5 cents per experimental cent. Payments averaged $19.50 for a session lasting approximately 90 minutes.

At the start of each session, subjects were seated at linked computer terminals that were used to transmit all decision and payoff information. The experiment was conducted with software hosted by the Econport digital library (Cox and Swarthout, 2006). Once subjects were seated and logged into Econport, a set of instructions was distributed. Subjects were asked to follow along as the instructions (located in Appendix 1) were read aloud.

Each session, or stage game, consists of a fifteen-period trading horizon with assets paying a state contingent dividend at the end of each period. The dividend value is common across all assets within a period and represents an independent draw from the set {0, 8, 28, 60} experimental cents. As each possible dividend is drawn with equal probability, the expected value of the dividend in each period is 24 experimental cents. The underlying distribution from which dividends are drawn is common knowledge amongst all traders and continuously displayed on the trading screen. Given this information, traders can readily calculate the *fundamental value* of the asset which is the expected value of the dividend from the current period, t, to the end of the session or $(16-t)*24$ cents.[7]

Traders were able to enter bids and offers at specific prices, and to enter market orders for immediate execution at the best available prices. The market was closed book, i.e. bids and offers off-the-market remain in a queue, however only the current best bid and offer are observed. Throughout a period, traders could retract any off-the-market bid or offer. Following

[7] The fundamental value of the asset in each period is provided in the experimental instructions and is also continually displayed on the trading screen.

each transaction the highest bid (lowest offer) in the queue became active and could not be retracted until it was replaced by a higher bid (lower offer).[8]

The link between generations was created by allowing subjects in the first- and second-generation sessions to provide written advice to the next generation of traders. Subjects were largely unconstrained with regard to the content and amount of time they could take in preparing the written advice.[9] In addition to the written advice, two additional pieces of information were provided to traders in the second and third generations of our advice plus history treatment. The first was a graphical depiction of the prices for all transactions in the session from which the advice came. The second was detailed information on the market activity of their advisor including (i) the prices for all bids, offers and trades, (ii) the volume of asset and cash holdings throughout the session, and (iii) final earnings for the session. The experimental instructions in Appendix 1 provide further details on the available information and its transmission.

Treatment Design

A total of twenty-eight sessions were conducted at the University of Nevada – Reno, and the University of Alaska Anchorage using 234 student subjects, none of whom had previous experience trading in experimental asset markets. Table II summarizes the key features of our experimental design along with the number of participants in each treatment. As noted in the table, there were three sessions conducted as first-generation, or progenitor sessions, in which traders received no advice but left written advice for those that followed. These progenitor sessions were linked with seven second-generation sessions and eleven third-generation sessions. Traders received advice from the generation of players immediately preceding them and no

[8] We employed a closed book as this design feature has been shown to encourage price bubbles in prior work (see, e.g., Caginalp, Porter and Smith, 2001).

[9] Subjects were not allowed to (i) use profanity, (ii) identify themselves or (iii) suggest meetings outside of the lab. All subjects elected to provide some form of written advice.

advice was left by the third generation. The number of traders who received advice in the second- and third-generation markets varied across sessions. In the partial advice sessions either three or six traders received advice.[10] Figure 1 contains a schematic of the linked sessions. To provide a link to the existing literature, we conducted four control sessions in which no advice was received or collected and a treatment where a common cohort of traders thrice repeat the SSW stage game.

Before proceeding to the results section, we should highlight a few important design issues. First, every advice only session has a parallel session where traders received both advice and history. This holds the content of advice constant allowing us to use difference in bubble measures across parallel sessions to measure the importance of history. Second, we were careful to ensure that advice was transferred between traders with identical initial endowments. Similarly, traders in the own-experience session had the same initial allocation of cash and shares in each replication of the SSW stage-game. Finally, the experimental instructions did not divulge the number of traders that would receive advice from a predecessor.

II. Results

The experimental sessions yield a rich dataset of more than 10,000 individual decisions consisting of bids, offers, and trades. We begin our analysis by summarizing aggregate market outcomes and associated measures of bubble size. Figures 2 and 3 illustrate aggregate activity by plotting the median transaction prices and fundamental values across periods for a subset of our experimental sessions.[11] As highlighted in the figures, bubbles occur in the first generation

[10] Traders were informed, truthfully, that there was a positive probability that their advice would be used in a future session. For sessions followed by a partial advice session it was not possible to use all advice and subjects were randomly assigned to a predecessor that had the same mix of assets and cash in their initial endowment.

[11] The remaining sessions are similar in substance to those presented, and the complete set of figures is available on request from the authors. [and included in appendix for purposes of review]

markets: median transaction prices are below fundamental values in early market periods and follow the basic dynamic of a pricing bubble and subsequent crash.

Figure 2 depicts the influence of others' advice on aggregate market outcomes. The left-hand panel illustrates the path of prices for the progenitor session. Panels on the right-hand side depict price paths for second- and third-generation markets linked to the progenitor. As noted in these figures, the severity and duration of bubbles is diminished when traders receive advice from an immediate predecessor – prices are closer to fundamental values in early market periods and peak at much lower levels in the middle periods.

To confirm that advice serves to attenuate asset price bubbles, we examine three measures of bubble size employed in previous experimental settings; (i) price amplitude, (ii) normalized absolute deviation, and (iii) total dispersion.[12] Table III summarizes these bubble measures for our various experimental treatments. Cell entries in Table III can be read as follows: the average amplitude (normalized deviation) is 4.44 (9.06) in markets populated by inexperienced agents (pooled data). As all three measures are significantly different from zero at the $p < 0.05$ level using a one-sample t-test, the data suggest the presence of a price bubble in such markets. However, as a common cohort of traders acquire experience by repeating the SSW stage game, bubble measures are reduced. For example, measures of amplitude are

[12] The measures differ as follows: (i) *Amplitude* measures the difference between the largest and smallest percentage deviations of the mean period trade price from fundamental value in a session. It is calculated as: $Amplitude = \max_t\{(P_t - f_t)/f_t\} - \{\min_t (P_t - f_t)/f_t\}$, (ii) *Total dispersion* is the sum of the absolute value of the deviation of the median price from the fundamental value in a period, summed across all periods: $Total\ Dispersion = \sum_t |medianP_t - f_t|$, and (iii) *Normalized Deviation* is the sum of the absolute value of differences between all trading prices in a period and the fundamental value, summed across all periods, and therefore captures both price and quantity characteristics of the bubble: $Normalized\ Deviation = \sum_t \sum_i |P_{it} - f_t| \big/ 100 * TSU$. For all three measures larger values indicate larger deviations from fundamental values, so the measures will increase when trading prices are less than as well as greater than fundamental value.

approximately 42.8 percent (66.9 percent) lower in the second (third) round of our own-experience sessions than those observed in round 1.

We observe similar reductions in our advice treatments. Measures of amplitude are approximately 66.0 percent (71.1 percent) lower in second generation (third generation) markets than those observed in our progenitor sessions – reductions that occur whether all nine or only a subset of traders receive advice from a predecessor. Moreover, we observe only small differences in bubble measures across "advice only" and "advice plus history" sessions. Using either a Mann-Whitney U-test or a matched pairs t-test, we are unable to reject the null hypothesis that measures of Amplitude and Normalized Deviation are equal across these treatments. When examining Total Dispersion, the matched pairs t-test suggest that the measure is significantly smaller in the "advice only" treatment.[13]

Perusal of the data presented in Table III suggests a first set of results:

> *Result 1a: Price bubbles form in markets populated by subjects that have no prior experience trading in an experimental asset market. The severity of price bubbles is attenuated when a common cohort of traders repeat the SSW stage game.*

> *Result 1b: The severity of price bubbles is attenuated when inexperienced traders are linked to and receive advice from an immediate predecessor.*

> *Result 1c: The convergence of prices towards fundamental values holds whether only a subset or all traders in a session are linked to and receive advice from an immediate predecessor.*

[13] The sessions matched for these statistical tests are those that received identical advice. To shed further light on the importance of history we incorporate treatment dummy variables in several of our conditional tests of bubble size.

Result 1a conforms to previous studies (see, e.g., SSW, 1988; Porter and Smith, 2003; DLM, 2005) and provides a useful benchmark against which to evaluate the impact of inter-generational transfers of advice. The remaining results are novel to the literature and highlight a similarity between the receipt of others' advice and the acquisition of own-experience.

In this regard, our results extend to a market setting prior work showing that others' experience is a close substitute for own-experience when considering individual decision tasks (see, e.g., Canessa et al., 2009, 2011; Burke et al., 2010).[14] Moreover, Result 1c extends insights from DLM (2005) who found that trading at fundamentals can be *sustained* in mixed-experience markets.[15] Data from our partial advice sessions suggest that markets can *converge* towards fundamentals when only a fraction of all traders are advised.

To augment insights from our unconditional tests, we estimate a series of linear random effects models for the various bubble measures as:

$$B_{\mathrm{it}} = \alpha D_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \qquad (1)$$

where B_{it} is the associated bubble measure for the t$^{\mathrm{th}}$ session in the i$^{\mathrm{th}}$ family of sessions linked to a common progenitor and D_{it} is a vector of indicators for our various experimental treatments. We specify the error structure as $\varepsilon_{it} = \delta_i + u_{it}$ where the random effects δ_i capture important heterogeneity across sessions linked to different progenitors that would be left uncontrolled in a standard cross-sectional model.

[14] We should note that Result 1b shares a degree of similarity with Engelmann et al. (2009) who show that "expert" financial advice impacts decision-making under uncertainty. Yet, our study differs from this work in an important dimension. Engelmann et al. (2009) explore the effect of "expert" advice on an individual decision task – the choice between a certain payment and a lottery.

[15] DLM introduce mixed-experience markets as a fourth replication of an SSW stage game that had largely converged to fundamentals. Hence, they are unable to examine convergence and instead focus on the ability to sustain fundamental pricing.

Table IV provides results for three different specifications for each bubble measure. Model 1 contrasts the reduction in the size of bubbles in markets with advised traders and those trading based on their own experience. This model also provides a comparison the impact of the ‘advice only’ and the ‘advice plus history’ sessions. Model 2 allows the influence of advice to vary according to the number of traders receiving advice. And, model 3 allows the influence of both advice and experience to vary across generations.

Model 1 indicates that measures of amplitude are approximately 49.1 percent (53.2 percent) lower in sessions where traders receive advice from an immediate predecessor (are experienced). We observe similar reductions of 59.9 percent (62.2 percent) for measures of total dispersion and 66.5 percent (54.9 percent) for measures of normalized deviation. All of these reductions are significant at the $p < 0.05$ level lending statistical support for results 1a and 1b. Moreover, we find no significant differences in the magnitude of the coefficients across the ‘advice only’ and ‘advice plus history’ treatments for any of the measures of bubble size. We therefore pool these treatments in the remaining regression models.

Results from model 2 provide statistical support for result 1c: the reduction in bubble measures holds whether three, six, or all nine traders receive advice. For example, as indicated in column 8, the measure of normalized deviation is reduced by 59.2 percent when all nine traders are advised. The corresponding reduction when only three (six) traders receive advice is 82. percent (69.6 percent) with all three of these differences significant at the $p < 0.05$ level.

Advice, Price Momentum, and Fundamentals

The measures of bubble size provide strong evidence that advice has an effect on market outcomes. We next examine the path of prices during the course of a session, to shed light on the mechanism through which advice affects market outcomes. We employ an empirical approach that relates price changes across trading periods to momentum arising from imbalances in supply and demand (e.g., SSW, 1988; Lei, Noussair and Plott, 2001). To investigate this relationship we estimate a regression model of the form:

$$P_{it} - P_{it-1} = \alpha + \beta\left(B_{it-1} - O_{it-1}\right) + \varepsilon_{it} \qquad (2)$$

where P_{it} and P_{it-1} are the average transaction prices in session i for periods t and $t-1$ respectively, B_{it-1} is the number of bids in period $t-1$ and O_{it-1} is the number of offers in period $t-1$. In a rational expectations framework with risk neutral traders, α should equal the change in the expected fundamental value of the asset and β should be zero (Tirole 1982). However, in markets characterized by bubbles, β is often positive, indicating that excess demand (supply) leads to higher (lower) prices in the following period.

The first three columns of Table VI present results from a linear random effects regression designed to examine the extent of momentum trading. Across all specifications, the coefficient β is positive and significant in control and progenitor treatments containing naïve agents. However, as indicated in model 2, the influence of excess demand on price changes is significantly reduced in second and third generation markets. Model 3 indicates that reductions in momentum trading are primarily associated with the full advice sessions.

Exploring this result a level deeper, we find that differences in activity by advised traders are largely responsible for the observed changes in momentum trading and subsequent pricing dynamics. At market opening, advised agents are the first to act at in each of our mixed markets and are more likely to enter on the buy side with their first activity. In fact, advised traders account for approximately 61.2 percent of all bids during the first minute of round one – a proportion that is significantly different than would be expected if trader types were equally likely to submit a bid. Moreover, the average bid submitted by advised traders in round one is dramatically and significantly higher than that observed in our control and progenitor sessions (210.6 versus 36.26). This leads to higher initial transaction prices in treatments with advice and a subsequent reduction in both the average number of bids (13.55 versus 19.04) and associated trade volume (7.8 versus 9.2) over the first five trading periods.

Examining the relationship between price movements and departures from fundamental values provides additional evidence on the impact of advice. To this end, we modify equation 2 and regress the change in average prices between periods *t* and *t-1* on the one-period lagged difference in the average price and fundamental value, ($p_{t-1} - FV_{t-1}$). The final three columns of Table VI present results for a series of linear random effects models designed to examine the influence of fundamentals on price changes.

Across all model specifications, the coefficient on the lagged departure from fundamentals is negative and statistically significant, meaning that prices move towards fundamental values after deviations. For example, model 4 indicates that if prices in period *t-1* are 100 cents greater than fundamentals we would expect average prices to decline by approximately 20 cents in the following period. Model 5 indicates that adjustments are much more pronounced in markets with advised traders. For every dollar prices exceed fundamentals in period *t-1*, the decline in a second (third) generation market is approximately 51 cents (47 cents) more than that expected in a market populated by naïve counterparts – differences that are significant at the $p < 0.05$ level.

Combined the data in Table VI suggest a second set of results:

> *Result 2a: Naïve agents exhibit the type of momentum trading that has been shown to generate bubbles in previous studies. Advice serves to mitigate such tendencies.*

Result 2b: Advised agents are more responsive to deviations from fundamentals than unadvised counterparts.

Results 2a and 2b share similarity with Engelmann et al. (2009) who show that the receipt of "expert" advice serves to change the probability weighting function used by subjects when evaluating risky outcomes.

Taken jointly, our first two results suggest the potential channel through which advice influences market outcomes – it triggers fictive learning. Observing the suggestions of predecessors trading in a market with pricing "anomalies" draws attention to strategies that would have proven profitable in such environments – buying shares in early market periods when prices are low and selling in the middle periods before prices crash. As such strategies are akin to those that would be adopted by a fundamentalist trading in the underlying market, individual behavior becomes more responsive to deviations from fundamentals and driven less by momentum. Thus, the adoption of strategies through fictive learning serves to drive prices towards fundamentals and mitigates the severity of bubbles.

The Content and Evolution of Advice

The first two results consolidate our evidence that advice serves to attenuate the severity of price bubbles. To better understand the underlying mechanism driving this result, we now explore both the content of advice and its evolution across generations. We employed methods similar to those used by Cooper and Kagel (2005) to organize advice into four main categories that include *trading strategy*, *trading tactics*, *price dynamics*, and *fundamentals*.[16] Coding was binary: a message was coded as a one if the advice contained the relevant content and zero

[16] We also observed a number of *other* messages that did not fit easily into one of these four broad categories. Messages in the *other* category included discussion of the mechanics of the trading software, and admissions of confusion and of errors.

otherwise. There were no restrictions on the number of message types that could be coded for in any given advice letter. Coders were allowed to check as many or as few message types as deemed appropriate and the bulk of the messages contained more than one type.

As every progenitor and second-generation trader left advice, we observe a total of seventy-two messages. Table V displays the message categories and their frequency by generation. As noted in the table, the most common type of advice was that discussing trading strategy. Eighty-five percent of progenitors and eighty-seven percent of second generation advisors left advice in this category. A representative quote on trading strategy is, "Buy at first when the market is really cheap. Then sell in the middle when the market is the highest." While such messages do not focus explicitly on fundamentals, they describe a heuristic akin to that of a fundamentalist trading in the markets from which the advice was generated – i.e.., buy (sell) in periods when prices are less than (greater than) expected value.

Advice related to price dynamics was similar in content to the trading strategy messages, but lacked specific suggestions for trade entry and exit. These messages tend to simply report on what traders observed during their session. A typical price dynamics message from a progenitor session stated that, "…prices were inexpensive in the beginning…you will notice an increase in prices as the phases go by…in the ending phases the prices significantly dropped." Despite the absence of specific trading strategies, price dynamic messages help traders envisage the dynamics of a bubble, and thus to better respond to market prices. As one would expect, the frequency of advice based on pricing dynamics declined as bubble size decreased – second generation advisors were 46.2% less likely to leave advice coded as such.

Messages that explicitly mention market fundamentals are observed less frequently – only 26% of traders in our progenitor sessions leave such messages. However, messages reflecting fundamentals increase across generations; such messages are 38.5% more likely to arise from traders in second generation markets. Examples of this type include, "…the key to doing well is the EXPECTED VALUE sheet they will give you at the beginning…as long as prices are below the expected value, buy…" and "…try to sell your shares at more than their holding value…if you do the math, you are making more money than they are worth in dividends…"

To summarize, we find that the content of advice is largely reflective rather than sophisticated; few messages suggest that the transmission of advice will alter market dynamics. In this regard, our data suggest that messages provide fictive learning signals and highlight strategies that would have proven more profitable than those pursued by the advice-giver. Messages thus serve to coordinate expectations and drive prices towards fundamentals. Advised traders best-respond to their "beliefs" about future price movements to avoid the types of "mistakes" experienced by their predecessors. Interestingly, this mechanism shares similarities to the evolution of expectations noted by Haruvy, Lahav, and Noussair (2007) as traders gain market experience.[17]

Advice and Trader Compensation

Results 1 and 2 demonstrate that the presence of advised agents affects aggregate bubble measures and market dynamics, causing prices to move towards fundamental values. Yet, observed prices do not perfectly follow fundamentals allowing the possibility that some traders may benefit at the expense of others.[18] Since advice outlines trading strategies that are profitable

[17] In their study, beliefs about future prices were elicited directly from traders in an asset market also based on the SSW (1988) design. Traders' predictions were based on recent price history and therefore biased. However, traders best-respond to such beliefs by reducing the number of purchases (increasing the number of sales) prior to anticipated price peaks. Since expectations were adaptive, prices and expectations converged towards fundamentals.

[18] Recall that in our experiment total available surplus is a constant (the initial cash balances) plus the sum of a randomly determined stream of dividends. As the total number of shares is exogenously fixed, subjects have no influence over available surplus. Their decisions, however, can impact the distribution of rents in the market.

in markets when prices diverge from fundamentals, it is intuitive to expect that advised traders earn more on average than unadvised counterparts. Surprisingly, however, our data suggest no difference in average earnings across advised and unadvised agents. Rather our data suggest that the returns to advice accrue at the market level in the form of lower variation in earnings across agents.

Table VII summarizes average earnings across treatments for both advised and unadvised agents. As noted in Column 1, advised agents in sessions with three (six) agents linked to an immediate predecessor earn approximately 74.7 (58.4) cents less (more) than unadvised counterparts in these markets. Neither difference is statistically significant. However, we observe significantly less variation in earnings for sessions with advice. For example, the standard deviation in earnings for sessions with three (six) advised agents is approximately 53.6 percent (58.6 percent) lower than that in progenitor sessions.

To augment these unconditional results, we estimate a series of linear random effects models for the magnitude of individual earnings. Specifically we estimate:

$$\$_{ij} = \beta X_{ij} + \varepsilon_{ij} \tag{3}$$

where X_{ij} includes a series of indicator variables for advised agents, the average dividend value for session *j*, indicators for the initial cash balance of agent *i*, and the interaction of these variables with the indicator for an advised agent. We assume that the error structure can be written as $\varepsilon_{ij} = \alpha_i + u_{ij}$ with the individual random effects α_i designed to capture unobserved heterogeneity across agents within a session.

Empirical estimates for three different specifications of the model are contained in Table VIII and support our unconditional insights.[19] As noted in model 1, advised agents in our experiment earn approximately 8 cents more than unadvised counterparts although this difference in not significant at any meaningful level. We observe similar results when we allow the influence of advice to vary by generation as in model 2. Neither the approximate 170 cent increase in earnings for advised agents in second generation sessions nor the approximate 95 cent reduction in earnings for such agents in third generation sessions are significant at meaningful levels.

To examine the variation in earnings across agents within a session, we estimate a series of linear regression models for the standard deviation of earnings. Specifically we estimate:

$$Y_j = \gamma X_j + \varepsilon_j$$

where Y_j is the standard deviation in earnings for session *j* and X_j includes a series of indicators for the various sessions with advice. Empirical estimates for two different specifications of the model are contained in Table IX. The specifications differ in that the first model allows the influence of advice to vary according to generation whereas the second allows for the influence to vary with the number of advised agents.

As noted in Table IX, the standard deviation in earnings is approximately 25 percent (55 percent) lower in second (third) generation sessions with the latter of these differences significant at the $p < 0.05$ level. Further, these differences hold for sessions with both partial (six advised) and full advice. The final column in Table VIII provides insights to why the variation in payoffs is lower in sessions with advice – agents with initial cash endowments of 945 experimental cents earn less in such markets. While such agents earn significantly more than

[19] In estimating the model we exclude data from the own-experience session so that we hold constant the experience level of subjects. However, the qualitative nature of the empirical results are similar if we include data from these sessions.

those with lower initial endowments in our control and progenitor sessions, there is no significant difference in earnings across endowments for sessions with advice.

Combined these data lead to a third result:

> *Result 3: There are no differences in the earnings of advised and unadvised agents. The returns to advice accrue at the market level in the form of a lower variation in earnings across agents.*

While result 3 is at odds with insights from DLM (2005) and Slonim (2005), it is consonant with results from List and Price (2005) who find that the returns to buyer experience in collusive markets accrue at the market level in the form of lower prices for all. Such differences suggest that the returns to experience depend on underlying market structure. In markets with prices trading close to fundamentals, the actions of experienced agents can have little impact at the aggregate level. However, experienced agents in such markets may garner better terms of trade and earn greater rents than inexperienced counterparts. In markets trading at prices away from fundamentals, competition among the advised agents influences aggregate market outcomes by driving prices towards fundamentals. This lowers the variance in earnings across agents as it prevents the large gains/losses often associated with the dynamics of a bubble.

III. Discussion and Conclusions

Asset market experiments have provided a number of unique insights into price formation that are difficult to achieve with field data. Although such experimental environments are simplified constructs of naturally occurring markets, the pricing dynamics of a bubble and subsequent crash are readily observed in the lab and have proven difficult to eliminate. Previous results suggest that repeated experience amongst a common cohort of traders is the only reliable means to generate convergence towards market fundamentals. We extend this line of inquiry to examine the influence of others' advice and experience on overall outcomes in markets populated by novice (naïve) agents. In this spirit, we overlay the intergenerational framework pioneered in Schotter and Sopher (2003) on the standard asset market experiment of Smith, Suchanek and Williams (1988).

Data from sessions with intergenerational links yield an important result: others advice is a close substitute for own-experience. Prices move towards fundamentals at a rate similar to that observed in control sessions where a common cohort of traders thrice repeats the SSW stage-game. Moreover, convergence towards fundamentals holds whether all or only a subset of traders in a session is linked to a prior predecessor. Our results thus extend to a market setting prior work showing that others' experience is a close substitute for own-experience with individual decision tasks (see, e.g., Canessa, 2009, 2011; Burke et al., 2010).

However, there appear to be subtle differences when comparing advice and own-experience markets. For example, whereas Dufwenberg, Lundquis, and Moore (2005) find that the experienced achieve greater profits than inexperienced counterparts, we find no impact on earnings at the individual level. Instead our data suggest that advice serves to reduce the variation in earnings across agents in a market.

Examining the content of messages, we find that advice is largely reflective and outlines strategies to profit in markets with pricing dynamics akin to those experienced by the advice giver. This suggests the underlying mechanism through which advice influences behavior – it provides a fictive learning signal and triggers counterfactual learning. Advised traders thus avoid the types of "costly" behavior – i.e., momentum trading – shown to generate bubbles in prior studies. In this regard, the evolution of messages and the associated impact on behavior is similar to that noted for the evolution of expectations in Haruvy, Lahav, and Noussair (2007).

Undoubtedly our research has raised more questions than it has answered. For example, how does advice and trading behavior change once markets have converged to fundamentals? In particular, it is important to examine whether markets converge to the non-trade rational expectations equilibrium or if price bubbles rekindle (see, e.g., Hussam, Porter, and Smith, 2008; Deck, Porter, and Smith, 2011). Examining how traders respond to changes in underlying market fundamentals remains an important question that is largely unanswered in the literature. We suspect that extending our approach across a larger number of generations and to settings with changing fundamentals will further our knowledge in these areas and lead to fresh insights.

Table I: Endowments and Dividend Structure

Number of Traders	Cash Endowment	Asset Endowment	Dividend Structure	Expected Dividend	Fundamental Value per share
3	945	1			
3	585	2	{(0,.25);(8,.25);(28,.25);(60,.25)}	24	24*(16-*t*)
3	225	3			

*The dividend structure is common across all assets, and all periods with ($,p) representing the dividend value and its probability.

Table II: Experimental Design

	Round 1	**Round 2**	**Round 3**
Control	4 Sessions N = 36 Participants No Advice No Future Links		
Progenitor	3 Sessions N = 27 Participants Linked to Immediate Successor		
9 Advice		5 Sessions N = 45 Participants 3 Sessions: Advice and History 2 Sessions: Advice Only Linked to Immediate Successor	6 Sessions N = 54 Participants 2 Sessions: Advice and History 4 Sessions: Advice Only No Future Links
6 Advice		1 Session N = 9 Participants 2 of Each Type Get Advice and History Linked to Immediate Successor	3 Sessions N = 27 Participants 2 Sessions: Advice and History 1 Session: Advice Only No Future Links
3 Advice		1 Session N = 9 Participants 1 of Each Type Gets Advice and History Linked to Immediate Successor	2 Sessions N = 18 Participants 1 of Each Type Gets Advice and History No Future Links
Own Experience	1 Session N = 9 Participants All Participate in Three Rounds	1 Session Same Participants as Round 1 Same Initial Endowment as Round 1	1 Session Same Participants as Round 2 Same Initial Endowment as Round 2

Table III: Summary Statistics - Average Bubble Measures

Sessions	Amplitude	Total Dispersion	Normalized Deviation
All Data Pooled			
Round 1	4.44	2602.94	9.06
Round 2	2.46	1262.22	5.21
Round 3	2.09	889.70	3.11
Advice & History Sessions			
Progenitor	7.23	4353.81	14.01
Second Generation Pooled	2.57	1300.95	3.83
Partial Adv. & Hist. (3)	0.71	691.15	2.76
Partial Adv. & Hist. (6)	5.24	1280.5	3.59
All receive Adv. & Hist.	2.31	1511.04	4.26
Third Generation Pooled	1.93	875.29	3.39
Partial Adv. & Hist. (3)	0.838	489.5	1.84
Partial Adv. & Hist. (6)	2.61	899.94	2.92
All receive Adv. & Hist.	2.33	1236.45	5.41
Own Experience Sessions			
Round 1	4.60	1347.5	9.69
Round 2	2.63	1114.5	5.95
Round 3	1.52	852.95	2.35
Advice Only Sessions			
Second Generation	2.07	1239.25	7.20
Third Generation	2.41	914.64	2.47

Note: Cell entries provide average bubble measures across our various experimental treatments.

Table IV: Random Effects Regression Models for Bubble Size

	Amplitude			***Total Dispersion***			***Normalized Deviation***		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant – Session with Inexperienced Agents	4.44** (0.64)	4.44** (0.56)	4.44** (0.64)	2603.1** (307.1)	2603.1** (300.9)	2603.1** (302.2)	8.87** (1.26)	8.87** (1.24)	8.87** (1.22)
Advice Only Session	-2.12** (0.94)			-1595.7** (449.6)			-5.85** (1.91)		
Advice & History Session	-2.23** (0.84)			-1534.3** (403.6)			-5.84** (1.72)		
Experience Session	-2.36* (1.43)	-2.36* (1.26)		-1619.3** (686.7)	-1619.4** (672.8)		-4.83* (2.86)	-4.84* (2.82)	
3 Advised		-3.65** (1.07)			-2046.4** (576.1)			-7.32** (2.34)	
6 Advised		-0.34 (0.73)			-1501.3** (521.1)			-6.18** (2.13)	
9 Advised		-2.46** (0.74)			-1445.8** (395.4)			-5.25** (1.24)	
Second Generation Advice			-2.01** (0.93)			-1319.8** (442.40)			-4.80** (1.82)
Third Generation Advice			-2.30** (0.84)			-1709.9** (397.2)			-6.82** (1.72)
Second Round Experience			-1.81 (1.92)			-1488.6* (906.6)			-3.06 (3.54)
Third Round Experience			-2.91 (1.92)			-1750.2* (906.6)			-6.66** (3.54)
# of Linked Families	8	8	8	8	8	8	8	8	8
Number of Obs	28	28	28	28	28	28	28	28	28
Log Likelihood	-56.41	-52.81	-56.27	-229.2	-228.6	-228.8	-74.62	-74.16	-73.56

** Denotes statistical significance at the $p < 0.05$ level. * Denotes statistical significance at the $p < 0.10$ level

Note: Cell entries are parameter estimates and associated standard deviations (in parentheses) for a series of linear regression models examining the effect of advice, history, and experience on various measures of bubble size.

Table V: Message Content Categories

	Progenitor	2nd Generation All Agents	2nd Generation Advised Agents Only	2nd Generation Unadvised Agents Only
Trading Strategy	85%	87%	89%	78%
Trading Tactics	67%	62%	67%	44%
Price Dynamics	78%	42%	44%	33%
Fundamentals	26%	36%	33%	44%
Other	63%	67%	69%	56%
Number of Agents	27	45	36	9

Note: Cell entries provide the percentage of agents that left a message in a particular category for their immediate successor.

Table VI: Predicting Average Price Changes – Linear Random Effects Models

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-14.61** (4.18)	-17.50** (3.97)	-16.24** (4.15)	-1.77 (5.59)	4.65 (6.63)	1.66 (6.00)
Difference in Bids and Offers	2.90** (0.45)	4.68** (0.67)	3.82** (0.60)			
Diff in Bids and Offers in 2nd Generation Session		-2.15* (1.38)				
Diff in Bids and Offers in 3rd Generation Session		-3.24** (1.01)				
Diff in Bids and Offers in Session with 3 Advised			-1.98 (1.65)			
Diff in Bids and Offers in Session with 6 Advised			-1.81 (1.81)			
Diff in Bids and Offers in Session with 9 Advised			-2.05** (1.04)			
1-Period Lagged Difference from Fundamentals				-0.29** (0.03)	-0.20** (0.04)	-0.23** (0.04)
Diff from Fundamentals in 2nd Generation Session					-0.51** (0.09)	
Diff from Fundamentals in 3rd Generation Session					-0.47** (0.10)	
Diff from Fundamentals in Session with 3 Advised						-0.42* (0.23)
Diff from Fundamentals in Session with 6 Advised						-0.19 (0.18)
Diff from Fundamentals in Session with 9 Advised						-0.43** (0.08)
Session Random Effects	Yes	Yes	Yes	Yes	Yes	Yes
# of Observations	330	330	330	330	330	330
R-Squared	0.19	.22	.21	0.17	0.20	0.20

** Denotes statistical significance at $p < 0.05$ level
* Denotes statistical significance at $p < 0.10$ level

Note: Cell entries provide estimates and associated standard deviations (in parentheses) for a series of linear random effects models examining the change in average prices across periods. All models specify the error structure as one-period auto-regressive.

Table VII: Average Earnings in Dollars

	All Agents	225¢ Cash Endowment	585¢ Cash Endowment	945¢ Cash Endowment
Control Sessions	1618.3 (957.6)	1677.5 (1077.4)	1232.2 (744.9)	1945.1 (958.7)
Progenitor Sessions	2065.5 (1755.1)	1718.9 (2156.5)	2134.9 (1157.4)	2342.8 (1947.9)
Sessions with 9 Agents Advised	1720.45 (894.3)	1685.0 (1072.3)	1819.9 (925.8)	1656.4 (653.4)
Sessions with 6 Agents Advised	1894.0 (725.4)	1913.8 (557.0)	1530.7 (774.7)	2237.6 (700.4)
Advised Only	1913.6 (654.2)	1828.9 (385.6)	1740.4 (642.2)	2171.6 (852.3)
Unadvised Only	1854.8 (881.4)	2083.5 (856.1)	1111.1 (941.5)	2369.6 (262.3)
Sessions with 3 Agents Advised	1845.5 (814.1)	1418.9 (891.4)	1929.8 (861.9)	2187.8 (521.4)
Advised Only	1795.7 (825.8)	1221.7 (901.8)	2084.8 (977.6)	2080.5 (488.7)
Unadvised Only	1870.4 (831.1)	1517.6 (954.5)	1852.2 (890.6)	2241.4 (573.6)

Note: Cell entries are average earnings and associated standard deviations (in parentheses) observed in our various treatments.

Table VIII: The Determinants of Average Earnings with AK

	Model 1	Model 2	Model 3
Constant	857.7** (269.4)	785.5** (272.2)	741.2** (300.8)
Average Dividend	40.1** (10.4)	43.0** (10.4)	40.1** (11.5)
Advised Agent	8.06 (133.9)		
2nd Generation Advised Agent		170.9 (171.1)	
3rd Generation Advised Agent		-95.2 (149.6)	
585¢ Cash Endowment			-112.3 (245.0)
945¢ Cash Endowment			461.7* (245.0)
Advised Agent with 225¢ Cash Endowment			43.4 (227.0)
Advised Agent with 585¢ Cash Endowment			299.7 (227.0)
Advised Agent with 945¢ Cash Endowment			-318.9 (227.0)
Session Random Effects	Yes	Yes	Yes
Number of Observations	225	225	225
Log Likelihood	-1868.7	-1867.5	-1865.4

** Denotes Statistical Significance at the $p < 0.05$ level
* Denotes Statistical Significance at the $p < 0.10$ level

Note: Cell entries are parameter estimates and associated standard deviations (in parentheses) for linear random effects models examining the determinants of individual earnings.

Table IX: The Variation in Earnings within a Session

	Model 1	Model 2
Constant	1199.6** (146.8)	1199.6** (173.6)
Second Generation Session	-300.4 (207.6)	
Third Generation Session	-660.4** (187.8)	
Session with 3 Advised		-478.6 (296.0)
Session with 6 Advised		-558.2* (268.8)
Session with 9 Advised		-518.1** (207.4)
# of Observations	25	25
R-Squared	0.37	0.26

** Denotes Statistical Significance at the $p < 0.05$ level
* Denotes Statistical Significance at the $p < 0.10$ level

Note: Cell entries are parameter estimates and associated standard deviations (in parentheses) for a series of linear regression models examining the factors that influence the variance in earnings within a session.

Figure 1: Experimental Design - Linked Sessions

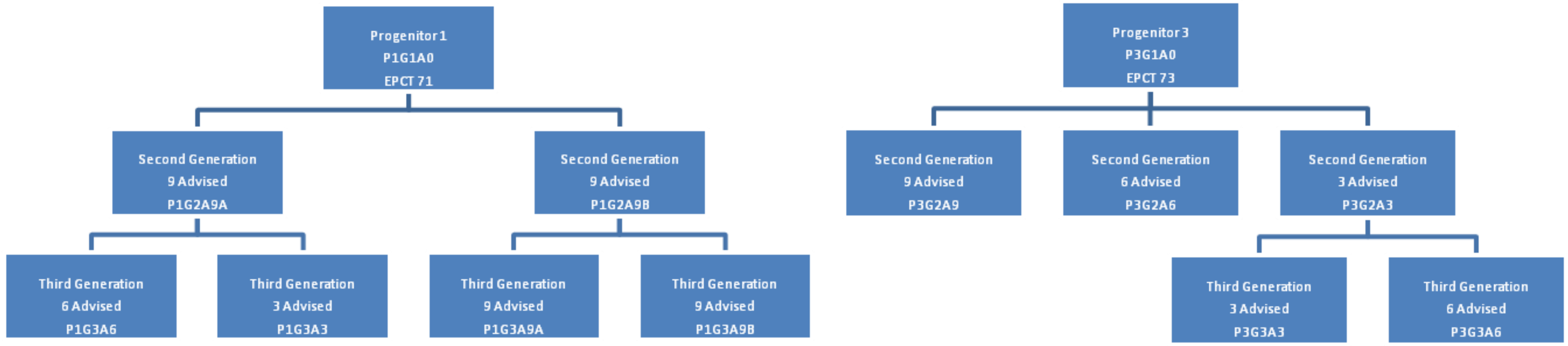
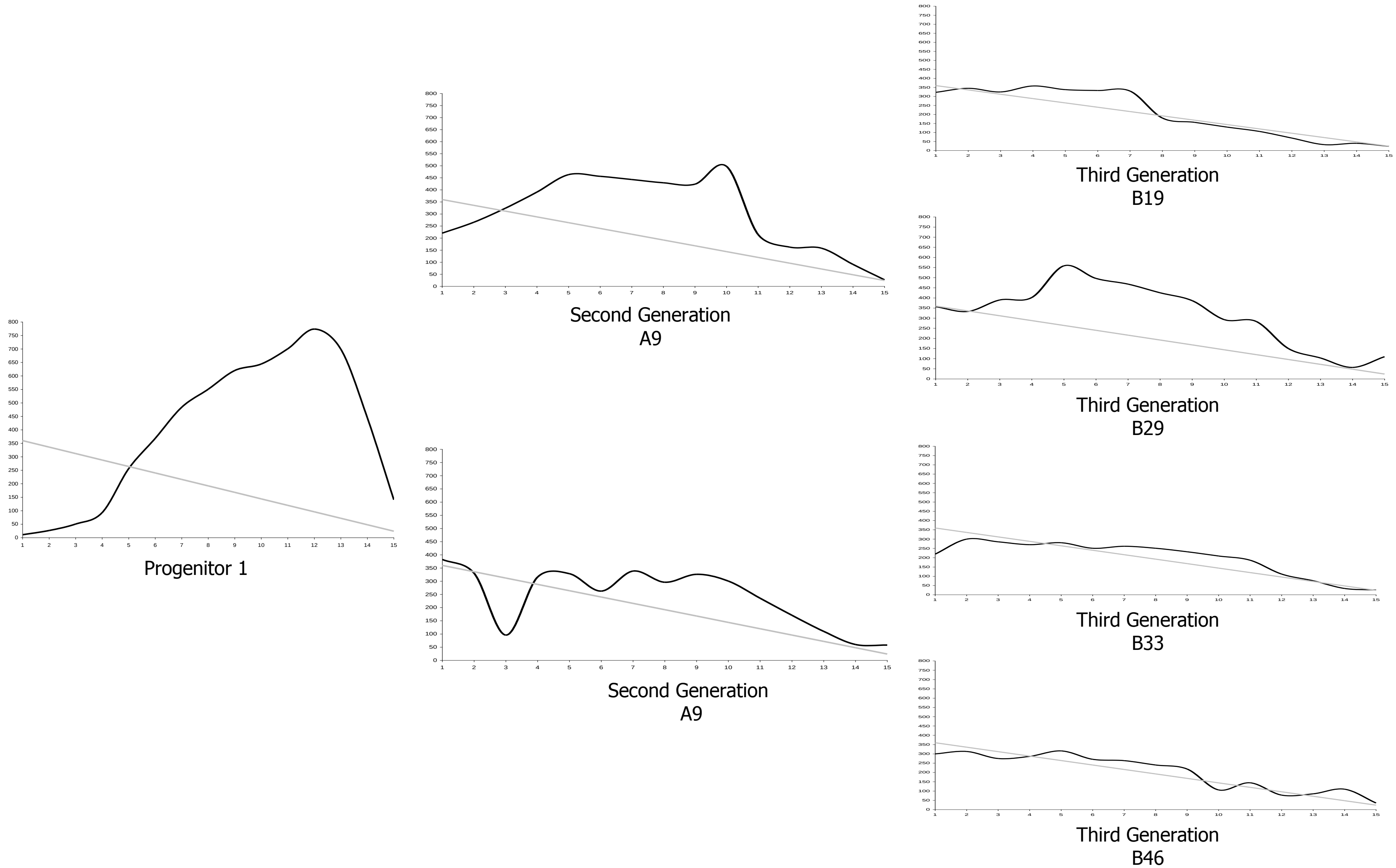
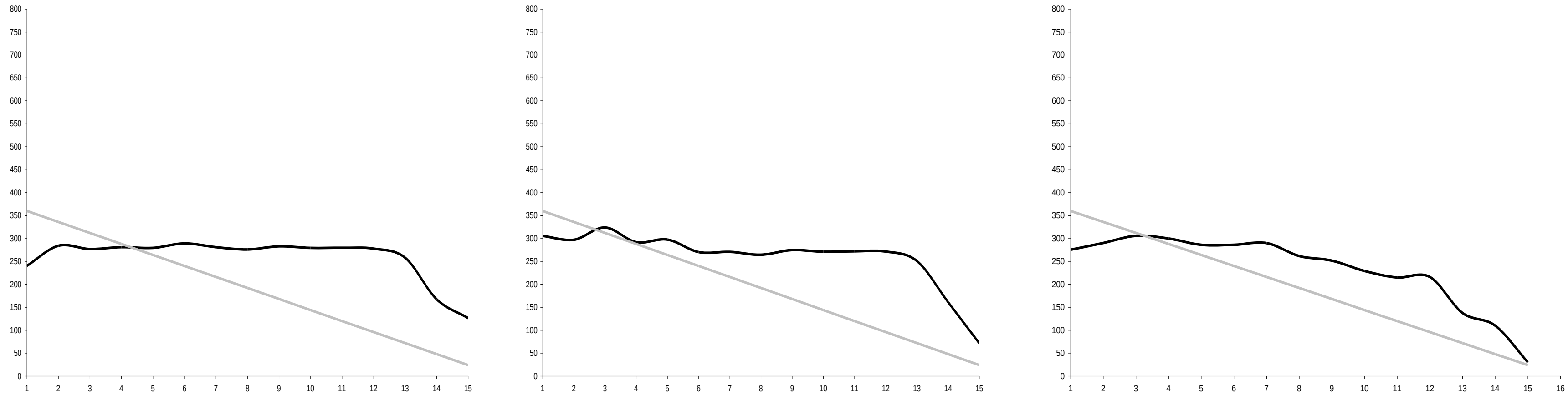


Figure 2: Observed Trading Prices – Advice and History Sessions from Progenitor 1



Note: The figure plots average transaction prices per period and the fundamentals. The scale for the Y-axis is held constant at 0 - 800 cents in each figure.

Figure 3: Observed Trading Prices – Own Experience Sessions



First Round Second Round Third Round

Note: The figure plots average transaction prices per period and the fundamentals. The scale for the Y-axis is held constant at 0 - 800 cents in each figure.

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Appendix 1: Experimental Instructions

General Instructions

This is an experiment in economic decision-making. If you follow the instructions carefully, and make good decisions, you can earn a considerable amount of money. Your earnings will be paid to you in cash at the end of the experiment. The experiment will consist of sequence of trading periods in which you will have the opportunity to buy and sell shares in a market. All trading will be in terms of experimental cents. Experimental cents will be converted into US dollars at the end of the experiment at a rate of $1.50 for every 100 experimental cents you have earned. Your earnings from this portion of the experiment will be added to your earnings from the previous experiment and will be paid to you in cash at the end of the session. Please do not speak with any other participants during this experiment.

Market Description

At the beginning of the experiment, you will be endowed with cash and a number of shares that you can trade. <u>Unless you are in the first group</u> to participate in this experiment, you will also receive written advice on how to make your decisions from an individual who participated in the experiment <u>prior to you</u>. Each of you will receive advice from one participant in an earlier session. Importantly, the advice that each of you will receive comes from a different participant in this earlier session. In addition to the written advice, each of you will receive a chart that depicts the prices for all trades that occurred in this session along with a detailed summary of the trading history for the individual from whom you received the written advice. At the end of the session you will be asked to leave advice to the next group of participants in the experiment.

Your initial cash balance and your initial allocation of shares will appear on your screen at the beginning of the first trading period. Throughout the trading session, the number of shares that you hold and your available cash balance will be displayed on the computer screen. This information will be updated automatically throughout the session whenever your holdings of cash or shares change.

The experiment will consist of 15 trading periods. In each period you can buy or sell shares. Each share is an asset with a life of fifteen periods. Your inventory of shares and your cash balance carries over from one period to the next and each period will last two minutes. A counter on the computer screen will tell you what period you are in and the amount of time remaining in the period. At the end of each period, a dividend will be declared. There are four possible dividend amounts. The amount and probability of each possible dividend are in the table below.

Probability	Amount of Dividend
25%	0¢
25%	8¢
25%	28¢
25%	60¢

From the information shown in the table you should expect that, on average, you will receive a dividend of 24 cents for every share you hold at the end of each period.

$$\text{Expected Dividend} = 0.25 \times 0 + 0.25 \times 8 + 0.25 \times 28 + 0.25 \times 60$$

$$\text{Expected Dividend} = 2 + 7 + 15$$

$$\text{Expected Dividend} = 24$$

The dividend received at the end of each period will be the same for all traders and for each share. For example, if the dividend at the end of the period is 28 cents, you will receive 28 cents for every share that you own. If you own 5 shares, your total dividend payment for the period would then be 5 x 28 = 140 cents. Similarly, every other trader in the market will receive 28 cents for every share that they own. If you do not own any shares your dividend payment for the period will be zero.

The draws determining the realized dividend value in each period are independent of those in all other periods. This means that the probability of a particular dividend at the end of any period is not affected by the dividend received in any previous period nor does it influence the dividend value in any future period. Thus, in every period the probability that any given dividend value is drawn is 25% regardless of what dividend values have been drawn in all previous periods.

At the end of each period a message on your screen will indicate the dividend amount. At this point your cash balance will be updated to include your total dividend payment for the period. For example, if the dividend value for a period were 28 cents and you held 5 shares, your total cash balance at the end of the period would increase by 140 cents – your total dividend payment for the period.

Buying and Selling Units

To buy shares you must have a cash balance greater than the purchase price so that you are able to pay for them. Buying a share reduces your cash balance by the purchase price and you can only buy a single share in any transaction. You may sell any of the shares that you have at any time during a trading period, although you are only able to sell a single share in any transaction. Selling a share increases your cash balance by the sale price.

If you wish to submit a proposal to buy a share (this is called a “bid”) click on “buyer actions” in the lower left region of your screen, enter the price in the white area and click on “bid”. If you wish to submit a proposal to sell a share (this is called an “ask”) click on “seller actions” in the lower left region of your screen, enter the price in the white area and click on “ask”.

When you submit a bid (a proposal to buy), the computer automatically checks whether your bid price is greater than the existing best bid and if you have enough cash to pay for the purchase at a price equal to your bid amount. If your bid is greater than the existing high bid amount and you have enough cash to pay this bid, the current best bid is replaced by your bid in the area marked best bid in the upper left region of your screen.

When you submit an ask (a proposal to sell), the computer checks if your ask price is less than the existing best ask and whether you own at least one share that could be sold. If your ask price is less than the existing best ask and you own at least one share, the current best ask is replaced by your ask in the area marked best ask in the upper left region of your screen.

You can buy a share in two different ways. First you can submit a bid and wait for someone to accept it. Of course there is no guarantee that this bid will be accepted by another seller in the market. Second if you see a best ask price which you would like to accept, click on “buyer actions” and then click on “buy” in the lower central region of the screen.

Similarly you can sell a share in two different ways. First, you can submit an ask and wait for someone to accept it. Again, there is no guarantee that this ask will be accepted by another buyer in the market. Second if you see a best bid price which you would like to accept, click on “seller actions” and then click on “sell” in the lower central region of the screen.

If you buy or sell a share the number of shares you hold and your cash balance will be updated automatically and displayed on your screen. When you buy a share your cash balance will be reduced by the purchase price and when you sell a share it will be increased by the sales price.

The band along the lower edge of your screen indicates the prices at which recent trades have taken place. The band will include information on the transaction prices for up to the most recent six transactions that have occurred in the current trading period. In reading the band, the most recent transaction will be listed on the left hand side. As you move to the right prices reflect transactions made earlier in the period with the oldest transaction listed on the far right hand side of the band.

In this experiment there is a queue. When a better bid or ask replaces an existing bid or ask that has not yet been accepted, this initial proposal remains in the queue but cannot be part of a transaction unless it again becomes the highest bid or lowest ask. Once a transaction occurs, all existing bids and asks remain in the queue with the highest existing bid and lowest existing ask coming to the front of the queue.

During each period, you may buy or sell as many times as you wish provided that you have shares to sell and enough cash to pay for any purchases you make. However you are not required to buy or sell any units.

Holding Value Table

You can use the table on the final page of these instructions to help you make decisions. There are five columns in the table.

- The first column, labeled “Ending Period” indicates the last trading period of the experiment. As there are 15 periods in the experiment, the value in the first column is always 15.

- The second column labeled “Current Period” indicates the trading period during which the average holding value is calculated.
- The third column, labeled “Number of Holding Periods”, gives the total number of periods from the current period in the second column until the end of the experiment. For example, if the current period is period 4 there are 12 periods remaining so the value in column three will be 12.

- The fourth column, labeled “Average Dividend” gives the average dividend for a share. Note, this average value does not change over periods as the dividend values and associated probability remain constant throughout the experiment.

- The final column, labeled “Average Holding Value”, gives you the expected value of dividend payments for a share held from the “Current Period” to the end of the experiment. The “Average Holding Value” is calculated by multiplying the “Number of Holding Periods” times the “Average Dividend”.

Suppose for example, that there are 4 periods remaining. Since the average dividend paid on a share is 24 cents per period, the “Average Holding Value” is simply the expected total dividend paid on this share over these 4 remaining periods or 4 x 24 = 96.

Your Earnings

The payment you will receive is equal to your cash balance at the end of period 15 once it is adjusted for the final dividend payment. Your final payment is thus equal to your initial cash balance plus all dividends received, minus cash you spend on the purchase of shares, plus cash you receive from the sales of shares.

YOUR TOTAL EARNINGS IN THE MARKET = INITIAL CASH BALANCE + ALL DIVIDENDS RECEIVED – CASH SPENT ON THE PURCHASE OF SHARES + CASH RECEIVED FROM THE SALE OF SHARES

Note that you do not have to calculate your cash balance for yourself. The computer will do this for you automatically.

Each of you will be paired with two other individuals who you will not know and who will participate in the experiment <u>immediately after you</u>. These individuals will participate in two different sessions and will receive written advice from you. Importantly, each of the other participants in these sessions will also receive written advice from a participant in this session. Thus each of you will be linked to a unique participant in two future sessions. You will receive a second payment equal to 25% (one-fourth) of the amount that each of your immediate successors earns. You will be told how to collect this second payment at the end of the session today.

Average Holding Value Table

Ending Period	Current Period	Number of Holding Periods	Average Dividend Value per Period	Average Holding Value per Unit of Inventory
15	1	15	24	360
15	2	14	24	336
15	3	13	24	312
15	4	12	24	288
15	5	11	24	264
15	6	10	24	240
15	7	9	24	216
15	8	8	24	192
15	9	7	24	168
15	10	6	24	144
15	11	5	24	120
15	12	4	24	96
15	13	3	24	72
15	14	2	24	48
15	15	1	24	24