The Effects of Liquidity, Information, and Beliefs in Experimental Asset Markets

Daniel Quinn Harper
Lumberton, North Carolina

Master of Arts, Economics, University of Virginia, 2018
Bachelor of Science, Economics, North Carolina State University, 2017
Bachelor of Science, Mathematics, North Carolina State University, 2017

A Dissertation presented to the Graduate Faculty
of the University of Virginia in Candidacy for the Degree of
Doctor of Philosophy

Department of Economics

University of Virginia
May, 2023

Charles Holt
Anton Korinek
Ana Fostel
Bo Sun

Abstract

In the first chapter, I evaluate the effects of credit constraints in an asset market experiment with present value considerations induced by interest payments on cash. [1] All markets exhibit price bubbles, with peak prices exceeding the present value of dividends and redemptions by 30-130 percent. Starting with a baseline condition (low income, tight credit), a relaxation of credit constraints generates significantly higher price bubbles. A price increase of similar magnitude results from an increase in exogenous income, holding credit tightness constant.

The second chapter uses a laboratory experiment to study the channels through which cash and *q* affect the production of capital goods. In the experiment, subjects trade and produce capital goods in a dynamic multi-period market where capital depreciates and is subject to convex production costs. Treatments vary the cost of production, aggregate cash level, and subjects' individual cash holdings. Across all treatments, less than half of subjects' production decisions are consistent with *q*-theory. Aggregate cash is significantly correlated with the likelihood of a subject making an optimal decision. Increasing the level of cash in a market decreases the rate of optimal production decisions. After accounting for the magnitude of previous price deviations, cash in the market has a significantly weaker effect on the rate of optimal decision making. Increased price deviations significantly reduce the rate of optimal decisions, these deviations are increased when cash in the market increases.

The third chapter evaluates the extent to which laboratory markets disseminate private information about durable assets. [2] Subjects trade dividend-paying assets for 15 periods, which are then redeemed for a randomly determined value that is revealed in advance to "insiders." Rational expectations models and the efficient market hypothesis predict prices will incorporate insider information, which precludes bubbles. Markets with both insiders and outsiders exhibit bubbles, with magnitudes uncorrelated with the proportion of insiders. Insiders make more attempts to purchase assets than outsiders, potentially stimulating demand in markets with more insiders. Moreover, insiders make predictions closer to the fundamental value.

---

[1] A portion of this chapter is published as "Capital constraints and asset bubbles: An experimental study," with Lee Coppock and Charles Holt in the *Journal of Economic Behavior and Organization*, volume 183.
[2] A portion of this chapter is included in the working paper "The Efficient Market Hypothesis in Experimental Asset Markets: Private Information, Public Information, and Bubbles," with Charles Holt and Margaret Isaacson.

Signatures

Charles Holt, ______________________

Anton Korinek, ______________________

Ana Fostel, ______________________

Bo Sun, ______________________

Acknowledgements

I would like to thank my dissertation committee chair, Charles Holt, for his advice, mentorship, and guidance. His training has been invaluable in my becoming the scholar I am today. I would also like to thank my second and third committee members, Anton Korinek and Ana Fostel. Their feedback, advice, and assistance have incredibly useful and helpful. I would like to thank Bo Sun for serving as my outside reader on this dissertation committee. Also, I would like to thank Lee Coppock for his mentorship as both a teacher and a scholar. I thank Kenneth Elzinga for his mentorship and guidance professionally and personally.

This dissertation was made possible by the financial support of several organizations and foundations. I would like to thank the International Foundation for Research in Experimental Economics, the University of Virginia Quantitative Collaborative Bynam Grant, the Bankard Fund for Political Economy, and the University of Virginia College of Arts and Sciecnes Dean's Dissertation Completion Fellowship for their generous financial support.

I have been fortunate to receive research assistance from several talented research assistants working in the University of Virginia Veconlab. I would like to thank Margaret Isaacson, Erica Sprott, Sophia Lochner, Madison Smither, Yilin Huang, Julliette Sellgren, Anna Hartford, Madeleine Green, Elizabeth Amorosi, Nicholas Anderson, and Georgia Beazley for their helpful research assistance.

I would like to thank my parents, Eric and Melanie Harper, for their lifelong support and encouragement. They instilled in me a love for learning that has driven me to this throughout my life and education. I would like to thank my brother, Bradley Harper, for his support and encouragement, and always believing in me. I would like to thank my friends Snigdha Das, Paul Miller, Joseph Roessler, Anna Taylor, Tyler Wake, Jacob Walley, and Caitlyn Wetzel. They have been my source of relaxing, companionship, and fun throughout graduate school. Finally, and most importantly, I would like to thank my beloved fiancé Ayessa Marie Aviso Hoybia.

Table of Contents

Introduction

This dissertation uses laboratory experiments to understand aspects of behavior in financial markets. Laboratory experiments allow me to set up financial markets where market conditions can be independently varied, and market parameters can be directly set or measured. My first chapter uses the independent control of market conditions to show that loosening credit constraints and expanding the money supply have similar effects on increasing the magnitude of asset price bubbles. In my second chapter I focus on markets for producible durable goods – i.e., capital. I find that increases in available cash in a market tend to increase aggregate production, and decrease the rate at which individuals make privately optimal production decisions. This analysis is made possible by the measurement opportunities and control over parameters available in laboratory experiments. The final chapter controls individual and market parameters and conditions to find that private information over the long term value of an asset is not disseminated by the market. However, individuals with such information tend to be more active participants in financial markets.

Throughout this dissertation, a key data point will be the difference between various asset prices and the fundamental value. I define the fundamental value as the sum of the asset's future payoffs, discounted by the interest rate. In cases where these payoffs are uncertain, the expectation of the payoffs is used. This expectation is the expected value of the future payoffs based on the actual distribution. The experimental asset markets in this dissertation range from 10 to 20 periods. In these markets, price bubbles are also an important outcome of the market. Price bubbles are prolonged deviations of the asset price from the fundamental value. These bubbles form over the course of the market, and their magnitude is a measure of the efficiency of the market. There are multiple methods of measuring the size of a price bubble, with different methods being preferred in different contexts. However, the aim of all measures is to quantify how far the market as a whole deviated from the fundamental value.

The use of laboratory experiments to study markets for durable assets began with Smith, Suchanek, and Williams (1988) seminal study on experimental asset markets. Their subjects traded shares of an asset that paid a random dividend over several rounds, with the shares having no value at the end of the experiment. These trades were executed at an endogenously determined price. In this experimental design, the fundamental value of the assets declines each period. Smith et al. (1988) observed prices systematically exceeding the fundamental value for sustained periods in their markets. Understanding the reason for these bubbles, and possible ways to abate such bubbles, forms the basis of a large literature on experimental asset markets. One of the core findings of this literature is that increasing the amount of cash in an asset market increases the magnitude of price bubbles (Caginalp et al., 2001). The first chapter of my dissertation shows that not only does increasing the amount of cash in the market increase bubble magnitudes, but that loosening credit constraints in the market also increases these magnitudes. Subjects in the second chapter are able to produce as well as trade asset units. In this setting increasing the amount of cash in the market not only increases price bubbles, as in Caginalp et al. (2001), but it also increases the production of assets.

While the Smith et al. (1988) framework is useful in establishing several results regarding behavior in asset markets, the declining fundamental value provides some limitations and possible confusion to subjects (Kirchler et al., 2012). The experiments presented in this dissertation are based on an experimental design where the fundamental value of assets is flat across the different trading periods in the experiment. This flat fundamental value is induced using the method of Bostian et al. (2005). The key features of the flat fundamental value, are the payment of a positive interest rate on cash holdings, causing future payments to be discounted in present value, and the payment of a final cash redemption value for each asset held at the end of the experiment. When this final redemption value is set equal to the value of a consol with the same dividend probabilities, the fundamental value of the asset will be constant across time. This reduces confusion in subjects in all chapters (Kirchler et al., 2012). It also allows for the addition of production in chapter two, and makes possible the study of long term information in chapter three. In addition to these benefits, this framework has been shown to give qualitatively similar results using professional traders or students as experimental subjects (Weitzel et al., 2020).

Each chapter of my dissertation makes different modifications to the flat fundamental value experimental asset market framework to study novel questions relating to behavior in asset markets. I describe these questions and the main findings of each chapter in the remainder of this introduction.

1. Separating the Effects of Capital Constraints and Income on Asset Bubbles

The first chapter of my dissertation studies the effect of increased incomes and looser capital constraints on price bubbles in experimental assets markets.[3] In economic data, credit

[3] Some portions of this chapter have been published in Coppock, Harper, and Holt (2021).

conditions and income tend to move simultaneously. That is, when incomes fall, such as in a recession, capital constraints tend to tighten (the amount of borrowing banks allow per asset decreases), and when incomes rise, as in a boom period, capital constraints tend to loosen (the amount of borrowing banks allow per asset increases). This makes it difficult to empirically separate the effects of credit constraints and income in naturally occurring financial markets. By separately increasing incomes and loosening capital constraints, in a controlled laboratory experiment, I find that both significantly increase price bubbles.

The experiment in this chapter consists of a 20-period asset market for trading asset shares. Three treatments are used to separate the effects of increasing income and loosening capital constraints. In the baseline treatment incomes are low and traders are not allowed to borrow much per share (limited to 9% of the share price). In the second treatment incomes are unchanged, but traders are allowed to borrow more per share (80% of the share price). Finally, in the third treatment incomes are increased (tripled), and borrowing limits remain the same as in the first treatment. To measure the bubble magnitudes for this chapter I develop a new bubble measure, the positive value deviation (PVD), that weights price deviations from the fundamental value by the number of shares traded in a given period. In the baseline treatment, the average PVD is 35.89, in the second treatment it is 87.48, and in the third treatment it is 91.17. This shows that both increased income and loosened capital constraints increase bubbles (at the 95% confidence level).

In some markets of this experiment, traders were asked to predict the share price for the current period, next period, and two periods ahead. I use this prediction data to show how traders' current period and next period forecasts can be explained using a double adaptive forecasting model. Holt et al. (2017) derived this double adaptive model for current period predictions. I extend their approach, to model next period forecasts as well as current period forecasts. The current period model estimates current period predictions to an average accuracy of 0.57%, and the next period model, which I develop, estimates next period predictions to an average accuracy of 0.28%.

2. Tobin's Q, Liquidity, and Speculation in Laboratory Markets

This study uses laboratory experiments to examine how changes in market fundamentals and cash-on-hand affect decisions to produce new capital – i.e. investment decisions. Theoretically, subject's who are not cash constrained should produce capital until the marginal cost of capital is equal to the market price. This is the core prediction of *q*-theory. In the experiment, subjects trade and create capital goods in a dynamic multi-period market where capital depreciates and is subject to convex creation costs. Capital goods pay a fixed dividend per period and a known redemption value at the end of the market, with dividends and redemption values based on the amount of capital remaining after depreciation. Each period subjects can choose to create units of capital goods at an increasing marginal cost that is based on their individual production decisions. Capital units can also be traded between subjects each period, including the period in which they are created, through a call market. This tests if subjects make decisions consistent with q-theory, which predicts they will produce more units when the marginal cost is lower than the market price.

The results of this experiment are mixed in their support for q-theory. When the marginal cost of production is reduced, subjects produce more capital goods. This increase in production is consistent with the predictions of q-theory. In low aggregate cash environments, the majority of subjects' production decisions are close to the predictions of q-theory. These are both positive findings for the q-theory of investment. However, when aggregate cash is increased, subjects tend to produce significantly more capital units, and make production decisions that are consistently further away from the theoretical predictions. This is in an environment with the same fundamental value of capital, but more cash in the market, and subjects who do not know that another treatment with less cash occurred. In these high aggregate cash markets, capital price bubbles are significantly higher than in low aggregate cash markets. I show that the greater deviations from theoretical predictions observed in high aggregate cash markets can be explained by price bubbles and subjects' persistence in making investment decisions.

The control of a laboratory experiment also allows me to clearly define a first best allocation of capital and capital production. I am able to compare production levels to their first best, and find that increasing aggregate cash increases production relative to the first best. Given the larger price bubbles in high aggregate cash models this is expected, as the first-best solution does not maximize individual profit when prices are above the fundamental value. These results place a strong emphasis on the effects of aggregate cash. The experiment also tests for differences in individual production behavior due to differences in individual cash holdings. I find that individual cash does not systematically affect production decisions.

3. **Evaluating the Efficient Market Hypothesis in Experimental Asset Markets and Analyzing the Effects of Private Information**

The third chapter studies the extent to which the efficient market hypothesis holds in experimental asset markets. In particular, the experiment in this chapter tests whether markets are able to disseminate private information about the long term returns of an asset, given to select traders, "insiders." The strong form of the hypothesis states that "prices accurately summarize all information, private as well as public." (Burton and Shah, 2013 p. 8). This theory is an important assumption about the efficiency of markets underlying numerous finance models. In this experiment, the number of insiders (out of 9 traders) is varied from 1 to 9 in a series of asset markets, while holding the type of insider information constant. I find that the strong form of the efficient market hypothesis does not hold, all markets experience price bubbles. Additionally, there is no significant change in the magnitude of bubbles as the number of insiders increases. Increasing the number of insiders effectively makes the private information more public, so this result is somewhat inconsistent with weaker forms of the efficient market hypothesis.

To better understand these deviations from the efficient market hypothesis, I analyze the individual decisions of traders who attempt to buy or sell shares. This analysis shows that insiders are significantly more likely than outsiders to attempt to buy shares in any given period, and are more aggressive in their attempts to purchase shares. These effects are significant at the 99% confidence level. Insiders' greater likelihood of purchasing shares implies that increasing the number of insiders in a market increases the demand curve for asset shares in that market. Increasing a demand curve weakly increases the price, so this could explain why increasing the number of insiders does not decrease bubble magnitudes.

Despite the lack of a decline in bubble magnitude from increasing the number of insiders, insiders make share price predictions that are closer, than those of outsiders to the fundamental value in periods where price bubbles are at their largest. In these periods, insiders' predictions are 9.22 percentage points closer to the fundamental value than outsiders' predictions. This might be expected to reduce bubbles as the number of insiders increases, since purchase and sale decisions are inherently tied to a trader's price expectations.

Chapter 1: Separating the Effects of Capital Constraints and Income on Asset Bubbles

I. Introduction

Mild recessions become deep contractions when mixed with financial market turmoil. The Great Recession of 2007-9 is a prime example. Some might debate the primary cause of this recession, but few question that financial market problems deepened and lengthened the downturn. The financial turmoil was primarily related to assets tied to real estate markets in the United States. Securitization spread these problems across the globe through financial firms and governments who invested heavily in mortgage debt securities.

The real estate market bubble (and subsequent crash) prior to 2007 was inflated by significant leverage on the part of individuals, financial institutions, and even governments. This insight follows a long line of economists that tie easy credit to subsequent downturns. Tobin (1989) calls leverage "the Achilles heel of capitalism." Similarly, Rajan and Ramcharan (2015) show that credit availability led to higher asset prices prior to the Great Depression and contributed to the severity of the subsequent bust. Schularick and Taylor (2012) examine bank loan data and recessions in 14 countries from 1870 to 2008 and conclude that financial-crisis recessions lead to bigger output declines, followed by slower recoveries. Gjerstad and Smith (2014, pp. 8-11) document the expansion of easy mortgage credit in excess of income increases that is observed prior to most US recessions. They conclude that "leverage cuts deep on the downside."

This chapter presents results from a laboratory experiment that allows participants to leverage their purchases of a risky asset. Since price bubbles tend to occur in good times with high incomes and easy credit, these two factors are changed exogenously, one at a time. Subjects were financially motivated in that cash earnings depended on gains and losses from trading asset "shares," and on randomly determined share dividends. In addition, participants could earn interest on holding a safe asset (lab cash). The final-period "redemption" value of each asset share was structured to generate a present value that is unchanging from period to period, so that price increases above this "flat" fundamental value provide a clear indication of a bubble. Small financial incentives were also used to elicit participants' price forecasts for several periods ahead. Observed forecasts involve some elements of trend extrapolation and speculation, although such forecasts tend to be too low on the upswing and too high on the downswing. The primary result, however, is that easy credit produces larger bubbles and subsequent crashes. This provides support for the idea that tightening of capital and loan requirements might help reduce the risk of a financial collapse, especially in an overheated economy.

The next section summarizes insights from two largely separate literatures on asset market experiments and on the macroeconomic effects of credit conditions. The experiment design is presented in section III, followed by an analysis of the observed price bubbles in section IV. Section V introduces a model for subjects' price predictions, and section VI concludes.

II. Literature Review

The importance of leverage in business cycles is well documented in macroeconomic theory. Kiyotaki and Moore (1997) show how leveraged asset purchases can amplify negative economic shocks, and cause shocks in the collateralized sector to spill over into other sectors. In their model, agents with the highest evaluation of an asset make leveraged purchases of the asset. When they face a negative shock, they sell the asset to buyers with lower evaluations, decreasing the price. In this experiment, traders are forced to sell when an asset's price falls below the amount borrowed using the asset as collateral. The sellers of such assets tend to be the most enthusiastic traders who previously expressed the highest willingness to pay. The buyers of these assets are generally less enthusiastic about the asset price (or they would have purchased the asset at higher prices) and therefore are only willing to purchase at lower prices. This is similar to the amplification mechanism proposed by Kiyotaki and Moore, which illustrates the role leverage can play in triggering a bubble burst and then magnifying the price decline. However, Kiyotaki and Moore are silent on the role leverage plays in pushing asset prices above an asset's fundamental value.

Leverage can also contribute to bubbles since agents value the ability to borrow against an asset. Fostel and Geanakoplos (2008) define this as the "collateral value" of an asset, and develop a generalized model characterizing the collateral value of a leveraged asset. Geanakoplos (2003) uses a simplified example of the Fostel and Geanakoplos model (with two periods and binomial payoffs in the second period) to show that leverage and differing beliefs about the future can cause assets to trade at prices other than their fundamental value. In this context, the ability to leverage an asset effectively creates an Arrow security that pays off in the high state next period, which is bought by the agents who are most optimistic about the future. This setting is more closely related to this experiment, as the arguments used can extend to multiple time periods.

This experiment contains some of the same factors that caused the asset in the Geanakoplos (2003) model to trade at a price other than its fundamental value. Although the final payoff and the probability of high versus low dividends are known in this experiment, traders still differ in their beliefs about the potential capital gains available. The most optimistic traders believe that they can make large capital gains by timing the purchase and resale of assets during a bubble. When these traders make a leveraged purchase of the asset, they are effectively creating a new security that earns a higher anticipated rate of return (on unborrowed cash) than the asset itself. The traders with the most optimistic beliefs about the asset price will be willing to pay more for such a security than the unleveraged asset, pushing the price above fundamental value in periods when the bubble is growing. The mechanism is different from that in Fostel and Geanakoplos (2008) and Geanakoplos (2003) in that the states of the economy are more complex than a binomial environment and subjects are unable to leverage assets to the point that they create an Arrow security. However, the basic mechanism is still present, and could be a factor in explaining any tendency for high leverage to enhance price bubbles.

The key structural prerequisite for generating an asset bubble is the use of a durable commodity that provides utility or dividends over a series of periods. In that case, extrapolation of observed price increases can trigger strong speculative motives that dominate the modest attraction of future dividends. Smith, Suchanek, and Williams (1988) were the first to demonstrate that laboratory markets for durable asset "shares" often generate price bubbles. Their setup includes a known number of periods, T, after which the asset is worthless, and random dividends with a known expected value, D paid at the end of each period, 1, … T. In this case, the fundamental value is D times the number of periods remaining, so that value declines linearly from period to period. The use of a fixed endpoint makes bubble formation even more notable.

The classic Smith, Suchanek, and Williams declining-value setup has been used extensively in a large literature on factors that affect bubble formation. These include prior experience, clarity of instructions, short-selling, gender, testosterone, sleep deprivation, cognitive ability, trading rules, etc.[4] It is suggestive that bubbles are more pervasive in settings with high

[4] This literature is surveyed in Palan (2013), and Holt (2019, Chapter 24) summarizes some subsequent papers with flat values. Some variations test for the effects of heterogeneous agent characteristics, including gender (Eckel and Füllbrunn, 2015, 2017, Holt, Porzio and Song, 2017, and Wang, Houser, and Xu, 2017); testosterone (Nadler et al., 2015), experience (Smith, Suchanek, and Williams, 1988, Van Boening, Williams, and LaMaster, 1993, Dufwenberg et al., 2005), experienced agents but with new parameters (Hussam, Porter, and Smith 2008), cognitive ability (Corgnet et al., 2010, Bosch-Rossa, Meissner, and Bosch-Domenech, 2018), probability judgement biases (Ackert, Charupat,

cash endowments, which Caginalp, Porter, and Smith (2001) refer to as the "excess cash hypothesis." Indeed, many seemingly disparate experimental results can be organized by viewing them through the excess-cash lens. For example, Holt, Porzio, and Song (2017) report much higher peak prices on markets with 25-period duration, as compared with shorter comparable 15-period markets that offer less of an opportunity to build up cash reserves. Similarly, delaying the payment of share dividends until after the final trading period ends has a dampening effect on price speculation (Van Boening et al., 2000). The primary treatment comparison to be described in the next section will hold cash conditions (incomes, interest, dividends) constant and vary the ease or tightness of credit conditions.

The question of the effects of margin requirements on asset market bubbles is not new to experimental economics, but this is the first direct comparison of margin requirements to income levels. King et al. (1993) provides a general overview of proposed methods for reducing bubbles observed in experimental asset markets with declining fundamental values. They hypothesize that margin buying will act to attenuate rather than increase bubbles. On the basis of a limited number of sessions, they find suggestive evidence that margin buying increases bubbles, although no statistical tests were provided. The sessions with margin buying were combined with variations in experience and the ability to short sell, resulting in only one matched pair of sessions with and without margin purchases (for inexperienced subjects and no short sales).

Füllbrunn and Neugebauer (2013) build on King et al. (1993) and examine the effects of margin buying and short selling in a larger set of sessions with a standard declining-value framework. They find that allowing margin buying significantly increases asset price bubbles relative to when margin buying is not allowed. They do not allow subjects to hold both cash and debt and they allow subjects to borrow the entire price of a new asset purchase, with the constraint that debt must be less than equity. This experiment continues this inquiry, with three key differences. The first is that it uses a constant fundamental value framework. Kirchler et al. (2012) shows how declining value experiments can be confusing to subjects, and Holt, Porzio, and Song show how gender-based differences in bubbles with a declining value vanish when using a flat

Deaves, and Kluger, 2009), and sleep deprivation (Dickinson, Chaudhuri, and Greenaway-McGrevy, 2017). Other experiments involve variations in test conditions such as group size (Cheung and Palan, 2012), trading institutions (Deck, 2019), clarity of instructions (Kirchler, Huber, and Stöckl, 2012), excess cash (Caginalp, Porter, and Smith, 2001), the availability of futures markets and short selling (Porter and Smith, 1995 and Noussair and Tucker, 2005), and the timing of dividends (Van Boening, Smith, and Wellford, 2000).

fundamental value framework. Füllbrunn and Neugebauer mention in their conclusion that it could be interesting to test their results in a flat fundamental value setting, which is done in this experiment. The second difference is that subjects may hold both lab cash and debt, and secure borrowing based on each asset unit purchased rather than on the portfolio. This more closely matches actual market conditions where traders can borrow funds and hold cash, and face separate margin calls on assets bought from different brokers. The final difference is that this chapter compares differences in specific margin requirements rather than differences in the presence of margin requirements.

More recently, Fenig et al. (2018) consider the effects of margin buying in a much richer economic environment that includes production, consumption, endogenous interest rates, a central bank, and a flat fundamental value. They report that the ability to purchase assets on the margin does *not* significantly affect asset prices. They analyze the data from subjects' other decisions in the treatments where margin buying was not permitted. In those treatments, subjects chose to expend more labor on production in early periods to build up cash that they then used to speculate in the asset market. This means that subjects effectively used their labor choice to bring additional income into the asset market. In this experiment, the focus is on isolating the effects of margin requirements by holding income constant. This chapter also finds that higher income has similar effects as low margin requirements. The differences in these leverage results and those of Fenig et al. are likely a result of holding income constant as margin requirements change.

Gortner and Massenot (2020) find that higher leverage insignificantly decreases asset bubbles, when traders are exogenously endowed with leverage through an initial portfolio of assets, cash, and debt, where leverage corresponds to a higher cash endowment that is a debt to be repaid at the end. Using a treatment where traders receive the same payouts as in one of their leverage treatments but with a framing that avoids mentioning debt, Gortner and Massenot find that this result is possibly the result of debt aversion. It is also possible that such a debt dampens the effects of additional cash when both are exogenous. In contrast, traders in this experiment endogenously choose their leverage on new asset purchases, up to the maximum leverage allowed. Cipriani et al. (2018) use a two-period setup in an experiment (with only one trading period) to show that the ability to purchase an asset on the margin increases its price. This collateral value price effect may be present in this experiment, but it elicites asset price forecasts that indicate the importance of speculation driven by trend extrapolation, which would not be present in a two-period model.

III. Experiment Treatments and Design

Although the declining-value setup is the workhorse of the asset bubble experiment literature surveyed in the previous section, such a value trajectory is not typical of most financial assets (Oechssler, 2010). A flat value can be induced by introducing a safe asset that earns interest at a rate of *i* on each dollar in lab cash held at the end of a period and before dividends are paid. Random dividends have an expected value of *D* in each period for *T* periods, after which the share is redeemed for *R*. Since dividends are paid at the end of each period and the redemption value is paid at the end of the final period, the present value of a share at the beginning of the first period is the sum of the discounted dividends and final redemption value: $V_{(T\text{ periods remaining})} = \sum_{t=1}^{T} \frac{D}{(1+i)^t} + \frac{R}{(1+i)^T}$. Thus the change in share value for having one more period remaining is:

$$(1) \qquad V_{(T\text{ periods remaining})} - V_{(T-1\text{ periods remaining})} = \frac{(D+R)}{(1+i)^T} - \frac{R}{(1+i)^{T-1}} = \frac{1}{(1+i)^T}[D - iR]\,.$$

The final term indicates that the change in value is 0 if $R = D/i$, which results in a flat fundamental value in all periods. This redemption value ensures that the interest that would be paid to purchase a share for *R* dollars is just equal to the expected dividend. Since *D*/*i* is the value of a perpetuity that pays *D* forever, the final-period redemption (*R*) can be thought of as the discounted value of expected dividends that would have been received in the infinite future from that point onward.[5]

The experiment involves multiple, independent market sessions, each with 12 participants who interact in a sequence of trading periods, using treatment variations that manipulate available lab cash and credit. In all sessions, participants begin the first period with endowments of 6 asset shares and $10 in lab cash, as shown on the left side of Table 1.1. Participants receive lab cash vidends (*D*) each period with an expected value of $1.40 (the two possible outcomes, $1.20 and

[5] Ball and Holt (1998) used a random stopping technique to induce a flat fundamental asset share value. This was done with a fixed continuation probability used to determine a final-period redemption value that equals the *expected value* of subsequent dividends. The idea is that a dividend today is worth more than an equal dividend tomorrow if the asset might self-destruct in the meantime. Paying interest on cash provides an alternative way to induce present-value considerations. Bostian, Goeree, and Holt (2005) based the redemption value on the *present value* of future dividends from that point on. Teaching present value considerations is always difficult, and this insight was incorporated into the Bostian and Holt (2009) teaching paper that also implements a flat share value. The final redemption value can be increased or decreased relative to *D*/*i*, which produces an increasing or decreasing series of asset fundamental values (Giusti, et al., 2016). A third way to induce a flat value involves using a redemption value but no dividends (Caginalp et al., 2001), or similarly, to pay dividends that have a zero expected value (Noussair et al., 2001).

\$1.60 each had a probability of 0.5). The interest rate (*i*) on lab cash balances was set to 5% so that the fundamental value per share is constant at \$28 (*D*/*i*). All sessions consisted of 20 periods, except for a pair of 10-period sessions (in which the income per period was doubled to keep total income the same).

Participants could buy or sell shares. Those with available cash could submit limit orders to purchase, by specifying the number of shares desired and a maximum (limit) purchase price. Those who owned shares could submit limit sell orders, with a maximum number of shares offered and a minimum selling price. The buy orders were arrayed from high to low, creating a demand function, and the sell orders were arrayed from low to high, creating a supply function. The crossing of these arrays determined the price for all trades, with ties decided at random, and prices determined by the midpoint in the event of a vertical overlap. Sellers were not permitted to offer more shares than they owned, and buyers could not submit orders that would require more lab cash than they had *or could borrow*. A trader who submitted both buy and sell orders was required to have a sell price above the buy price, to prevent "self-trading." If the market value of a share fell below a trader's borrowings on that share, the trader was forced to submit a sell order in the subsequent period with a zero limit price to pay back the loan, with any shortfall taken out of the subject's cash account. Lab cash held at the end of the final period (after final trades, dividends, loan repayments, and redemptions) was converted into earnings at a pre-announced rate.

Table 1.1. Parameters and Treatments

Parameter Settings:		Treatments:
6	share endowment per participant	
\$10	lab cash initial endowment per participant	Tight Credit, Low Income: 4 sessions*
\$1.40	expected dividend (0.5 of \$1.20, 0.5 of \$1.60)	
5%	interest rate paid on cash held	
\$28	redemption value per share in final period	Easy Credit, Low Income: 4 sessions*
\$28	fundamental value per share	
\$1	for each accurate price prediction (some sessions)	
20	periods of trading (except as noted)	Tight Credit, High Income: 4 sessions
\$10 or \$30	exogenous income per period (except as noted)	
20% or 91%	down payment requirement (easy or tight credit)	

* In each low-income treatment, there was also a fifth session with 10 periods but with a doubled base income of \$20.

There are two credit variations, referred to as "tight" or "easy," and two income levels, "low" or "high." The baseline treatment, shown at the top on the right side of Table 1.1, includes low income (\$10 per period) and tight credit: a \$10 down payment was required for every \$1 in borrowing, yielding a down-payment requirement of 91% of the purchase price. This treatment was intended to severely restrict borrowing activity, while maintaining the same instruction format and procedural complexity as in other treatments. The first treatment variation involves easy credit (20% down payment) while keeping income low at $10, as shown in the middle part of the right side of Table 1.1. The final treatment (bottom right) raises income from $10 to $30 per period, but keeps credit tight (91% down payment) as in the baseline. In this manner, the treatments independently vary two factors (high incomes and easy credit) that are often associated with naturally occurring price bubbles. There were four 20-period sessions in each treatment, and in addition, there is a pair of shorter, 10-period sessions, with easy credit in one and tight credit in the other, and with the low income $10 doubled to $20 to compensate for only having half as many trading periods.

Speculative purchases of asset shares during price bubbles are not primarily motivated by fixed dividends, but rather by the prospect of speculative gains based on the anticipation of selling shares at a higher price. To learn more about participants' price expectations, they were required to make share price predictions for the current period, next period, and two periods ahead. Their predictions were incentivized with a reward of $1 in lab cash if their prediction turned out to be within a dollar of the actual market price. Of course, monetary payments for correct forecasts will inject cash into the system, which itself might induce bubble formation. Therefore, price forecasts were not elicited in all sessions, and sessions with forecasts were balanced across treatments in a manner that permits "stratified" statistical controls (details to follow).

Table 1.2. Decision Sequence in Each Trading Period

Decision	Information
Submit Limit Order (and Prediction Decisions)	Initial income payment received Initial lab cash and share balances List of prior loan amounts List of required predictions (if any)
Confirm or Rechoose	Possible warnings for missing predictions Warnings for inadmissible limit orders List of submitted limit orders and predictions Potential loan amounts for buy orders
Review Results and Continue	Asset market clearing price List of accepted bids and asks New share, lab cash, and loan balances Interest received or paid on loans Random dividend payments on shares held Payments for correct current and prior predictions Final lab cash balance

Table 1.2 shows the sequence of actions and announcements in each trading period, which begins with income endowments and information about lab cash and share balances at the top of a submit page. Subjects had the option to enter buy and/or sell orders (limit prices and quantities) and predictions (if elicited). A list of past loan amounts (if any) was shown in a table for them to see. Submitted decisions were checked to ensure that lab cash balances were sufficient for buy orders and that share balances were sufficient for sell orders. Possible loan amounts for accepted orders were also displayed on a confirm page. At that point the subject could click “Confirm” or “Rechoose,” but only the Rechoose button is shown if cash balances were insufficient to cover required payments or if the required price predictions were missing. Confirmation took the subject to a results page. After all orders were received, the accepted buy and sell orders were listed. The results page also showed the asset clearing price, interest on pre-dividend cash balances, the random dividend realization on end-of-period share balances, payments for correct current and prior price predictions (if any), final lab cash holdings, and a “Begin Next Round” button.

Inexperienced subjects were recruited from the University of Virginia student population in groups of 12 for each market. Lab cash was converted into cash payments in US dollars at a rate of \$1 per 50 in lab cash. Subjects also received a \$6 payment for their participation. Earnings averaged about \$36 (including the participation payoff) for sessions that lasted about ninety minutes. The experiment was run using the Leveraged Asset Market program on the V*e*conlab platform, which generates instructions that implement the particular parameter selections specified in Table 1.1. These instructions are included in the Experimental Instructions Appendix.

IV. Asset Price Bubbles

The discussion of the results begins with an overview of the main data patterns, followed by specific results and supporting statistical evidence. Figure 1.1 shows the effects of relaxing credit constraints or raising exogenous incomes relative to the low-income, tight-credit baseline treatment. The black line shows the average prices over all 20-period sessions for the low income and tight treatment in which buyers faced a 91% down payment requirement (at most \$1 could be borrowed for every \$11 spent). The dark gray line shows a higher trajectory of average share prices with easy credit (20% down payment), with the same low income as in the baseline treatment. Similarly, a comparison of the light gray line (tight credit and high income) and the black line indicates the effects of an increase in income holding tight credit conditions constant.

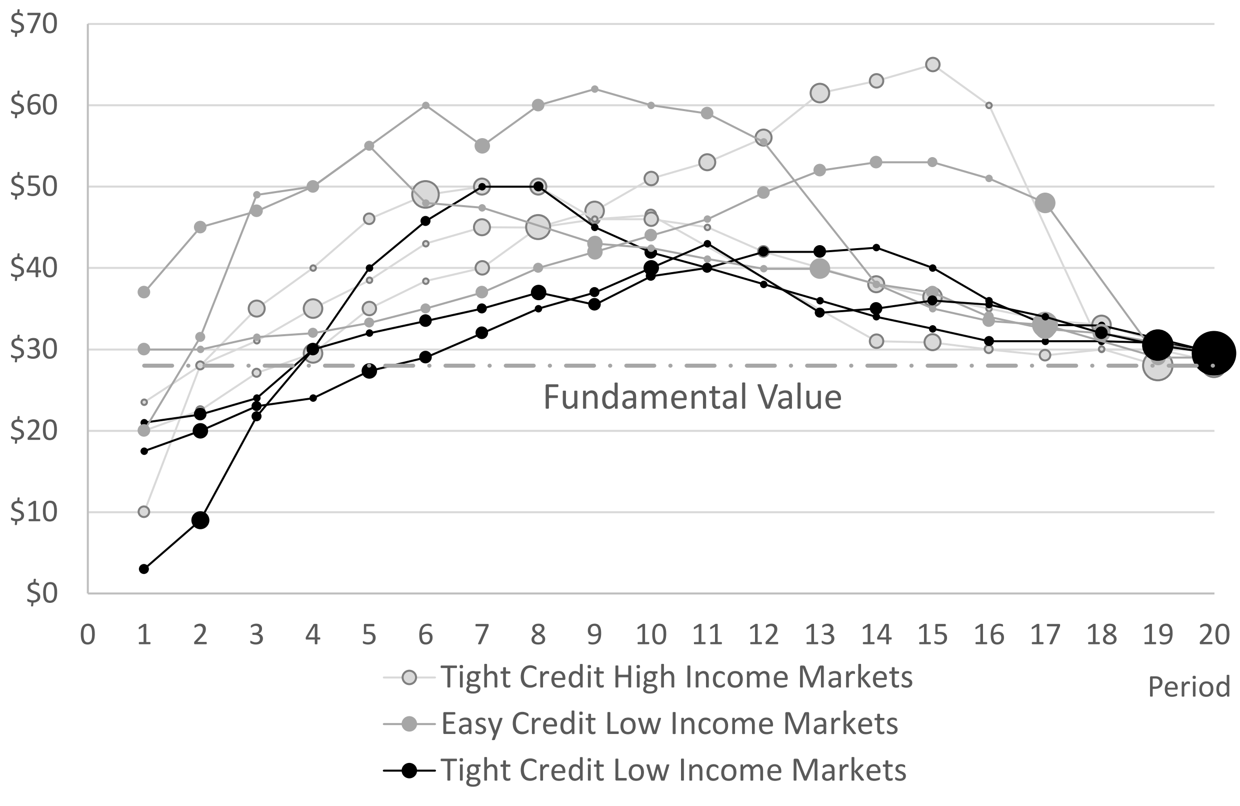
Recall that the fundamental value is $28, as indicated by the horizontal dashed line in Figure 1.1. Price bubbles are apparent in all treatments. Nevertheless, the peak and general amplitude of the bubble-shaped average price sequences are clearly higher the medium and light gray lines, i.e. when the down payment requirements are reduced (holding income constant) or when income is increased (holding credit conditions constant). The price-enhancing effect of the exogenous income increase is about the same as relaxing the credit constraint with a fixed income. Finally, prices begin below the fundamental value in initial periods in treatments with tight credit, which suggests that limited initial cash restrains prices when borrowing opportunities are limited.

Figure 1.1. Average Share Price Trajectories across All 20-Period Sessions in Each Treatment

Summary Bubble Measures

Interest compounding produced sufficiently high lab cash balances to permit aggressive buy orders, at least after several periods. As a result, bubbles were observed on all sessions, with peak share prices that ranged from 130-230% of the $28 fundamental value. There is considerable heterogeneity in bubble patterns: some surges occurred in the early periods, followed by a long slow decline, and others were slow to start. Price drops could be sharp after a period of no increase, which cooled speculative expectations. For heavily leveraged traders in the easy credit sessions, a price drop could result in forced sales in the next period if the price ended up being below the loan amount on a share. Such forced sell offers (at a zero limit price) would have no direct effect with increasing prices, but forced sales after price declines could result in dramatic price drops.[6]

Figure 1.2 shows all of the price sequences for 20-period markets without elicited predictions that would tend to inject cash. Each data point in the figure is scaled to reflect the number of transactions at that price. As before, the black lines with black dots are for the baseline treatment with tight credit and low income. The thin gray line with circles tracks prices for the tight-credit, high-income treatment, and the gray line with gray filled dots tracks prices for the easy-credit, low-income treatment. An increase in income from baseline tends to raise prices (gray circles), and an easing of credit constraints from baseline also tends to raise prices (gray dots). In the range above $40, there are very few black dots (baseline tight credit and low income), and those tend to be smaller, with the largest one corresponding to a transactions quantity of only 7 shares. Price sequences exhibit heterogeneity, as some bubbles break early and others break later.



[6] There were 11 separate incidents of forced sales occurring in 9 different periods, all in the five markets with easy credit and low income. These forced sales represent 43 shares out of 1659 total trades (and out of 572 total trades in the easy credit/low income treatment). In the 10-period market with easy credit and low income, there was a period in which a forced sale resulted in a $0 clearing price, which triggered additional forced sales in the next period.

Figure 1.2. Quantity-Weighted Share Price Sequences

Notes: All sequences are for 20-period markets with no elicited price predictions. The sizes of data dots are proportional to transactions quantities, so more vigorous bubble activity is characterized by larger data points near the peak. The dark lines show price sequences in the baseline (tight-credit, low-income) treatment, and the gray lines are for sessions with income increases above baseline or that involve easing of credit restrictions relative to baseline.

Given the heterogeneity in bubble shapes, the analysis is based on summary measures of the price trajectories. Table 1.3 provides measures of price, transactions, and borrowing activity for each of the sessions, grouped by treatment. The market identifiers are shown in the left column; e.g. EL indicates easy credit and low income. The credit and income treatment conditions are indicated in the second column, with the baseline with tight credit (20% down payment) and low income ($10) treatment in the middle band. Since the fundamental asset value is constant, the unadjusted average and peak prices are used for price-based comparisons.[7]

Table 1.3. Summary Results by Session

Market Number	Credit/Income Treatment	Avg. Price	Peak Price	Positive Value Deviation[a]	Offers to Trade per Period[b]	Avg. % Turnover per Period[c]	Total Borrowing[d]	Average Leverage[e]
EL1	Easy/Low	40.89	53	74.08	44.40	7.78%	293.44	0.072
EL2	Easy/Low	39.15	55	46.78	77.05	6.67%	544	0.160
EL3	Easy/Low	46.27	62	100.43	74.05	9.44%	1197	0.184
EL4P	Easy/Low	41.21	55.5	83.37	78.15	10.42%	1228	0.208
EL5PS	Easy/Low	37.40	65	132.75	61.60	10.83%	1476	0.397
Average		**41.63****	**58.1***	**87.48****	**67.05**	**9.03%**	**815.61****	**0.204****
TL1	Tight/Low	31.31	43	26.83	82.05	10.28%	0	0
TL2	Tight/Low	33.92	42.5	36.36	64.95	6.74%	45	0.014
TL3	Tight/Low	33.53	50	33.08	55.70	6.52%	17	0.010
TL4P	Tight/Low	36.38	61	60.58	80.00	8.75%	32	0.008
TL5PS	Tight/Low	32.05	36	22.60	56.60	7.78%	20	0.013
Average		**33.44**	**46.5**	**35.89**	**67.86**	**8.01%**	**23.5**	**0.009**
TH1	Tight/High	33.98	46.5	48.06	83.35	8.19%	13	0.003
TH2	Tight/High	42.11	65	144.91	87.05	13.33%	9	0.001
TH3	Tight/High	39.34	50	96.73	98.30	10.49%	36	0.007
TH4P	Tight/High	42.79	63	75.00	48.50	7.29%	16	0.003
Average		**39.56****	**56.13**	**91.17****	**79.30**	**9.83%**	**18.5**	**0.004**

Two-tailed Permutation Results: ** indicates $p \leq 0.05$ relative to the baseline center band, * indicates $p \leq 0.10$
Treatments: In the market number, easy and tight credit conditions are noted by E or T respectively. Also, high or low income is noted by H or L respectively. A market number followed by P indicates a session with elicited price predictions, and S indicates a short 10-period market.
[a] Positive Value Deviation = $\frac{1}{T}\sum_{t=1}^{T}\{(P_t - FV_t)q_t \text{ if } P_t > FV_t\}$.

[7] If the fundamental value was changing across periods, these price-based measures could be adjusted relative to the fundamental value, which is not necessary in this case. This is because when the fundamental value is constant, average price is an affine transformation of both "average bias" (Haruvy and Noussair 2006) and "relative deviation" (Kirchler et al. 2012). This implies that for this design, differences in all three of these measures will have the same implications for permutation tests reported below.

[b] Offers to trade per period is the total number of purchase and sale orders divided by the number of periods.
[c] Average percent turnover per period is the average percentage of the assets traded in a period.
[d] Total borrowing is the total of new borrowing across all periods, not including debt that is rolled over across periods, thus debt is only counted once when it is issued. The treatment averages do not include data for the 10-period markets.
[e] Average leverage is the average proportion of an asset price that was borrowed. This average is across all assets traded, not across time periods.

The average price (column 3 of Table 1.3) provides a perspective on the size of deviations from the fundamental value, although the implications for bubble size are distorted by initial prices below fundamental value, especially for tight credit sessions. The peak prices in column 4 indicate the maximum height of the bubble. This measure is independent of price in any period except the peak, and is thus not distorted by early prices below the fundamental value. However, the peak price measure does not consider the number of trades occurring at the peak. For example, high peak prices in some sessions resulted from limited trading activity.[8] This means that in these sessions when the bubble burst, only a small number of participants experienced capital losses that were benchmarked to the peak price. Many more participants experienced capital losses benchmarked to the lower prices at which they executed their last trade before the bubble burst.

The macro-finance literature emphasizes how leverage raises asset prices, which would increase the positive side of bubbles.[9] This suggests using a measure based only on positive deviations from fundamental value, which is motivation for considering the Eckel and Füllbrunn (2015) "positive deviation" measure. They define *positive deviation* as the sum (over all periods) of positive differences between price and fundamental value, i.e. negative differences are excluded. Although average price, peak price, and positive deviation measures reflect important aspects of bubbles, these measures are not sensitive to the volume of trade at each price. When only a few asset shares are traded at the peak price, most traders will experience a lower shock to capital gains when the bubble bursts than is implied by bubble measures based only on price. In this case, bubble measures that do not consider the quantity traded tend to overstate the impact of the bubble on the distributional aspects of capital gains/losses. This creates a measure of the bubble that distorts the magnitude of the redistribution of wealth (from the participants holding asset shares to

[8] For example, consider the baseline session represented by the dark line that starts below \$10 on the left side of Figure 2. This session reaches a peak price of \$50 in periods 7 and 8, but with very few trades as indicated by the small size of the black dots at the peak. These black dots are clearly inside the larger gray circles for the high-income treatment session that also has a peak at \$50 with more units traded at the peak. In contrast, bubble measures that are sensitive to the transactions volume can be strongly affected by trades at high prices below the peak, e.g. the very large circle in period 6 at a price of \$49 for the high-income session that subsequently peaks at \$50.
[9] For examples, see Bernanke et al. (1999), Fostel and Genakoplos (2008, 2014), Schularick and Taylor (2012), Jordà et al. (2013, 2015), and Geanakoplos and Zame (2014) and the citations contained in these papers.

participants holding cash) caused by the formation and bursting of the bubble. To address this bias, the primary measure this chapter uses in comparison is a *positive value deviation* (PVD), in which positive deviations are weighted by the numbers of shares traded, q_t:[10, 11]

$$\text{PVD} = \frac{1}{T}\sum_{t=1}^{T}\{(P_t - FV_t)q_t \text{ if } P_t > FV_t\}.$$

By weighting positive deviations by the number of shares traded, the PVD measure accounts for how much capital is being placed at risk by the purchasers of shares at each price. This capital at risk is the potential maximum loss, to the purchasers of the shares, that will occur if the shares are held until the end of the market when they are redeemed for their fundamental value. A loss of wealth that is redistributed to the participants who traded the shares for cash. Therefore, the PVD measures the magnitude of the bubble in terms of capital placed at risk. The PVD measures listed in the 5th column of Table 1.3 are higher with easy credit (top band) and high income (bottom band), which supports the general impression provided by Figure 1.1.

The 6th and 7th columns of Table 1.3 show measures of trading intensity, i.e. the average number of buy and sell orders ("offers to trade") per period, and the average percentage of total shares traded in each period ("turnover"). The averages of both measures are comparable and exhibit no clear ranking between treatments.[12]

The statistical tests used to support the main margin requirement and income results are based on permutations of treatment labels. Under the null hypothesis of no treatment effect, observed differences are due to chance, and any permutation of treatment labels between treatment groups would be equally likely. Each permutation could alter the average treatment difference, and the *p*-value for the test is the proportion of permutated treatment differences that are "as or more extreme" than the difference observed in the data. Although the literature supports strong prior beliefs that low margin requirements and high incomes would have larger bubbles (which could justify the use of one-tailed tests), the conservative approach is taken with the use of two-tailed tests based on proportions that are more extreme in either direction. In addition, the permutation tests are stratified to compensate for differences in nuisance variables (like the number

---

[10] The positive value deviation is similar to the "market value amplitude" developed by Hussam et al. (2008). However, market value amplitude reports the *maximum* market value deviation across all periods, whereas the PVD measure reports the average across periods in which the deviation is positive.

[11] PVD can be generalized for use in declining value experiments by dividing by the fundamental value in each period. The formula then becomes $\frac{1}{T}\sum_{t=1}^{T}\{\frac{(P_t - FV_t)}{FV_t}q_t \text{ if } P_t > FV_t\}$.

[12] The *p*-values for standard nonparametric tests of these differences are not significant at any conventional level.

of rounds or prediction payments). Notice that there are 5 rows of data in Table 1.3 for each of the top two treatment bands, so there are “ten take 5” = 252 ways that the treatment labels for these two treatments could be randomly permuted. Under a null hypothesis, each of these permutations is equally likely, so the *p* value for the most extreme outcome *in either direction* would be 2/252, i.e. when all 5 bubble measures for one outcome are higher (or all are lower) than for another. The problem with this approach is that the small payments for price predictions in some of the sessions do inject excess cash, which gets compounded over time. In addition, the process of eliciting predictions might suggest trend extrapolation or somehow bias behavior.[13] Therefore, sessions with predictions are placed in separate “strata,” as indicated by the thin horizontal lines that separate the data rows for sessions with “P” designations in the table.[14] This conservative approach restricts permutations of treatment labels to stay within a horizontal band, and this results in a *p*-value of 0.025 for the most extreme outcome.[15]

Effects of Credit Constraints

The main result pertains to the effect of changing credit tightness, holding income constant:

Result 1.1 (*Margin Requirements*): *In laboratory markets with a flat fundamental value for a risky asset that can be bought on margin, bubble magnitudes are higher with low margin requirements (easy credit) than with high margin requirements (tight credit) and the same income level.*

Support: The average price in Table 1.3 is significantly higher for low-margin markets than for high-margin markets with the same exogenous income ($10 per period). The *p*-value for the two-tailed stratified permutation test for this result is 0.025 (=2/80), which is consistent with the fact that the average prices in all low-margin markets are higher than the average prices in all high-margin markets. Similarly, the positive value deviation (PVD) measures are significantly higher in low-margin requirement markets than high-margin, yielding a *p*-value that is again 0.025. This

[13] Indeed, the average price data for the 20-period markets with predictions are higher than the average prices for the other three 20-period markets in each of the bottom two treatment bands in Table 3.
[14] Stratified permutation tests are discussed in Holt (2019). Holt and Sullivan (2019) compare permutation tests to a standard Mann-Whitney rank-based test.
[15] There are “6 take 3” = 20 possible permutations of data for the sessions in the top two bands with no price predictions, and there are 2x2 = 4 ways that the data in the two price prediction bands could be permuted, so in total there are 4x20 = 80 possible random permutations of treatment labels in the top two bands. Under the null hypothesis of no treatment effect, the most extreme outcome in either direction would have a *p* value of 2/80 = 0.025 for a two-tailed test.

indicates that low margin requirements increase both the positive side of bubbles, and the market value of bubbles. In contrast, there is some overlap in peak prices since the $61 peak in market TL4P in the middle treatment band is higher than the peak of $55.50 for the analogous market EL4P in the top easy credit band. This reversal actually results in 4 permutations with higher treatment differences than what was observed, for a p value of 8/80 = 0.10, as indicated by the single asterisk in the peak price column of Table 1.3. However, the differences in average price and positive value deviation show that the overall sizes of bubbles, as measured by magnitude and market value is higher in low-margin (easy credit) markets. As a robustness check, the positivel deviation (Eckel and Füllbrunn 2015) is calculated for each market. There values are reported in Table 1.4 below.

Table 1.4. Positive Deviation Measures[a]

Market Number	Credit/Income Treatment	Positive Deviation
EL1	Easy/Low	237.75
EL2	Easy/Low	228.22
EL3	Easy/Low	361.10
EL4P	Easy/Low	273.18
EL5PS	Easy/Low	132.00
Average		**246.45****
TL1	Tight/Low	102.00
TL2	Tight/Low	135.35
TL3	Tight/Low	160.83
TL4P	Tight/Low	216.30
TL5PS	Tight/Low	40.45
Average		**130.99**
TH1	Tight/High	155.71
TH2	Tight/High	290.05
TH3	Tight/High	220.24
TH4P	Tight/High	262.93
Average		**232.23***

Two-tailed Permutation Results: ** indicates $p \leq 0.05$ relative to the baseline center band, * indicates $p \leq 0.10$

[a] Positive Deviation = $\sum_{t=1}^{T}\{(P_t - FV_t) \text{ if } P_t > FV_t\}$.

This is a non-quantity weighted version of our positive value deviation. Low-margin requirement markets have a significantly higher positive deviation than high-margin requirement markets, with a p-value of 0.025.

The mechanism underlying the margin requirements result is, not surprisingly, leverage. The bolded treatment average rows in the far right column of Table 1.3 show that leverage for asset purchases is 0.205 in the top band with low margin requirements and low income, whereas average leverage is only 0.009 for comparable high-margin requirement markets in the middle treatment band. This leads to the second result:

Result 1.2 (Borrowing): When making new asset purchases, traders in low-margin requirement markets use significantly higher leverage and borrow significantly more than traders in high-margin requirement markets.

Support: Note that all of the leverage measures for individual sessions in the top band with low margin requirements are higher than in any of the leverage measures with high margin requirements. A stratified permutation test for the difference in average leverage between low- and high-margin markets yields a significant result, with a *p*-value of 0.025. Not only is leverage higher in low-margin requirement markets, but total borrowing (shown in the 8th column of Table 1.3) is also significantly higher (the *p*-value is 0.025 for a 2-tailed permutation test).

It is interesting to point out that average leverage in the right column of Table 1.3 is below the maximum allowed (80% with a low margin requirement, and 9% with a high margin requirement). In both treatments, average leverage is reduced by traders who never borrow when purchasing assets. Although some traders do use the maximum leverage in early periods, most do not. The most obvious explanation for below-maximum leverage levels is that future asset prices are ambiguous and risky. Traders exhibiting risk or ambiguity aversion would want to use less leverage even if they believe that the asset price will increase with high probability. This price uncertainty can cause traders to borrow less to reduce the risk of capital loss and forced sales. Another possible explanation for less than maximum leverage is that traders are exhibiting "debt aversion."[16]

Effects of Increased Incomes

Most of the average measures in Table 1.3 suggest that bubbles tend to be larger in high-income markets when compared to low-income markets with the same margin requirements, which motivates the next result:

[16] Meissner (2016) shows how subjects borrow less than is optimal in an intertemporal consumption/borrowing experiment. This aversion to debt could carry over to experimental asset markets and would contribute to traders borrowing less than the maximum allowed.

Result 1.3 (*Income Endowments*). *Bubble magnitudes are higher in markets with higher exogenous incomes, holding credit conditions constant.*

Support: Within each strata, the average prices and positive value deviations are higher in all high-income markets than in all low-income markets. Since there are no within-strata reversals, the extreme outcomes observed for average price and PVD measures yield a *p*-value of 0.05 (=2/40) for a two-tailed test.[17] Peak prices, however, are not uniformly higher in high-income markets, and the 2-tailed permutation test results are suggestive, but not significant at traditional levels. Two of the three bubble measures, however, do provide evidence of higher bubbles with high incomes, which is consistent with other evidence that bubbles are larger in high-income markets than in low-income markets.[18, 19]

Extensions and Discussion

This experiment shows that looser credit conditions and higher incomes tend to increase bubble magnitudes across time periods. An interesting extension of this result is to analyze the extent to which these differences in bubble magnitudes are only the result of dynamics occurring after the start of the market, or whether they are affected by treatment-specific structural conditions (income or credit tightness) present at the start of each market. Analyzing traders' first-period buy orders, finds evidence that some portion of the price differences may be due to these structural conditions. First period buy order values are significantly higher in easy credit markets than in tight credit markets (*p*-value of 0.0015), holding income constant, and are significantly higher in high income markets than in low income markets (*p*-value of 0.0033), holding credit constraints constant.[20] These differences suggest that before any price information, which might encourage

[17] When comparing 4 markets with 20 periods in each treatment, separated into no-prediction and prediction strata, there are 2x20 = 40 possible random permutations of treatment labels. Under the null hypothesis of no treatment effect, the most extreme outcome in either direction would have a *p* value of 2/40 = 0.05 for a two-tailed test, which is on the border of traditional levels of significance.

[18] The effect of income, endowments, and other sources of "excess cash" on asset market bubbles has been explored in many contexts. Caginalp et al. (2001) finds that in experimental asset markets with a declining fundamental value, increased cash endowments result in larger bubbles. Noussair and Tucker (2016) report a similar finding with a different dividend structure (zero expected value). Taking these studies into consideration provide some support for our conclusion, despite the insignificant test results for the peak price dimension.

[19] When using the positive deviation, reported in table 4, to measure bubbles, holding credit conditions constant, high-income markets have larger bubbles than low-income markets with a *p*-value of 0.10. In this case, the positive deviation provides weaker evidence than the positive value deviation. This highlights the importance of using the quantity-weighted measure, the positive value deviation.

[20] The *p*-values are calculated using stratified permutations tests with 3 strata for credit treatments differences, and 2 strata for income treatment differences.

speculation, is revealed, traders are willing to pay more for shares in markets that subsequently tend to experience larger bubbles. Additionally, there is suggestive, but not significant, evidence that first-period price forecasts exhibit the same result.[21] This difference in price forecasts suggests that structural market conditions (credit availability and income) influence traders' beliefs about the share price, even when the dividend profiles and fundamental values of shares are held constant.

All of these results pertain to markets with inexperienced subjects. Smith, Suchanek, and Williams (1988) show that bubbles are diminished when all market participants have prior experience in an asset market with a bubble, which would tend to diminish treatment effects. Dufwenberg et al. (2005) further show that bubbles are diminished when at least one third of market participants are experienced. Problems associated with forced sales and credit crunches might be particularly focal for experienced subjects. Therefore, it is possible that in markets with experienced traders, low margin requirements might not lead to larger bubbles or additional borrowing. However, Schularick and Taylor (2012) show that the effects of leverage are most significant in financial crises, which have cycles that can span decades (Reinhart and Rogoff, 2009). Given the typical lengths of these cycles and the importance of leverage, it is reasonable to assume that a significant fraction of market participants in a financial crisis lack first-hand experience that would tend to sharply mitigate bubbles. The effects of general knowledge second-hand experience are blurred by changes in market conditions and the tendency to believe that "this time is different" (Reinhart and Rogoff, 2009). Therefore, it is important to understand the effects of leverage with inexperienced subjects.

V. Forecasting Patterns

John Maynard Keynes stressed the effects of short-term speculative gains, and concluded that an investor "…need not lose his sleep merely because he has not any notion what his investment will be worth ten years hence." (Keynes, 1965, p. 153, originally 1936). Short-term speculative motives in the experiment are assessed by analyzing the current and future-period price forecasts obtained at the start of each trading period in five of the market sessions, balanced across

---

[21] The *p*-values for stratified permutation tests of forecasting differences across credit treatments are 0.1052, 0.0874, and 0.1036 for current-period, period-ahead, and two-period-ahead forecasts respectively. The *p*-values for stratified permutation tests of forecasting differences across income treatments are 0.0223, 0.0184, and 0.0178 for current-period, period-ahead, and two-period-ahead respectively.

treatments. Figure 1.3 shows price and forecast data for one of these markets, EL4P, with easy credit and low income. Notice that current and period-ahead forecasts are too low as the bubble forms. The period ahead (dashed) line is lower than the current forecast (black) line because subjects had a harder time anticipating price increases in future periods relative to the present period. Moreover, traders do not seem to anticipate the downturn that occurs after period 3, as forecasts for the current price forecast (solid black line) and the next period price forecast (dashed black line) overshoot the observed price (gray line) in periods 4 and 5. This pattern suggests that purchases at the peak in periods 3 and 4 were motivated by anticipation of further gains.

The particular bubble patterns observed in different markets exhibit a lot of heterogeneity in terms of how quickly prices initially rise and how sharply they fall. However, an analysis of forecast errors indicates that errors are relatively persistent, with average forecasts being about 8% below the price on average in periods when it is increasing, and about 5% above price when it is decreasing. A similar pattern is observed for the period-ahead forecasts, which are 19% below price when it is increasing, and 12% above price when it is decreasing. To summarize, the overall pattern is for forecasts to lag behind actual prices on the upswing and to hang above prices after the downturn, with larger errors for period-ahead forecasts. The qualitative similarity of these patterns across sessions is the motivation for specifying and estimating a behavioral forecasting model with elicited forecast data.

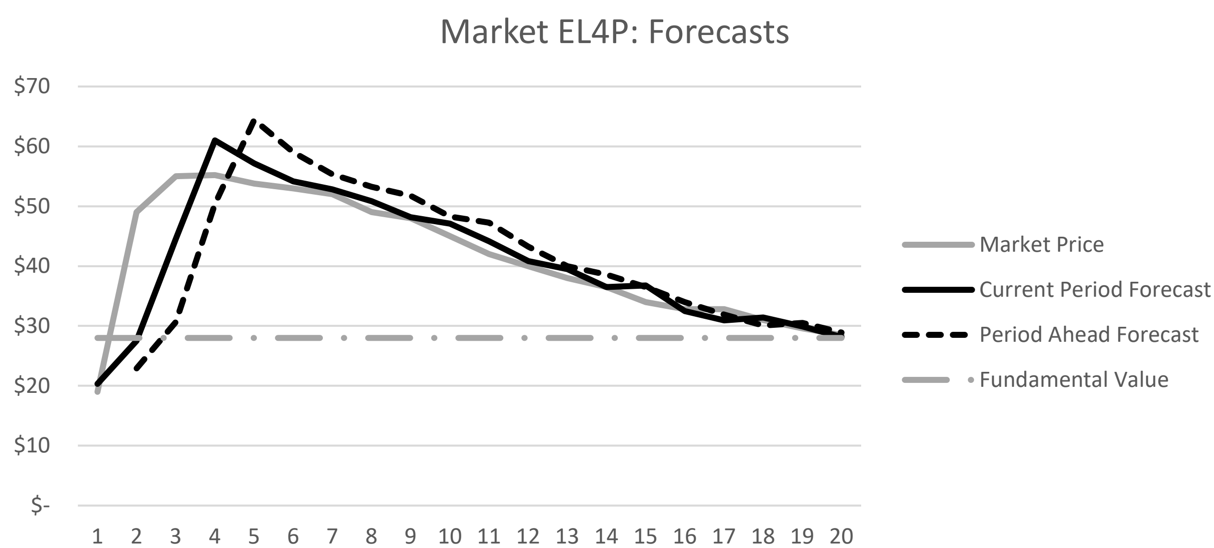


Figure 1.3. Current Period Share Prices (Grey Line), Current Period Forecasts (Black Line), and One-Period-Ahead Forecasts Made in the Previous Period (Dashed Line)

Current Period Forecasts

The inertia exhibited in the forecast data for the session shown in Figure 1.3 suggests that participants anchor on a prior forecast and adjust adaptively to prices that diverge from that forecast. There is a long history of considering a simple "adaptive rule" that generates a current period price forecast by taking the prior forecast, F_{t-1} and adding a correction based on the most recent forecast error ($P_{t-1} - F_{t-1}$):

$$F_t = F_{t-1} + \beta(P_{t-1} - F_{t-1}) \text{ with } 0 < \beta < 1 \text{ . } \quad (\textit{adaptive price forecast in levels})$$

If the previous forecast is too low, it will be raised and vice versa. Adaptive forecasts have been shown to fit data generated by human subjects in some laboratory experiments with price series that are approximately stationary (Williams, 1987). Simple adaptive forecasting, however, produces *systematic, correctable forecast errors* when there is a clear trend in the data.

With persistent price movements like those in Figure 1.3, people are likely to extrapolate the previously observed price trend. A linear extrapolation rule is: $F_t = P_{t-1} + \beta(P_{t-1} - P_{t-2})$, where $\beta > 0$.[22] Notice that this extrapolative rule is a function of the two most recent prices.[23] A "double adaptive" specification incorporates partial adjustments to the most recent forecast "errors" in both price levels and trends.[24]

Double Adaptive Forecast for Current Period Price:

$$F_{i,t} = F_{i,t-1}^{+} + \beta\big(P_{t-1} - F_{i,t-1}\big) + \gamma[(P_{t-1} - P_{t-2}) - \big(F_{i,t-1}^{+} - F_{i,t-1}\big)] + A_i.$$

with $0 < \beta, \gamma < 1$, where A_i is a fixed-effect term for individual i (the i subscripts will generally be omitted in the following discussion). Notice that the period t price forecast on the left is anchored on the most recent forecast, F_{t-1}^{+} on the right side, representing the prior one-period-ahead forecast for period t made in period t–1. This base is adjusted by a positive factor of β for the most recently observed forecast error in price levels $(P_{t-1} - F_{t-1})$. The second adaptive parameter, γ, adjusts for the most recently observed error in price trends, i.e. the bracketed difference between the most recently observed price change, $P_{t-1} - P_{t-2}$, and the predicted change in t–1: $F_{t-1}^{+} - F_{t-1}$.

---

[22] This is similar to the specification used by Haruvy, Lahav, and Noussair (2007) for the analysis of forecasts in the first 15-period market sequence of each session.

[23] In a similar vein, Hommes et al. (2005) report that the most common autoregressive structure estimated for individual subjects was a linear function of the previous two prices, which can be interpreted as trend extrapolation.

[24] The derivation is based on the approach taken by Holt et al. (2017).

The double adaptive model for the current period forecast is estimated using a fixed effects regression, using data for the 60 subjects in the 5 sessions with elicited forecasts.[25] The change in forecasts, $F_{i,t} - F^{+}_{i,t-1}$, is the dependent variable. The independent variables are the forecast error, $P_{t-1} - F_{i,t-1}$, and trend error, $(P_{t-1} - P_{t-2}) - \left(F^{+}_{i,t-1} - F_{i,t-1}\right)$. As anticipated, the estimates for β and γ shown in the top row of Table 1.4 are significantly different from zero and between 0 and 1, whereas the constant term is not significantly different from zero. The two-parameter model explains a reasonable amount of the variation in traders' current-period forecasts, with an R square of about 0.78.

Table 1.5. Double Adaptive Forecast Estimates (Standard Errors)

Forecast	# of Observations	Constant	β (adaptive level parameter)	γ (adaptive trend parameter)	R^2
Current Period	840	0.0000 (0.2001)	0.6919*** (0.0319)	0.0731** (0.0317)	0.7795
Period Ahead	780	0.0000 (0.2532)	0.6362*** (0.0464)	0.2154*** (0.0480)	0.7067

Note: For the first row, Current Period Forecast, the dependent variable is the change in forecasts for the current period, $F_{i,t} - F^{+}_{i,t-1}$. For the second row, Period Ahead Forecast, the dependent variable is the change in the forecast of the next period price, $F^{++}_{t-1} - F^{+}_{t-1}$. The regression uses subject level fixed effects.
Key: *** Significant t-test at the 1% level. ** Significant t-test at the 5% level. * Significant t-test at the 10% level. Standard errors are reported in parentheses beside each estimate.

Using the double adaptive parameter estimates from Table 1.5, the model forecasts can be generated. Figure 1.4 shows the market price series (grey line), average observed current period forecast (black line), and the model forecasts (black diamonds) for the same market considered previously (ELP4). A comparison of average actual forecasts (black line) and model forecasts (black diamonds) indicates that that the model replicates the main qualitative pattern in the data, i.e. under-forecasting prices on the upswing and over-forecasting a little after the downturn. The largest divergence between the model and the observed forecast average is in period 4, just after the actual prices peaked.

[25] In market TH4P, there was one current period prediction of 313, which (based on the trader's other forecasts), appeared to be a typo. This observation was corrected to 31 for these estimates.

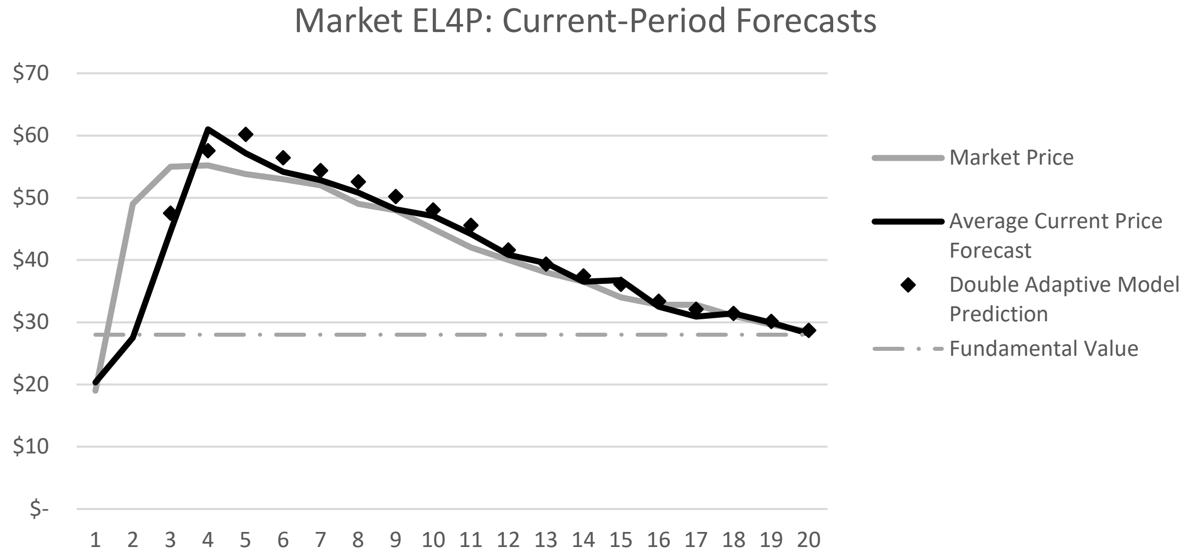


Figure 1.4. Current Period Prices (Grey Line), Average Observed Current Period Forecasts (Black Line), and Fitted Forecasting Model Predictions (Black Diamonds)

Formation of Period-Ahead Price Forecasts

In addition to predicting current price, traders were also asked to forecast the asset price in the subsequent two periods. The double adaptive framework can also be used to model forecasts of future prices. The analogous adaptive forecast uses an adjustment of the most recent period-ahead forecast, $F_{i,t-1}^{+}$, instead of the most recent current price forecast, as can be seen from the period-ahead adaptive rule: $F_{i,t}^{+} = F_{i,t-1}^{+} + \beta\left(P_{t-1} - F_{i,t-1}\right)$. Although the standard adaptive expectations rule captures the price *level* component of a behavioral model, a second correction can be added for trend errors to construct a double adaptive forecast for the current price. Similarly, a double adaptive rule can be derived to model *period-ahead* forecasts.

The double adaptive forecast of the period ahead asset price is derived from the same behavioral framework that Holt et al. (2017) uses to motivate the analogous procedure for forecasting current period price. A simple adaptive forecasting model is based on the idea that a subject constructs a forecast, F_t, as the combination of a forecast for a base level price, B_t^{*}, and a forecast of the change in the base (trend), C_t^{*}. In the period *t* forecast of the period *t*+1 asset price, F_t^{+}, this two-part approach involves a combination of a forecast for the base level price in period *t*+1, B_t^{*+}, and a forecast of the change in the base trend in period *t*+1, C_t^{*+}.

$$F_t^{+} = B_t^{*+} + C_t^{*+}$$

It is assumed that the forecast of the base level price in period t+1, B_t^{*+}, is formed using the extension of the standard adaptive expectations model that was discussed in section V:

$$B_t^{*+} = F_{t-1}^{+} + \beta(P_{t-1} - F_{t-1})$$

It is assumed that the forecast in the change in the base trend in period t+1, C_t^{*+}, will be formed using the standard adaptive expectations forecast updating the most recently predicted future change in the base level price, C_{t-1}^{*+}, adjusted by the most recently observed error in the trend prediction, $C_{t-1} - C_{t-1}^{*+}$:

$$C_t^{*+} = C_{t-1}^{*+} + \gamma(C_{t-1} - C_{t-1}^{*+})$$

The most recently observed change in the base level price, C_{t-1}, is the difference between the period t−1 and period t−2 asset price: $P_{t-1} - P_{t-2}$. The most recently predicted future change in the base level price, C_{t-1}^{*+}, is the difference between the previous two-period-ahead forecast and the previous one-period-ahead forecast: $F_{t-1}^{++} - F_{t-1}^{+}$. Substituting these terns into the above equation gives:

$$C_t^{*+} = C_{t-1}^{*+} + \gamma(C_{t-1} - C_{t-1}^{*+}) = F_{t-1}^{++} - F_{t-1}^{+} + \gamma[(P_{t-1} - P_{t-2}) - (F_{t-1}^{++} - F_{t-1}^{+})]$$

The expressions for the forecast in the change in base trend, and the change in base can be combined to give the double adaptive forecast of the period ahead asset price:

$$F_t^{+} = F_{t-1}^{+} + \beta(P_{t-1} - F_{t-1}) - F_{t-1}^{+} + \gamma[(P_{t-1} - P_{t-2}) - (F_{t-1}^{++} - F_{t-1}^{+})]$$

The expression can be simplified into the following double adaptive forecast model equation:

$$F_t^{+} = F_{t-1}^{++} + \beta(P_{t-1} - F_{t-1}) + \gamma[(P_{t-1} - P_{t-2}) - (F_{t-1}^{++} - F_{t-1}^{+})]$$

For estimation purposes, this equation becomes:

Double Adaptive Forecast for Period Ahead Price:

$$F_{i,t}^{+} = F_{i,t-1}^{++} + \beta\left(P_{t-1} - F_{i,t-1}\right) + \gamma\left[(P_{t-1} - P_{t-2}) - \left(F_{i,t-1}^{++} - F_{i,t-1}^{+}\right)\right] + A_i$$

with $0 < \beta, \gamma < 1$, and with subject-specific fixed-effect terms, A_i (i subscripts will be omitted in the following discussion). In this model, the period t forecast of the period t+1 price, F_t^{+}, is specified to be the period t−1 forecast of the period t+1 price, F_{t-1}^{++}, plus two adaptive terms that adjust for the most recently observed "errors" in price levels and trends. In particular, the trend error is the difference between the last observed change in the price, $P_{t-1} - P_{t-2}$, and the period t+1 price change predicted in period t−1: $F_{t-1}^{++} - F_{t-1}^{+}$.

The double adaptive adjustment parameters are again estimated using a fixed effects regression, with the change in forecasts, $F_t^{+} - F_{t-1}^{++}$, as the dependent variable, and the forecast and trend errors as independent variables. The estimates for β, and γ , shown in the bottom row of Table 1.5, are significantly different from zero and positive. The R-squared of the fixed effects regression is 0.7067, which indicates that a double adaptive model explains a reasonable amount of the variation in subjects' period-ahead price forecasts.

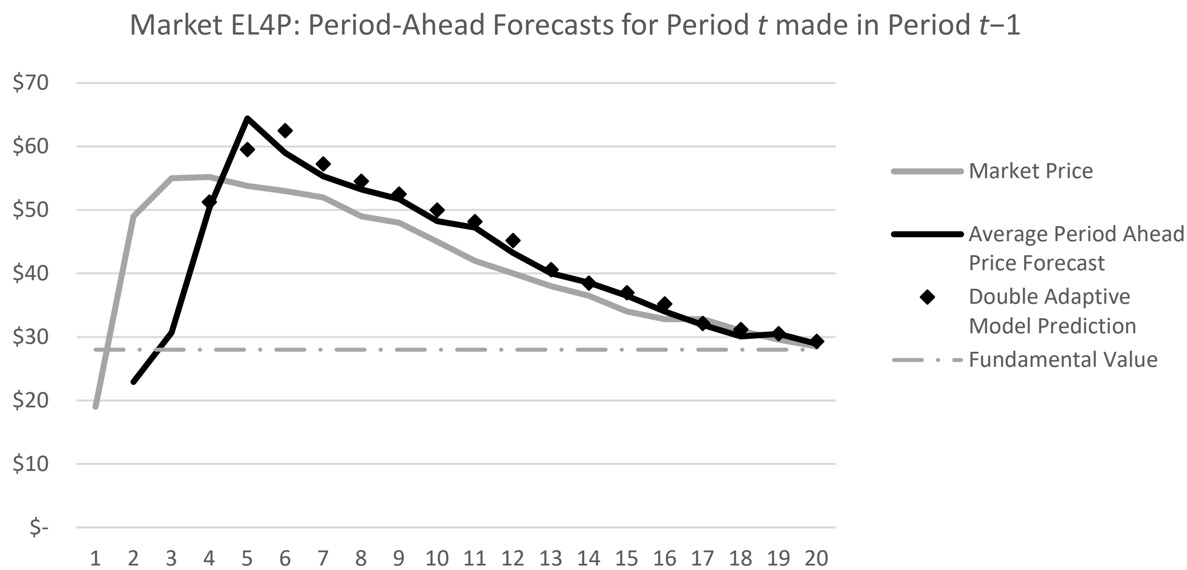


Figure 1.5. Current Period Prices (Grey Line), Average Observed Period Ahead Forecasts Made in Period t−1(Black Line), and Fitted Forecasting Model Predictions (Black Diamonds)

The period-ahead model forecasts can be calculated using the estimated coefficients taken from the bottom row of Table 1.5. Figure 1.5 shows the market price (grey line), the average of traders' period-ahead forecasts (black line), and the double adaptive model forecast (black diamonds) for market EL4P. Both the traders' forecasts, and the model's forecasts are shown for the period being forecasted, rather than for the period in which the forecast was made. A comparison of average actual forecasts (black line) and model forecasts (black diamonds) shows that the double adaptive model replicates the main qualitative pattern in the data, i.e. under-forecasting prices on the upswing and over-forecasting a little after the downturn.

Result 1.4 (Double Adaptive Forecast Models): Double adaptive forecast models for both current-period and period-ahead prices explain a reasonable amount of the variation in traders' forecasts and predict the average forecast with an accuracy of 0.57% and -0.28% respectively.

Table 1.6. Percentage Deviations of Model Estimates from Average Elicited Forecasts

Market	Deviation at Peak		Average Deviation		Average Deviation (Price Increasing)		Average Deviation (Price Decreasing)	
	Current Period	Period Ahead	Current Period	Period Ahead	Current Period	Period Ahead	Current Period	Period Ahead
EL4P	-5.64%	-7.54%	2.31%	1.77%	0.46%	-2.84%	2.55%	2.39%
EL5PS	1.45%	8.65%	-5.88%	-10.70%	-3.26%	-5.86%	-7.46%	-14.33%
TL4P	1.21%	1.19%	-1.17%	-1.54%	-4.46%	-4.35%	2.11%	1.61%
TL5PS	-0.95%	-3.76%	2.20%	2.79%	2.28%	2.41%	2.11%	3.28%
TH4P	-3.81%	-2.89%	2.71%	1.97%	0.77%	1.14%	3.26%	2.23%
Overall Average	-1.54%	-1.00%	0.57%	-0.28%	-1.67%	-2.19%	1.59%	0.70%

Note: The deviation at peak is the difference between the model prediction and the peak of the average elicited forecasts. Average deviation is the average of the differences between the model predictions and the average elicited forecasts across all periods in the market. The right half of the table shows average deviation measures for periods in which price is increasing or decreasing. The overall averages reported in the bottom row for deviations at peak are the average of those measures for each market. All other overall averages in the bottom row are the averages across the pool of all predictions, not across deviations for each market.

Table 1.6 shows several measures of deviations of the model estimates from elicited forecasts, with overall averages across all sessions in the bottom row. The Average Deviation measures for all periods in the 4th and 5th columns indicate that the models are quite accurate, but that the current period model predictions tend to slightly overestimate the average elicited forecast and the period ahead model predictions tend to slightly underestimate the elicited forecasts. The right side of the table separates periods of increasing and decreasing prices for each market. The models tend to underestimate the average elicited forecasts as the actual price increases, and overestimate the average elicited forecasts as the actual price decreases. At the peak of the average elicited forecasts, the models on average underestimate the average elicited forecast. However, when considering the per market deviations from the peaks, there appears to be variability in the direction of the deviation, with the model sometimes overestimating the peak and sometimes underestimating the peak.

VI. Conclusion

The primary treatments in this experiment are motivated by the observation that asset price bubbles in naturally occurring markets are typically associated with both high incomes and easy credit, both of which are characteristic of boom times. The advantage of a laboratory experiment is that it is possible to hold incomes constant and relax credit constraints, or to hold credit constraints constant and increase incomes. This experiment finds that both of these factors tend to enhance share price bubbles.

The main conclusion (Result 1.1) is that lower margin requirements significantly increase bubbles when their effects have been isolated. The experimental design separates the effects of increased cash and lower margins on bubbles by keeping income and all other variables constant while changing margin requirements. Differences in cash across treatments are unique in that they are endogenously determined by traders' borrowing decisions, subject to margin requirements. In this environment, only the traders who want debt have debt. In addition, the experiment's results support the conclusion that increases in exogenous income (holding credit constraints constant) tend to increase bubble magnitudes.

Chapter 2: Tobin's Q, Liquidity, and Speculation in Laboratory Markets

I. Introduction

Tobin's q, and q-theory more generally, provides a basis for predicting firms' decisions to invest in capital goods based on the ratio of capital goods' market price to their production costs. This ratio is commonly referred to as q, and in a frictionless market equilibrium it should be 1. When q is greater than 1, a profit-maximizing firm will increase capital goods production to exploit the arbitrage gain of selling at a higher price than the production cost. At a ratio less than 1, profits are maximized by scaling back production and purchasing additional capital units on the market. Tobin (1969) first proposes this ratio as a predictor of investment behavior and defines q as "the value of capital relative to its replacement cost" (p. 21).[26] This measure of q, commonly referred to as Tobin's q, is effectively $\frac{Price}{Average\ Cost}$ and is observable to outsiders of a publicly traded firm. For a profit-maximizing firm, it is the marginal cost of production that predicts a firm's investment behavior (Hayashi, 1982). This forms the basis for marginal q, which is $\frac{Price}{Marginal\ Cost}$. In neoclassical investment theory without financial constraints, marginal q is a sufficient statistic to predict the investment behavior of a firm.

Empirical studies of investment behavior find that q is not the only variable with a significant effect on investment, which is contrary to the predictions of neoclassical investment theory. Measures of cash (such as net worth, cash flow, and retained earnings) are frequently found to have a positive relationship with investment—i.e., firms with more cash have higher investment levels (Hubbard, 1998; Chalak and Kim, 2020). Many of these empirical studies use Tobin's q, which can be an imperfect and noisy proxy for marginal q (Erikson and Whited, 2000). This measurement error could explain the role cash plays in explaining investment behavior. Alternatively, cash might be an important part of a firm's decision-making process; this element is not present in the q theory of investment. Such missing theoretical aspects may include financial frictions (such as in Fazzari et al., 1988, and Cao et al., 2019) and behavioral biases toward free cash (Richardson, 2006). In this paper, I use a laboratory experiment to eliminate measurement error in marginal q and test its ability to predict investment behavior in an environment with minimal financial frictions.

[26] Lucas and Prescott (1971) develop a similar measure of optimality in a neoclassical model.

I develop a theoretical model of investment, which I implement in a laboratory experiment. The model and experiment both analyze subject's trading and producing capital goods across 20 time periods. These capital goods are created by converting cash into capital through a decreasing returns to scale process. In each period, capital pays a fixed dividend, depreciates, and can be traded with other subjects. Capital is priced endogenously through subjects' trades each period. Subjects also report their expectations of this price, which measures the numerator of marginal q. A major advantage of the experiment is that the denominator of marginal q—the marginal cost of producing a capital good—is observed and measured precisely. This observability and precision are a direct result of being able to control for and vary the production cost function in the experiment. I use the controlled setting of the lab to vary three main margins of the environment. To measure the effects of a subject's individual cash on production decisions, I independently vary cash endowments across individual participants while holding all aggregate variables constant. To measure the effects of changing marginal cost by reducing the marginal production cost while holding all else constant. Finally, I consider the effects of aggregate cash in the market by independently varying, across markets, the aggregate value of initial cash endowments. From the analysis of these treatment variations, I find three main results.

The first result is that increasing the amount of aggregate cash in the market increases production above the aggregate first-best level and increases the magnitude of capital price bubbles. In the experiment, the first-best level of production for an agent occurs when they produce capital at the level that maximizes total societal resources. In comparing aggregate cash effects, I use the aggregate first-best level, which is the sum of each agent's first-best production level. Holding all else constant, increasing the amount of cash in the market, increases total production across all time periods from 104% to 151% of the aggregate first-best production level. This overproduction harms market efficiency and reduces the total surplus and payout of the experiment relative to the first-best level. A similar increase in the magnitude of price bubbles is observed when increasing aggregate cash. In my experiment a price bubble occurs when capital prices are above the fundamental value, net present value, of capital. Average capital price bubbles, measured by the geometric mean of prices relative to fundamental values, increase from 121% of the fundamental value in low aggregate cash markets to 159% of the fundamental value in high aggregate cash markets. Given these price bubbles, some overproduction relative to the first-best is expected since subjects are maximizing their private payoffs rather than social welfare.

The second main result is that subjects make fewer privately optimal production decisions when aggregate cash is increased. A privately optimal production decision occurs when the marginal cost of the last unit produced by a subject is equal to their expectation of the capital price. This is measured with some allowance for small errors. To simplify the experimental environment, subjects make discrete integer production decisions. These decisions are optimal if $q \geq 1$ for their production decision and $q < 1$ for a counterfactual decision to produce one more until of capital. I compare the rate of privately optimal decisions across markets with the same capital production function. In low aggregate cash markets 65% of production decisions meet this definition of private optimality compared to 43% in high aggregate cash markets. The increased suboptimal production in high aggregate cash markets is divided evenly between over and under production. A portion of the decreased rate of private optimality in high cash markets is caused by the larger price bubbles experienced in these markets. Across all markets, increased price bubbles significantly reduce the rate of privately optimal decision making. I interpret this as the result of behavioral biases that increase the likelihood of some subject's underproducing relative to their privately optimal level.

The third main result is that decreasing the marginal cost of production increases the quantity of capital units produced. In contrast to the second result, this is a positive finding for q-theory. Holding constant the relative cash level in the market, production is significantly increased when marginal production costs decrease. Aggregate production is also significantly closer to the first-best level when marginal costs are decreased, 120% of the first-best versus 151% when marginal costs are higher. Price bubbles persist in markets with lower marginal costs and are not significantly different from bubbles in markets with higher marginal costs and high aggregate cash. The geometric mean of prices relative to the fundamental value is 167% and 159% for low and high marginal cost markets respectively.

I develop the first experiment in which subjects face a choice between investing in a capital good that is both durable and producible and a safe asset such as accumulable cash. The experimental methodology I use to study investment behavior builds on the asset market experiments first developed by Smith et al. (1988). In their experiment, subjects trade asset shares that pay a random dividend for a fixed number of periods, with the shares having no value at the end of the final period. This framework has been modified numerous times to understand a wide range of phenomena in equity markets (Palan, 2013). However, only limited attempts have been made to study capital markets through the introduction of endogenous asset production in these experiments. Lei and Noussair (2002) study growth models in an asset market experiment in which subjects can accumulate cash and trade and produce nondurable capital goods that depreciate after one period. Gjerstad et al. (2015) study durable goods trading in an experiment in which some subjects can produce durable goods that last for multiple periods, but subjects are unable to accumulate cash. My experiment allows all subjects to produce capital and accumulate cash, following Lei and Noussair. The capital they produce lasts for multiple periods with some depreciation, following Gjerstad et al. This allows me to study capital production and investment decisions when cash is a safe alternative investment that can be saved and used to produce or purchase capital in the future.

In my experiment I control and observe the capital production cost function, eliminating the measurement error in marginal *q* present in empirical studies. My knowledge of the production function allows me to calculate marginal *q* directly, eliminating the need to use Tobin's q as a proxy. A popular explanation for empirical findings in which cash has a positive effect on investment is that Tobin's *q* is subject to measurement error and a noisy proxy for marginal *q*. Hayashi (1982) specifies the conditions under which Tobin's *q* is not only a proxy, but is equivalent to marginal *q*. Based on arguments of adherence to these conditions, Tobin's *q* can be used as a proxy for marginal *q* in empirical reseach. Erickson and Whited (2000, 2012) argue that after using econometric techniques to address measurement error, cash effects on investment are no longer significant, which confirms *q*-theory models.[27] In this experiment, I find that without measurement error, increasing the amount of aggregate cash in the market increases production relative to the first-best, and decreases the rate of privately optimal investment decisions. This is despite a theoretical prediction that neither individual nor aggregate cash should affect investment decisions if agents are unconstrained, as they are in the experiment.

The control of the lab also allows me to observe investment decisions in an environment where subjects are not financially constrained. A theoretical explanation for the relevance of cash is that financial frictions prevent firms from investing as predicted by *q*-theory (Fazzari et al., 1988). Some dynamic stochastic general equilibrium models of investment focus on the role of

[27] In a dynamic stochastic general equilibrium setting, Abel (2018) shows that introducing measurement error over marginal *q* allows the model to generate correlations between cash and investment similar to those found empirically. These correlations are not present in Abel's model when *q* has no measurement error.

constraints on both inside and outside funds in generating correlations between investment and cash flows (Cao et al., 2019).[28] This experiment abstracts away from inside and outside funds—and from financial frictions more generally—by endowing subjects with enough cash (inside funds) that they are almost always unconstrained in their production decisions. Subjects are not allowed to borrow, but this is generally not necessary, since the no-borrowing constraint was only binding for 0.625% of all production decisions.[29] In the experiment, aggregate cash has an effect on investment decisions, even when subjects have no need and desire to access outside funds through borrowing. This indicates that financial frictions, and in particular borrowing constraints, are not necessary to explain the empirically observed relationship between investment and cash.

The relationship I observe between aggregate cash and investment decisions may be the result of behavioral biases surrounding cash holdings and price bubbles. Empirical research on the behavioral elements of investment has studied the effects of individual cash holdings. These studies have found that firm managers tend to overinvest when the firm has large free cash flows or receives large cash windfalls (Blanchard et al., 1994; Richardson, 2006). Firms also have a documented focality on retained earnings in making investment decisions (Cyert et al., 1979; Sengul et al. 2019). In this paper, the experiment varies cash endowments (liquid net worth) between subjects in the same market Individual cash differences are only significant in markets with a low marginal cost of capital and a large amount of aggregate cash. In these markets, subjects with a higher cash endowment overinvest more than those with a lower cash endowment. The decrease in the rate of optimal decision-making associated with aggregate cash cannot be directly explained by these previous findings on individual cash. I will demonstrate that this effect is partly explained by price deviations and may be related to decision-making under confusion.

The remainder of the paper is structured as follows. Section II introduces the theoretical model that will be implemented in the lab. Section III describes the experimental methodology and treatments. Section IV discusses the results, and Section V concludes.

---

[28] For a more comprehensive review of financial frictions, cash, and q in DSGE models, see Cao et al.'s (2019) introduction.

[29] Each of these cases occurred after a series of suboptimal production decisions by the subject.

II. Theoretical Model

II.A. Overview of Theoretical Model

To test the q-theory of investment in the lab I first develop, a theoretical model incorporating q-theory, which can be taken to the lab. This is a finite time model, of length T, which replicates the finite time nature of laboratory experiments. A finite number of agents, $i \in \Phi = \{1, ,2, \ldots, N\}$, exist and own capital, $k_{t,i}$, and cash, $b_{t,i}$. Agents are assumed to be price takers and have linear utility. These agents represent firms or investors in capital stock, who seek to maximize their final profits at the end of time T – i.e. they do not consume in each time period. The agents are heterogenous in their initial endowments of cash, $b_{0,i}$, and capital, $k_{0,i}$. They may form their own expectations of the price of capital, $E_i\left[P_{t+j}\middle|\mathcal{I}_{t-1}\right]$ based on the information set $\mathcal{I}_{t-1}$, which contains the history of prices and capital stocks through period $t-1$.

The level and distribution of the capital stock is endogenous to the model, in that agents produce and trade capital, which pays a set return and depreciates each period. Agents are initially endowed with a capital stock $k_{0,i}$, and chose to produce $x_{t,i} \geq 0$ new units of capital each time period. This production of capital requires cash and is costly, with a total cost function of $C(x_{t,i})$ which is weakly positive, strictly increasing, strictly convex for all $x_{t,i} \geq 0$, and has derivatives satisfying $C'(\cdot) > 0,\ C''(\cdot) > 0$ for $x > 0$. Also, there are no fixed costs for firms that do not produce – i.e. $C(0) = 0$. All agents have the same production technology. Each period, every unit of capital stock pays a fixed cash return, D. Additionally, the capital stock depreciates each period at a rate δ. For example, if an agent ends period $t-1$, with $k_{t-1,i}$ units of capital, they will begin period t with $(1-\delta)k_{t-1,i}$. They may then choose to produce more capital or sell their capital at the market price P_t. Capital cannot be sold short, $k_{t,i} \geq 0$, but capital can be traded in the period in which it is created. Trade in capital is subject to the following market clearing condition, where $K_t = \sum_{i\in\Phi} k_{t,i}$.

$$K_{t,i} = (1-\delta)K_{t-1,i} + \sum_{i\in\Phi} x_{t,i}$$

Agent's cash holdings, $b_{t,i}$, are used to finance the production and purchase of capital. Cash held at the end of a period pays a fixed interest rate r. Borrowing is not permitted, $b_{t,i} \geq 0$. Cash is also necessary for production, as there is a cash-in-advance constraint on the production cost, $(1+r)b_{t-1,i} + Dk_{t-1,i} \geq C(x_{t,i})$. This cash-in-advance constraint requires that the total cost of production in period t, $C(x_{t,i})$, be less than or equal to the amount of cash an agent holds at the beginning of period t, $(1+r)b_{t-1,i} + Dk_{t-1,i}$.

At the end of period T, after interest is paid, the returns on capital stock are paid, and depreciation occurs, each unit of capital stock an agent owns, $k_{T,i}$, is redeemed for cash (purchased by an external buyer) at a value, Υ. Thus, agents are attempting to maximize their final period portfolio value, $V_{T+1}(b_{T,i}, k_{T,i}) = (1+r)b_{T,i} + ((1-\delta)\Upsilon + D)k_{T,i}$.

They achieve this optimization by maximizing the expected future value of their portfolio given their price expectations in each period. This maximization is subject to the following budget constraint for all time periods $1 \leq t \leq T$.

$$b_{t,i} + P_t k_{t,i} + C(x_{t,i}) = (1+r)b_{t-1,i} + ((1-\delta)P_t + D)k_{t-1,i} + P_t x_{t,i}$$

The left-hand side of the budget constraint is the value of an agent's portfolio at the end of a period, $b_{t,i} + P_t k_{t,i}$, plus their total expenditure on producing new capital units that period, $C(x_{t,i})$. The right-hand side of the budget constraint is the wealth available to an agent during a period. This includes cash holdings carried from the previous period, $(1+r)b_{t-1,i} + Dk_{t-1,i}$, the post-depreciation value of the previous period capital holdings, $(1-\delta)P_t k_{t-1.i}$, and the market value of newly produced capital units, $P_t x_{t,i}$.

In every time period, agents' optimization problem is constrained by the budget and cash-in-advance constraints and the non-negativity constraints on $b_{t,i}$, $k_{t,i}$, and $x_{t,i}$. Taking prices and price expectations as given, agents solve the following problem to maximize the value of their portfolio every time period.

$$V_{t,i}(b_{t-1,i}, k_{t-1,i}) = \max_{b_{t,i}, k_{t,i}, x_{t,i}} E_i[V_{t+1,i}(b_{t,i}, k_{t,i}) | \mathcal{I}_{t-1}]$$

$$s.t$$

$$b_{t,i} + P_t k_{t,i} + C(x_{t,i}) = (1+r)b_{t-1,i} + ((1-\delta)P_t + D)k_{t-1,i} + P_t x_{t,i}$$

$$(1+r)b_{t-1,i} + Dk_{t-1,i} \geq C(x_{t,i})$$

$$b_{t,i} \geq 0,\ x_{t,i} \geq 0,\ k_{t,i} \geq 0$$

If P_t is greater than any fixed costs faced by producing agnets, optimal production will be weakly greater than zero, $x_{t,i} \geq 0$. Equation (1), which is derived from the first order conditions of the optimization problem, characterizes the optimal amount that an agent should produce at a given price, assuming this condition is meet the cash-in-advance constraint is not binding.

$$C'(x_{t,i}) = P_t \tag{1}$$

In addition to production, agents' decision to buy or sell capital can also be characterized from the first order conditions of the optimization problem. Equation (2) characterizes an agent's buy or sell decision when they do not expect the borrowing constraint or the cash-in-advance constraint to bind in the future. In this equation, $\mu_{t,i}$ is the Lagrange multiplier on the capital no-short sell constraint, $k_{t,i} \geq 0$, and $\gamma_{t,i}$ is the Lagrange multiplier on the no-borrowing constraint, $b_{t,i} \geq 0$.

$$P_t = \frac{(1-\delta)E_i[P_{t+1}|\mathcal{I}_{t-1}] + D}{1 + r + \gamma_{t,i}} + \frac{\mu_{t,i}}{1 + r + \gamma_{t,i}} \tag{2}$$

When the no-borrowing constraint is not binding, the first term on the right-hand side of this expression is an agent's expected value of holding a unit of capital until the next period, $(1-\delta)E_i[P_{t+1}|\mathcal{I}_{t-1}] + D$, discounted by the interest rate. The second term represents the shadow value of being able to sell capital short. Whenever the discounted expected value of holding capital until the next period is less than the price, an agent will want to sell all of their capital stock and take a short capital position, but they are unable to take a short position. If an agent's no-borrowing constraint is binding, then the price is less than their discounted expected value of capital, so they will purchase as many capital units as they can afford. The affordability of these purchases being determined after accounting for the cost of optimal production as characterized by equation (1).

Given that agents need to decide $x_{t,i}$ before observing P_t, expectations mater. This is especially the case when capital is traded using a double auction or Walrasian market.[30] It is therefore an agent's expectation of a given period's capital price that determines their optimal production decision. The cash-in-advance constraint on capital production is necessary to ensure the budget constraint holds, because production decisions occur before the market clears. Taking this into account, I modify equation (1) to depend on price expectations. This is a modification of the first order conditions from the above maximization problem, which is necessary since the

[30] These considerations are particularly important for the application of this model to the experimental design employed in this paper. In the experiment, capital units are traded using a call market, in which prices are not revealed until after subjects have made their production decision.

budget constraint must hold at actual, rather than expected, prices. Equation (3) characterizes the optimal production decision for an agent when the cash-in-advance constraint is not binding.

$$E_i\left[P_{t,i}|\mathcal{I}_{t-1}\right] = \mathrm{C}'\left(\mathrm{x}_{\mathrm{t,i}}\right) \tag{3}$$

This equation states that an agent's optimal production of new capital, $\mathrm{x}_{\mathrm{t,i}}$, occurs when the marginal cost is equal to their expectation of the price of capital.

Given that optimal production decisions are based on expected prices, rather than realized prices, measuring how often agents follow q-theory in the experiment requires a definition of q that accounts for expected prices. This form of q is expressed below as q^E.

$$q_{t,i}^E = \frac{E_i[P_t|\mathcal{I}_{t-1}]}{C'\left(x_{t,i}\right)}$$

This q^E is measured for each agent, and is the ratio of their expected price at time *t* and the marginal cost of their production at time *t*. From equation (3), optimal production for an agent will occur when $q_{t,i}^E = 1$. When $q_{t,i}^E < 1$, an agent expects the price of capital to be less than the marginal cost they paid for the last unit of capital they produced. Thus, it would be more profitable to reduce their production of new capital and attempt to purchase more existing capital. When $q_{t,i}^E > 1$, the marginal cost of the last unit of capital an agent produced is less than what they expect to be the price of capital. Producing additional capital and selling it on the market is expected to be a profitable activity.

II.B. First Best Allocation

In this economy, a first best allocation will be any allocation that maximizes the total value of resources after the conclusion of period *T*, $(1+r)\sum_{i\in\Phi} b_{T,i} + \left((1-\delta)\Upsilon + D\right)\sum_{i\in\Phi} k_{T,i}$. Maximizing these total resources allows the planner to grant the maximal amount to each agent according to the welfare weight the planner assigns to that agent. Proposition 1 describes the conditions for an allocation to be a first best allocation.

Proposition 1 *An allocation* $\left\{\{x_{t,i}\}_{i\in\Phi}\right\}_{t\in\{1,\ldots,T\}}$ *is a first best allocation iff*

(a) $C'(x_{t,i}) = FV_t$ *and* $C(x_{t,i}) \leq (FV_t)x_{t,i}\ \forall t,i$ **OR**

(b) $x_{t,i} = 0\ \forall\ t,i$ *and* $\nexists\ \left\{\{x_{t,i}\}_{i\in\Phi}\right\}_{t\in\{1,\ldots,T\}}$ *such that* $x_{t,i} > 0$, $C'(x_{t,i}) = FV_t$, *and* $C(x_{t,i}) \leq (FV_t)x_{t,i}\ \forall t,i$

Where $FV_t = \left(\frac{1-\delta}{1+r}\right)^{T+1-t}\Upsilon + \frac{1}{1+r}\sum_{i=1}^{T-t}\left(\frac{1-\delta}{1+r}\right)^{i} D$

Proof See Proofs Appendix

□

Proposition 1 shows that first best allocations will occur when every agent is producing in every period at a level where the marginal cost of production is equal to the fundamental value of a capital unit. The fundamental value is the net present value of all future dividends, and the redemption value. The symmetric production across agents is due to all agents having access to the same production technology and having the same utility function. If either of these conditions were violated, this condition would no longer hold. Beyond the restriction of each agent's production, there are no additional restrictions on a first best allocation. This means that any allocation of capital and cash can be a first best allocation if production follows proposition 1.

II.C. Stationary State

Given that this is a finite time model, there is not a steady state in the traditional sense of an equilibrium capital stock to which the economy will always revert given enough time. However, there can be a "stationary state" of the economy at which the level of capital stock remains constant over time. As will be shown in proposition 2, this stationary state exists when the fundamental value of a unit of capital is constant in every time period of the economy.

Proposition 2: Stationary State: *If* $K_0 = \overline{K}$, $\Upsilon = \frac{D}{r+\delta}$, $C'\left(\delta\frac{\overline{K}}{N}\right) = \Upsilon$, $C\left(\delta\frac{\overline{K}}{N}\right) \leq \delta\frac{\overline{K}}{N}\Upsilon$, $r \geq 0$, $\delta > 0$, *and* $rb_{0,i} + Dk_{0,i} \geq C\left(\delta\frac{\overline{K}}{N}\right)\ \forall i$, *then the rational expectations equilibrium will be stationary and will entail* $FV_t = P_t = \Upsilon$, $K_t = \overline{K}$, *and* $x_{t,i} = \delta\frac{\overline{K}}{N}\ \forall t,i$.

Proof See Proofs Appendix

□

Proposition 2 defines a stationary state for this model. When the conditions of proposition 2 are met, capital will remain at a constant level in the economy, and the price will remain at the fundamental value. This means that the economy is "stationary" in the sense that the price and aggregate variables do not change from period to period, and the fundamental value is constant. Proposition 2 *does not* define an allocation of capital between the different agents, only the aggregate level of capital, and the level of production for each agent. Any allocation of capital between the agents that does not result in the cash-in-advance constraint, $(1+r)b_{t-1,i} + \mathrm{D}\mathrm{k}_{\mathrm{t-1,i}} \geq C\left(\delta \frac{\overline{K}}{N}\right)$, being violated, can be part of a stationary state equilibrium. I will design the experiment such that each treatment fulfills the conditions for a stationary state equilibrium if subjects' expectations are rational.

When agents do not follow rational expectations, the price, optimal production, and aggregate capital results of the stationary state equilibrium break down. However, whenever $\Upsilon = \frac{D}{r+\delta}$, the fundamental value will be constant at Υ.

II.D. Optimality Theoretical Results

Proposition 2 describes a stationary state of the economy under the assumption that agents are forming their expectations rationally. This is a strong assumption to carry into a laboratory environment. To better understand possible laboratory outcomes, it is useful to analyze optimal outcomes without any assumptions over how agents form their expectations – i.e. taking expectations as given. Taking expectations as given, lemma 1 describes an agent's optimal production decision.

Lemma 1: Individually Optimal Production *If agent i has the price expectation $E_i[P_t|\mathcal{I}_{t-1}]$ and*

(a) $(1+r)b_{t-1,i} + Dk_{t-1,i} \geq C\left(C'^{-1}(\boldsymbol{E_i}[P_t|\mathcal{I}_{t-1}])\right)$, *then their optimal production decision is* $x_{t,i} = C'^{-1}(\boldsymbol{E_i}[P_t|\mathcal{I}_{t-1}])$ *and* $q^E_{t,i} = 1$.

(b) $(1+r)b_{t-1,i} + Dk_{t-1,i} < C\left(C'^{-1}(\boldsymbol{E_i}[P_t|\mathcal{I}_{t-1}])\right)$, *then their optimal production decision is* $x_{t,i} = C'^{-1}\left((1+r)b_{t-1,i} + Dk_{t-1,i}\right)$ *and* $q^E_{t,i} > 1$.

Proof See Proofs Appendix

□

This optimal production decision in lemma 1 depends only on an agent's price expectation, regardless of how the expectation was formed, and whether the agent's cash-in-advance constraint is binding. Even if an agent is deviating from rational expectations in forming their price expectations, optimality dictates that they should produce according to lemma 1. Whenever the cash-in-advance constraint is not binding, production decisions should be such that $q_{t,i}^{E} = 1$, which is consistent with Lucas and Prescott (1971). Consistent with Fazzari et al. (1988), when cash-in-advance constraints bind production decisions should result in $q_{t,i}^{E} > 1$. With these findings, it is only important that an agent's cash is sufficient to cover the cash-in-advance constraint, not their exact cash holding. Holding more cash than is necessary to prevent the constraint from binding should not lead to additional production. Additionally, this optimality only depends upon an individual agent's cash holdings, not the aggregate cash holdings in the economy.

While lemma 1, characterizes the optimality condition for individual production choices, this is not necessarily aligned with the socially optimal levels of production. Socially optimal levels of production only depend on the redemption rate, dividend, and cost function. Lemma 2 characterizes this optimal production decision for the capital market structure that I will use in the experiment.

Lemma 2: Socially Optimal Production *If* $\Upsilon = \frac{D}{r+\delta}$, $C'\left(\delta\frac{\overline{K}}{N}\right) = \Upsilon$, *and* $C\left(\delta\frac{\overline{K}}{N}\right) = \delta\frac{\overline{K}}{N}\Upsilon$, *then any solution to a social planner's problem will require* $x_{t,i} = \delta\frac{\overline{K}}{N}\ \forall t, i$.

Proof See Proofs Appendix

□

This optimal production level only depends on the fundamentals of the capital market, specifically the cost function, redemption value, return, interest rate, and depreciation. The optimal level does assume that there is sufficient cash in the economy to fund the optimal production. However, beyond that the result is independent of aggregate cash in the economy.

II. E. Testable Implications

When implementing this model in the lab, there are four main theoretical results that I aim to test in the experiment. These results constitute the testable implications of the model. The first of these testable implications relates to the first best allocation, which is a useful benchmark for measuring experimental outcomes.

Testable Implication 1: For a set of parameters $\{D,\ \Upsilon,\ \delta,\ r,\ C(\cdot)\}$ *that satisfy Lemma 2, and for which* $rb_{0,i} + Dk_{0,i} \geq C\left(\delta\frac{\overline{K}}{N}\right) \forall\ i$*, production levels will be constant and at the first-best..*

The first testable implication provides a benchmark against which experimental subjects' production decisions can be measured. As will be shown in Section III, I will pick the experimental parameters on the capital market such that they will always satisfy lemma 2. This means that there is a first best production level at $x_{t,i} = \delta\frac{\overline{K}}{N}\ \ \forall t, i$. In testable implication 1, the added assumption that $rb_{0,i} + Dk_{0,i} \geq C\left(\delta\frac{\overline{K}}{N}\right) \forall\ i$ ensures that subjects making decisions under rational expectations will have sufficient cash to produce at the first best level, as is proved in proposition 2. This production level will be both privately and socially optimal for a subject as long as their expectations are rational and the price remains at the fundamental value. From lemma 1, the first best will no longer be privately optimal if the expected price of capital deviates from its fundamental value. The predicted price of capital is subject of the second testable implication.

Testable Implication 2: In all periods, the price of capital is equal to its fundamental value.

This second testable implication concerns the price of capital. The fundamental value of capital is well defined in all periods based on the known interest rate, depreciation rate, capital dividend, and redemption value. Solving the optimization problem for the economy results in a predicted price of capital equal to the fundamental value, assuming that subjects are not cash constrained. As discussed above and in the proof of proposition 2, agents will not be constrained when the conditions of testable implication 1 are satisfied. Taken together, testable implications 1 and 2 predict a constant production level at the first best and price at the fundamental value. Changes in the fundamental value in capital will affect both predictions, as described in testable implication three.

Testable Implication 3: For two sets of capital market parameters, $\{D_1, \Upsilon_1, C_1(\cdot)\}$ *and* $\{D_2, \Upsilon_2, C_2(\cdot)\}$*, that both satisfy the conditions of lemma 2, and where* $C_1'(x) > C_2'(x)$*, production will be greater under set 2.*

Testable implication three predicts that changes in the structure of capital resulting in a lower marginal cost will result in increased production. This prediction is contingent upon the capital market parameters satisfying the conditions of lemma 2, which guarantee a constant first-best level of production. In the lab, this is testing if subjects respond to decreases in marginal cost by increasing production, as is predicted by q-theory. Assuming that the cash-in-advance constraint is not binding for any subject, a change in marginal cost (or the capital parameters more generally) is the only change that is predicted to affect production decisions. This is further clarified in testable implications 4 and 5.

Testable Implication 4: When an agent's cash-in-advance constraint is non-binding in a given period, production decision in that period will not be affected by individual cash holdings.

Testable implication four is a direct corollary from lemma 1. When an individual's cash-in-advance constraint is not binding then they will be in condition (a) of lemma 1. This predicts the individual's production decision based on the cost function, and their price expectation. In the experiment, I control the production cost function, and elicit subject's price expectations. Given that subject's are endowed with sufficient cash for the cash-in-advance constraint not to bind, this information is theoretically enough to predict their production decision. The amount of cash held by the un-constrained subject is not relevant to their production decision, nor is the amount of cash present in the market.

Testable Implication 5: Individual production decisions are not affected by the aggregate amount of cash in the market.

The fifth testable implication relates to the affects of aggregate cash on production decisions. Proposition 2 and lemmas 1 and 2 specify the cash conditions necessary for certain production outcomes. These are all conditions on individual cash holdings, not market level cash.

This implies that market level cash has no effect on individual decisions. In the experiment, subjects will not know the market cash level so it should not affect their decisions. In markets where the only difference is aggregate cash levels, differences in production must be explained through some indirect and behavioral channel.

III. Experimental Design

III.A Overview of Experimental Design

This experiment is designed to implement the model from section II in a laboratory environment. In each experimental session, 8 subjects trade units of capital for 20 periods. After the 20th period, capital is redeemed for an amount that varies with each treatment as explained in section III.B. This capital functions the same as capital in the theoretical model. That is, it depreciates, can be produced at an increasing marginal cost, pays a fixed return in lab cash every period, and is redeemed for a fixed amount after the final period. The cash return to capital is explained to subjects as a dividend.

In each period subjects have the ability to produce and trade units of capital in a call market. Subjects trade capital in the call market by submitting limit orders to buy and sell capital. A limit order specifies the number of capital units a subject would like to buy or sell, and the limit price they are willing to trade. Each period a subject can submit at most one limit order to buy capital (bid order), and at most one limit order to sell capital (ask order). The bid order is the maximum price buyers are willing to pay. A sell order is the minimum price sellers are willing to accept. After all orders are submitted, the market is cleared by finding the price at which the number of units subjects are willing to sell is equal to the number of units they are willing to buy[31]. Limit orders can only be submitted for an integer quantity of capital units, and subjects cannot sell more units than they own. To prevent self-trading, subjects who submit both bid and ask orders must submit an ask price that is higher than their bid price.

The primary goal of this experiment is to analyze subject's decisions to produce capital. In keeping with this goal, subjects are required to specify a capital production decision in each period,

[31] If there is no price at which the number of units subjects are willing to sell equals the number of units subjects are willing to buy, but trade is possible (at least one subject wants to buy at a price higher than at least one subject is willing to sell), then the price at which the most units are traded is selected. At this price there is excess supply or demand for shares, and the excess is delt with by the shares traded being randomly selected from the highest tradeable ask prices or lowest tradeable bid prices.

but this decision can be to produce zero units. Capital production also must occur in integer quantities. Subjects make their decisions by selecting the integer quantity of capital they wish to produce from a drop-down menu. This menu lists the number of units produced and the cost of production. Production transforms cash into capital via an increasing marginal cost production function that varies across treatments. Subjects' decisions to produce and buy capital are constrained by their cash holdings at the start of a period. The sum of a subject's production choice cost and the maximum cost of their bid order must be less than or equal to their cash holdings at the beginning of a period. Subjects cannot attempt to sell more units than the sum of their production and existing capital holdings. Subjects alco cannot sell capital short.

In addition to trading and producing capital shares in each period, subjects are also asked to make predictions over the market price of capital. Subject's must submit a price prediction for the price in the current period, the next period, and two periods ahead. If a subject's price prediction is within +/- $E 2.50 of the actual price in lab cash ($E), then they receive a bonus payment of $E 1.00 per correct prediction. This bonus is paid at the end of the period in which the relevant price is determined and is added to the subject's stock of lab cash. The bonus payment is not sequestered and can be used the same as cash from all other sources. These predictions allow for an analysis of how expectations over current and future prices influence production decisions. In particular, they allow for a measurement of q^E, defined in section II.

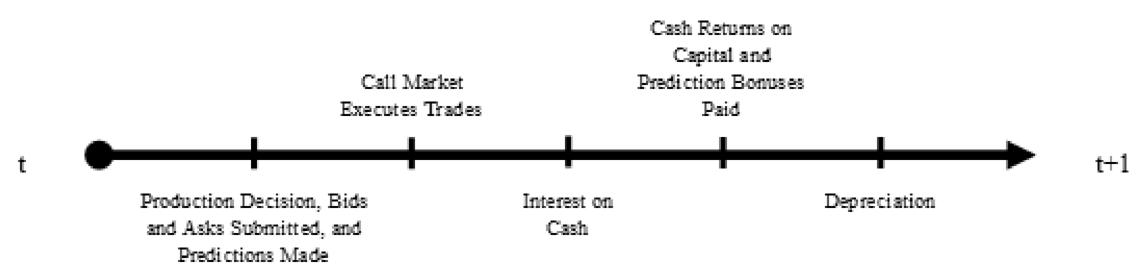


Figure 2.1 Timeline of events in period t.

Figure 2.1 shows the order of events for subjects in a period. After all subjects in a session have submitted their production decisions, limit orders, and price predictions for a period, the call market determines the market clearing price and executes trades. Interest is then paid on subjects' remaining cash balances and dividends are paid for each unit of capital held. At this point, any relevant prediction bonuses are also paid. These events are shown separately in figure 2.1 because interest is not paid on dividends in the period they are earned. Finally, the capital stock depreciates uniformly for all subjects before the beginning of the next period.

A call market is used to execute trades in this experiment because it results in all trades occurring at a single price. This is advantageous over a double auction in simplifying the environment for subjects and computing q. In a double auction, trades may occur at multiple prices in the same period with it being possible for an individual subject to trade capital units at multiple prices. These trades may be separated by time in the window for which the auction is open. This complicates subjects' production decisions since they are making these simultaneous to active trading. This may make it difficult for sellers to keep track of the number of units that they must produce to clear all of their trades. In the call market, productions decisions are made at the same time as the submission of limit orders, making it easier for subjects to keep track of their capital stock. Additionally, the single price of a call market makes the prediction task easier for subjects to understand. Subjects are predicting what the single market clearing price will be in a period, rather than the average price of their own or the total market trades in a double auction. This improves the quality of elicited expectations, making q^E a more reliable measure of production optimality.

In addition to the capital market production and trading task, each subject completes a task to measure their risk aversion. This task is completed after decisions for the first round of trading are submitted, but before the results of the call market are released. Risk aversion is measured using a version of Crosetto and Filippin's (2013) "bomb" risk elicitation task (BRET). In this task subjects are shown 12 boxes on their screen. Each box contains \$1, and one box also contains a virtual ink bomb. For each box the subject opens, by clicking the check mark on the box, they earn \$1. However, if they open the box containing the ink bomb, all the cash is destroyed, and they earn nothing from the task. To eliminate possible wealth effects, the location of the ink bomb and the earnings from this task are not revealed until after the final period of the capital market. The dollars in each box for this task are USD, not \$E. This risk aversion measure will be used in the results to control for production biases that may be induced by risk preferences.

III.B Treatments and Parameter Values

This experiment uses a 3x2 experimental design with three between session treatments and two within session treatments. Within each session there are two endowment treatments, each applied to half of the subjects in the session. These endowment treatments vary the amount of cash between a high and low initial cash level for the subject, while all subjects receive the same initial endowment of capital stock. Across the three between session treatments, the ratio of the total value of cash and capital endowments between these two groups is held constant.[32] In no treatment is any subject constrained such that they are unable to follow the first best production path. This variation in initial cash between subjects relates to testable implication 3, which predicts no production difference based on cash endowments. Varying cash endowments within the same session allows is useful for measuring differences in production decisions between two groups of subjects exposed to the same price and aggregate capital stock history. Any differences between these groups refute testable implication 3.

One of the three market level treatments is applied to each laboratory session. The primary differences between these treatments are the amount of cash subjects begin with, and the cost function, returns, and redemption value of capital. Across all treatments the interest rate and depreciation are the same. Cash holdings earn a 2% interest rate, and capital depreciates at a rate of 10%. Other parameters from the model, which vary across treatments, are described in Table 2.1. These values all fulfill the requirements for a stationary state to exist, satisfying proposition 2 and lemma 2. The goals of each treatment are described in the following subsections.

---

[32] The ratio is constant up to allowing for rounding of cash endowments to clean numbers.

Table 2.1: Parameter Values for Market Level Treatments

Treatment	(Low Cost) Low Cost/ High Aggregate Cash	(Baseline) High Cost/ High Aggregate Cash	(Low Cash) High Cost/ Low Aggregate Cash
Low Type Cash Endowment $((1+r)b_{0,L})$	\$E 1,800.00	\$E 1,200.00	\$E 140.00
High Type Cash Endowment $((1+r)b_{0,L})$	\$E 3,600.00	\$E 2,400.00	\$E 400.00
Capital Endowment $((1-\delta)k_{0,i})$	18 units	9 units	9 units
Cost Function	$C(x) = \begin{cases} 0 \; if \; x=0 \\ 10+5x^2 \; if \; x>0 \end{cases}$	$C(x) = \begin{cases} 0 \; if \; x=0 \\ 10+10x^2 \; if \; x>0 \end{cases}$	$C(x) = \begin{cases} 0 \; if \; x=0 \\ 10+10x^2 \; if \; x>0 \end{cases}$
Cash Return (D)	\$E 1.80	\$E 2.40	\$E 2.40
Redemption Value (Υ)	\$E 15.00	\$E 20.00	\$E 20.00
Fundamental Value (FV)	\$E 15.00	\$E 20.00	\$E 20.00
Stationary State Capital Stock ($\overline{K}$)	160	80	80
Socially Optimal Production ($\delta\frac{\overline{K}}{N}$)	2	1	1
Conversion Rate \$E:\$USD	150:1	100:1	25:1

III.B.1 Baseline Treatment

The goals of the baseline treatment are twofold: to develop an environment in which to test testable implications 1, 2, and 4, and to develop a baseline from which to test implications 3 and 5. The parameters for this treatment satisfy all of the conditions for these testable implications, and are described in the third column of Table 2.1. Both the low and high individual cash subjects have cash endowments sufficient to produce at the first best level. At the first best production level, each subject produces one unit of capital each period, for an aggregate production level of 8 units of capital. Since subjects can afford this production level, this is the level of production that I expect to be see in this treatment. The fundamental value of capital in this treatment is \$E 20 in all periods. Testable implication 2 predicts capital will be priced at this level. To test this, I will measure price deviations from the fundamental value. The cash endowments in this treatment are set sufficiently high such that both subject types can afford the privately optimal production levels predicted by lemma 1 for a wide range of price expectations. This means that even if prices deviate significantly from the fundamental value, testable implication 4 will still predict no difference in the rate at which subjects with high and low cash endowments make optimal decisions. This treatment also forms the baseline against which the other treatments will be measured.

III.B.2 Low Cost Treatment

In the low cost treatment, the cost function is altered to result in lower marginal and total costs at each non-zero production level. The cash return from capital, and the redemption value of capital are also altered so that the first best and stationary state production level are two units of capital per period per subject. The parameters for this treatment are in the second column of Table 2.1. These changes in the capital parameters create a second set of parameters to use in evaluating testable implication 3. Specifically, this treatment tests if subjects' increase their production when the marginal cost of producing capital falls. The treatment also provides another set of conditions in which to evaluate testable predictions 1,2, and 4.

A robust finding of the experimental asset markets literature is that the ratio of cash to the total fundamental value of assets is highly correlated with the size of price bubbles (Caginalp, Porter, & Smith, 2001). I want to control for the possibility that this effect also occurs in this experiment's capital markets with production. To do so, the cash endowments are selected to keep this ratio constant with the baseline treatment. The ratio of cash to the fundamental value of capital is measured at the stationary state level for the purposes of experimental design. At the stationary state, this ratio starts at 8.90 and grows to 13.42 as cash holdings increase due to interest and the cash returns on capital. These ratios are identical for both the baseline and low cost treatment. Additionally, the relative wealth of the high and low cash types at the start of the market is constant between the two treatments. By holding constant the sequence of cash to capital ratios, only the fundamentals of the capital market have changed. This isolates any differences in behavior between the low cost and baseline treatments to come from the changes to the capital parameters, creating a direct test of testable implication three.

III.B.3 Low Cash Treatment

The final between session treatment is a low cash treatment designed to evaluate testable implication 5, on the effects on aggregate cash. In this treatment the fundamentals of capital are unchanged from the baseline. What is changed is the level of the cash endowment for both the high and low types. The parameters for used in this treatment are in the fourth column of Table 2.1. The high type's cash endowment is reduced to $E 400, and the low type's cash endowment is reduced to $E 140. These values keep the total value of endowments, including the fundamental value of endowed capital, roughly the same as in the baseline treatment.[33] These reductions in cash result in a cash-to-capital value ratio that starts at 1.25 and grows to 2.28.

Because the capital parameters and the ratio of high and low cash type endowments are unchanged, this treatment isolates changes in production behavior due to changes in aggregate cash. The high and low individual cash types are both endowed with sufficient cash to produce at the first best level, which costs $E 20 per period. Therefore, there is no theoretical prediction that production should differ between the baseline and low cash treatments. Any such difference in production, or the rate of privately optimal production decisions, would be contrary to testable prediction 5.

III.C Subjects and Recruitment

Subjects were recruited from the University of Virginia undergraduate student population. There were 18 sessions, 6 sessions for each treatment, resulting in a total of 144 subjects. All sessions were conducted in-person in the V*e*conlab at the University of Virgina.[34] In addition to their earnings from the bomb task and capital market, subjects received a $6-$10 payment for showing up to the lab on time for their session.[35] Earnings for the capital market task averaged $27.03 before adding earnings from the BRET task and the show up payment. Earning by treatment are available in table 2.2. On average subjects earned $2.55 from the BRET task. The conversion of lab cash earnings to USD was varied across treatments to keep average earnings roughly equal for each treatment. The conversion ratios are available in the bottom row of Table

---

[33] In the baseline treatment the low type's endowment of cash and capital is worth 53.5% of the high type's endowment. In the low cash treatment this ratio is 55.2%. The difference comes from rounding values to result in endowments that were intervals of 10 and an initial cash-to-capital ratio of 1.25.

[34] Subjects were recruited for 90 minute sessions, with several sessions taking the full 90 minutes.

[35] Midway through conducting sessions the lab increased the show-up payment from $6 to $10 for all experiments. This was done to increase subjects' take home pay in response to inflation.

2.1. The experiment was run using the Investment program on the publicly available V*e*conlab platform. A sample of the instructions for the capital market task and BRET task are available in the experimental instructions appendix.

Table 2.2: Average Market Cash Earnings by Treatment

	Market Treatment		
Individual Treatment	Baseline	Low Cost	Low Cash
Low Individual Cash	\$19.35	\$19.21	\$21.00
High Individual Cash	\$32.21	\$35.54	\$32.71

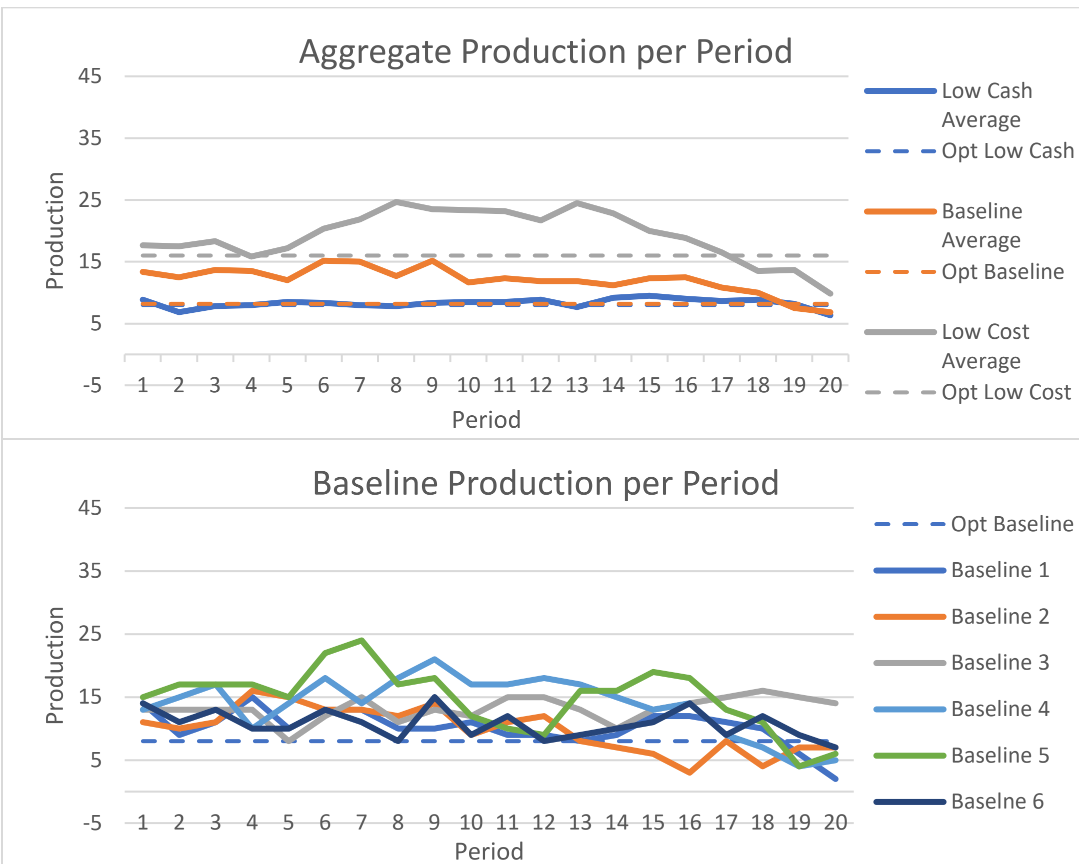
All subjects for each treatment we inexperienced with any of the treatments, and the market task was run once for each session. Previous results on subject experience in asset market experiments without production find experience may reduce the size of price bubbles (Smith et al., 1988, and Dufwenberg et al., 2005). More recent work has found contradictory evidence that experience does not always reduce price bubbles (Kopányi-Peuker and Weber, 2021). Given these conflicting findings, I do not consider the effect of experienced subjects and leave the question to future research.

IV. Results

The results from this experiment show that in general, subjects do not invest consistent with q-theory. In relation to the first testable implication, subjects tend to overproduce relative to the first-best level in the baseline and low cost treatments. In all treatments, capital trades above its fundamental value, which is contrary to the predictions of testable implication 2. The predictions of testable implication 3 hold, with subjects producing more capital in the low cost treatment than in the baseline. For testable implication 4, individual cash holdings only affect production decisions in the low cost treatment – subjects with high individual cash endowments are less likely to make privately optimal production decisions. Aggregate cash levels are an important predictor of the quantity of capital produced and the private optimality of capital production decisions. This is contrary to the predictions of testable implication 5. These results are discussed in detail in the following subsections, beginning with market level results.

IV.A. Market Level Results

Testable implication 1 is concerned with the first best level of capital production. The set of first-best allocations for a market are described in proposition 1. Lemma 2 further defines the first-best allocations for conditions present in all treatments. Thus, the first best production level is constant across periods. For the baseline and low aggregate cash treatments, a fist-best allocation occurs whenever all traders produce 1 capital unit per period. For the low cost treatment, a first-best allocation occurs whenever all traders produce 2 capital units per period. In no session is this strictly observed at the individual level. However, an allocation that is not first-best, but is close to the first best allocation, occurs when aggregate production is at aggregate first-best. That is, an aggregate production of 8 in the baseline and low aggregate cash treatments and an aggregate production of 16 in the low cost treatment. Figure 2.2 below compares aggregate production in each time period and session to the first best production level.



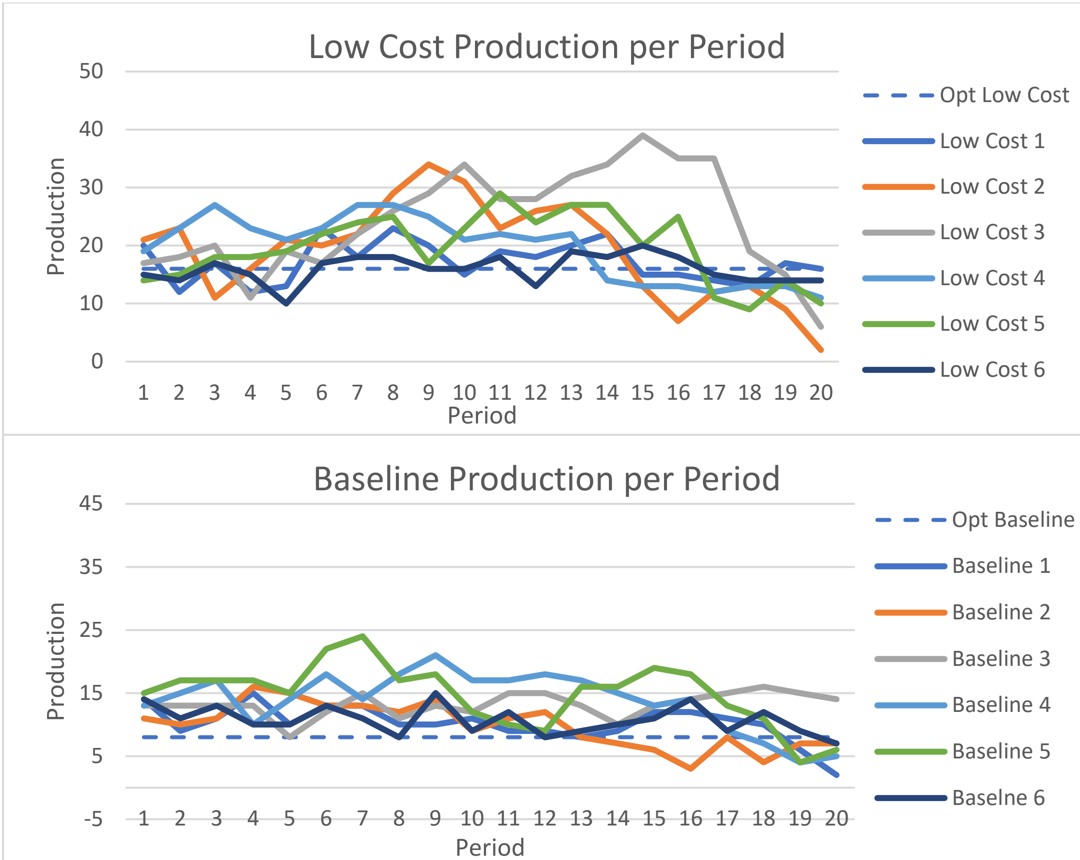


Figure 2.2 Aggregate Production per Period.

Notes: (a) Average aggregate production by treatment (solid lines) and socially optimal aggregate production by treatment (dashed lines). (b) Aggregate production for each market in the baseline treatment (solid lines) and optimal aggregate production for baseline treatment (dashed line). (c) Aggregate production for each market in the low cost treatment (solid lines) and optimal aggregate production for low cost treatment (dashed line). (d) Aggregate production for each market in the low cash treatment (solid lines) and optimal aggregate production for low cash treatment (dashed line).

The top panel of figure 2.2 compares the first best aggregate production level to the average production level observed in each period in each treatment. In the baseline and low cost treatments production exceeds the first best level in most periods and tends to decline in the final periods, dropping below the socially optimal level in the low cost treatment. On average, production in the baseline treatment roughly follows the first best level. The remaining three panels of figure 2.1 show the aggregate production levels for each market, segregated by treatment. The bottom panel shows the aggregate production trends in the low cash treatment. These capital production trends are closely grouped around the line representing the first best production level. This confirms that for the low cash treatment the average trend holds in the individual markets. The second panel shows production in the baseline treatment, and the third shows production in the low cost treatment. In both of these treatments production is seen to regularly exceed the first best level.

The production graphs in figure 2.2 appear to show testable implication 1 only holds in the low cash treatment. To quantify overproduction more carefully, I measure the relative deviation of production from the first best level in each market. This is measured both directly, using Market Production Deviation (MPD), and in absolute terms, using Absolute Market Production Deviation (AMPD). Market production deviation is the sum of the production deviation from the first best (opt.) in each period, $MPD = \frac{\sum_{t=1}^{T} Prod_t - Opt_t}{\sum_{t=1}^{T} Opt_t}$. Absolute production deviation is the same measure using the absolute value of deviations, $AMPD = \frac{\sum_{t=1}^{T} |Prod_t - Opt_t|}{\sum_{t=1}^{T} Opt_t}$. MPD measures the deviation of production across the market as a percentage of total first best production. This measure is useful in quantifying production behavior across a market, and comparing how different treatments affect overall production trends. However, from the standpoint of the first best, over and under production are both suboptimal, they should not be allowed to cancel each other out in measuring aggregate production's adherence to the first best. To account for this, AMPD measures as a percentage, the absolute difference actual production and optimal production.

The third and fourth columns of table 2.3 report the MPD and AMPD for each market, relative to the socially optimal level of production. These values form the basis for the first result.

Result 2.1: Reducing the level of aggregate cash in a market significantly reduces aggregate production deviations from the socially first best of production.

Measured by both Market Production Deviation and Absolute Market Production Deviation the average deviation in low cash treatment is less than the average deviation in the baseline and low cost treatments. Both the baseline and low cost treatments have the same cash to capital ratio in endowments, can therefore represent the same aggregate cash level. Pooling across aggregate cash levels, the Market Production Deviation is different in markets with low and high aggregate cash at the 95% confidence level (*p*-value 0.0103) and the Absolute Production Deviation is different at the 95% confidence level (*p*-value 0.0147).[36] These differences are tested

[36] Differences in MPD and AMPD can also be measured against the baseline and low cost treatments separately using two-tailed permutation test. At the 99% confidence level MPD and AMPD differ between the baseline and low

using a two-tailed permutation test (Holt and Sullivan, 2019). A two-tailed test is used because testable implication 1 predicts no difference across cash levels. These results reinforce the patterns observed in figure 2.2.

Table 2.3: Production deviations

Market	First Best Production	MPD[a]	AMPD[b]
Base 1	8	0.275	0.375
Base 2	8	0.231	0.406
Base 3	8	0.644	0.644
Base 4	8	0.725	0.825
Base 5	8	0.850	0.925
Base 6	8	0.344	0.356
Average	**8**	**0.512**	**0.589**
L. Cost 1	16	0.069	0.188
L. Cost 2	16	0.194	0.475
L. Cost 3	16	0.513	0.613
L. Cost 4	16	0.219	0.363
L. Cost 5	16	0.222	0.366
L. Cost 6	16	-0.003	0.122
Average	**16**	**0.202****	**0.355***
L. Cash 1	8	0.019	0.131
L. Cash 2	8	-0.019	0.194
L. Cash 3	8	0.056	0.144
L. Cash 4	8	0.125	0.288
L. Cash 5	8	-0.094	0.294
L. Cash 6	8	0.125	0.138
Average	**8**	**0.035*****	**0.198*****

Two-tailed Permutation Results: Asterisks represent significant differences against the baseline treatment, shown in the top band of the table. * p<0.1, **p<0.05, ***p<0.01

Notes: Column 2 shows the first best level of production for each period of a market. Columns 3 and 4 show MPD and AMPD measures for each market. Averages listed after treatments are of the market level measures in that treatment.

[a] $Market\ Production\ Deviation\ = \frac{\sum_{t=1}^{T} Prod_t - Opt_t}{\sum_{t=1}^{T} Opt_t}$

[b] $Absolute\ Market\ Production\ Deviaiton\ = \frac{\sum_{t=1}^{T} |Prod_t - Opt_t|}{\sum_{t=1}^{T} Opt_t}$

Differences in Market Production Deviation indicate differences in the total number of capital units produced relative to the aggregate first best production level. That is, a MPD of 0.275, as observed in baseline market 1, indicates that 27.5% more capital units were produced across the

---

aggregate cash treatments (p-value 0.0011 for MPD and 0.0022 for AMPD). At the 95% confidence level MPD differs between the low cost and low aggregate cash treatments (p-value 0.0476) At the 90% confidence level AMPD differs between the low cost and low aggregate cash treatments (p-value 0.0779).

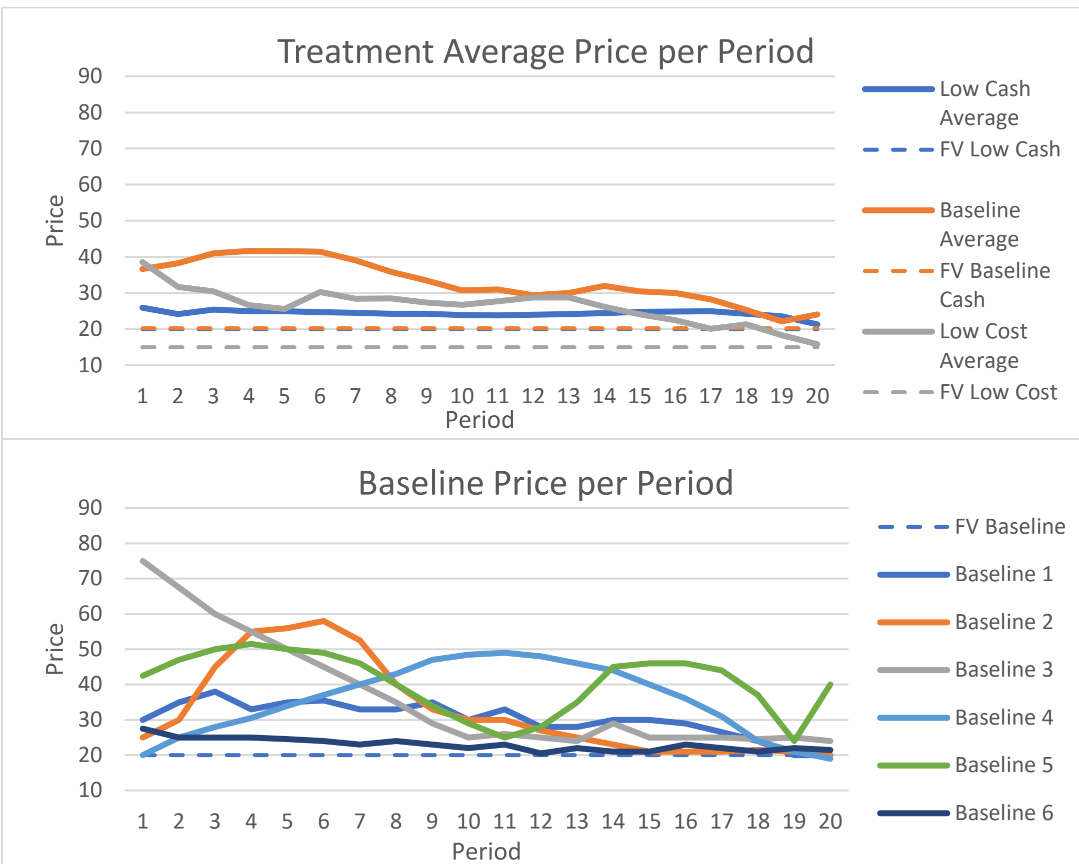
entire market than the first best quantity, and an MPD of -0.094, as observed in low cash market 5, indicates 9.4% fewer capital units than the socially optimal amount were produced. Therefore, the significantly lower Marker Production Deviation observed in markets with low aggregate cash indicates that subjects in these markets are producing less assets than subjects in high aggregate cash markets.

Absolute Market Production Deviation measures the absolute difference between actual and optimal aggregate production on a period-by-period basis. In low cash markets this deviation is on average 0.198, or a total production gap that is 19.8% of the first-best production level. For high cash markets (baseline and low cost markets), the deviation is 0.472 or 47.2% of the first-best level. In all markets, aggregate and individual cash levels are such that the socially first best production level is possible. Under these conditions, testable implication 1 predicts that there will be no difference in AMPD across markets. These findings contradict this prediction of testable implication 1 at the 95% confidence level, indicating that aggregate cash levels are important in aggregate production outcomes. When there is more cash in the market, aggregate production is further from the first best than when there is less cash in the market. Furthermore, since MPD is significantly different across cash levels at the 99% confidence level, and is higher for high cash markets, this deviation is towards overproduction.

The third testable implication focuses on production differences between the baseline and low cost treatments. It predicts that production in the low cost treatment will be greater than production in the baseline. Comparing the average production levels in the top panel of figure 2.2, this appears to be the case. To confirm this finding, I use a one-tailed permutation test on the difference in total market production, $\sum_{t=1}^{20} \sum_{i \in \{1, \ldots, 8\}} x_{t,i}$, between the two treatments. At the 99% confidence level, total production is greater in the low cost treatment than in the baseline (*p*-value 0.0011). This implies that production is greater in the low cost treatment, as predicted by testable implication 3. While production is greater in the low cost treatment, it is closer to the first best level than production in the baseline. MPD is lower than in the baseline at the 95% confidence level (*p*-value 0.0411), and AMPD is lower at the 90% confidence level (*p*-value 0.0996). Lower MPD and AMPD means that as marginal cost is lowered production is increased, but is closer to the first best level, as summarized in result 2.2.

Result 2.2: Lowering the marginal cost of production significantly increases production, and reduces production deviations from the first best level of production.

All of the production results discussed thus far have been in relation to the socially optimal production level. However, this aggregate production level is only consistent with private optimality if prices are also consistent with the stationary state that exists at the socially optimal production level. If prices, and more importantly expectations, differ from the stationary state price (which is the fundamental value), then the privately optimal production levels may differ from the socially optimal levels. It would then be natural to expect the deviations from the socially optimal levels described above, as subjects are attempting to maximize their individual market earnings in the experiment. To understand if this is occurring, I now consider the price trends in these markets. These trends are illustrated in Figure 2.3.



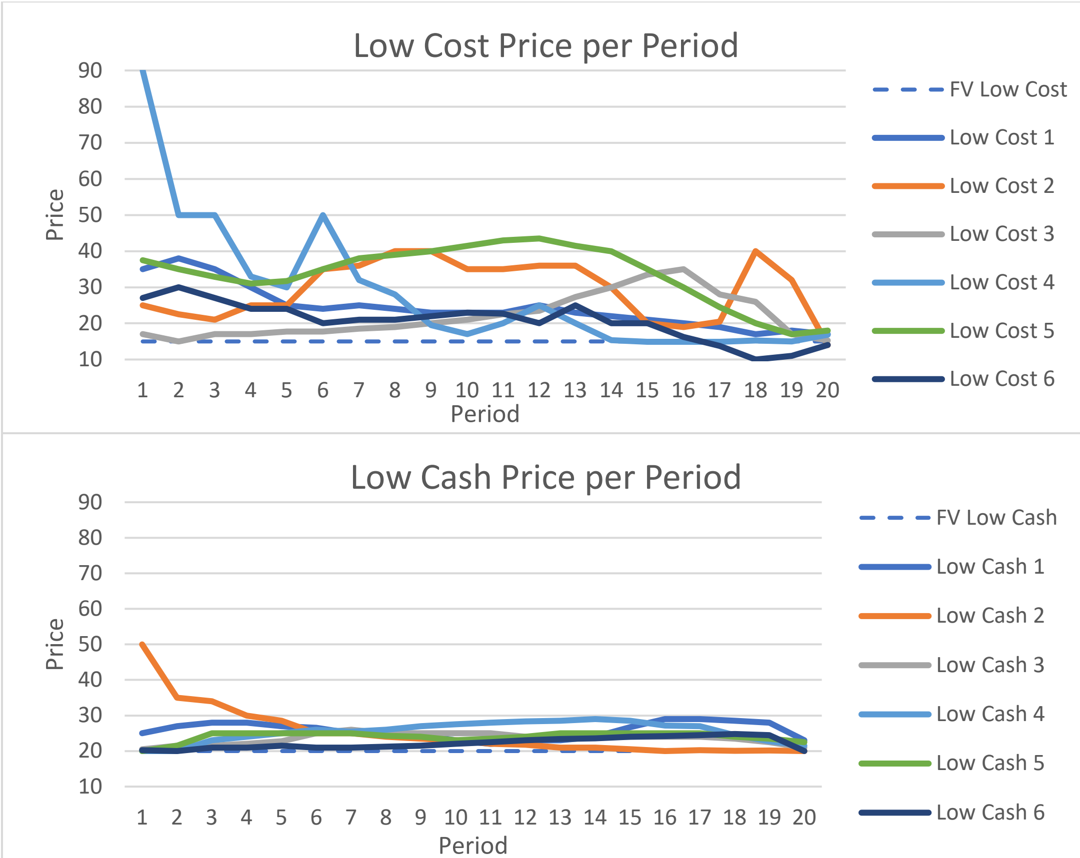


Figure 2.3: Capital price trajectories.

Note: (a) Average price trajectory for each treatment (solid lines) compared to the fundamental value of capital for each treatment (dashed lines). (b) Price trajectory for each market in the baseline treatment (solid lines) compared to the fundamental value of capital (dashed line). (c) Price trajectory for each market in the low cost treatment (solid lines) compared to the fundamental value of capital (dashed line). (d) Price trajectory for each market in the low aggregate cash treatment (solid lines) compared to the fundamental value of capital (dashed line).

The panels of figure 2.3 show the price trends across treatments and markets. The top panel shows the average price trend for each treatment compared to the fundamental value of capital. From this graph it is clear that in all treatments prices on average deviate from the fundamental value. However, it is also clear that the average deviation is lower in the low cash treatment. The bottom panel, which graphs market price trends for this treatment, shows stable price trends close to the fundamental value in each low cash market. Market level price trends in the baseline and low cost treatments are shown in the second and third panels. In both treatments there is a high degree of overpricing and variability in the price. The graphs of figure 2 show a general pattern of overpricing, relative to the fundamental value, which increases with aggregate cash. Table 2.4 quantifies these deviations.

Table 2.4 reports 3 different bubble measures for each market. These are the peak deviation, geometric deviation, and geometric absolute deviation. The peak deviation is the maximum deviation from the fundamental value, as a proportion of the fundamental value: $max\left\{\frac{P_t-FV_t}{FV_t}\right\}$. This measures the peak of the bubble, while controlling for differences across treatments in fundamental value. Measuring differences across the peak deviation is useful in understanding how different costs and aggregate cash conditions influence how far markets can deviate from fundamental values. If subjects are making production decisions that are privately optimal, larger price deviations result in larger production deviations from the first best level. Given the increasing marginal production cost of capital, large price deviations have the potential to be more socially costly than small deviations. This greater cost necessitates consideration of the peak deviation as a measure of bubble magnitude.

In addition to the peak deviation of a bubble, it is helpful to consider the magnitude across the entire market. The geometric deviation (GD) and geometric absolute deviation (GAD) offer numeraire independent measures of bubble size across the market (Powell, 2016). The geometric deviation is based on a geometric average of each periods price relative to the fundamental value: $GD = \left(\prod_{t=1}^{T}\frac{P_t}{FV}\right)^{\frac{1}{T}} - 1$. Similarly, the geometric absolute deviation aggregates these ratios, but uses the absolute value of logs to prevents underpricing from partially canceling out overpricing: $GAD = exp\left(\frac{1}{T}\sum_{t=1}^{T} |\, ln\left(\frac{P_t}{FV}\right) |\right) - 1$.

Testable implication 2 predicts that capital will be priced at its fundamental value in all periods of all markets. In a market where capital is always priced at its fundamental value, the peak deviation, GD, and GAD will all equal zero. This is not the case for any of markets in this experiment. A looser interpretation of testable implication 2 would be that prices are equal to the fundamental value plus some random mean zero error term. It is this looser interpretation that is tested to yield result 2.3.

Result 2.3: Under all treatments, the market price of capital is significantly greater than the fundamental value of capital.

Table 2.4: Capital Price Bubble Measures

Market	Fundamental Value ($E)	Peak Deviation[a]	GD[b]	GAD[c]
Base 1	20.00	0.900	0.494	0.494
Base 2	20.00	1.900	0.525	0.525
Base 3	20.00	2.750	0.694	0.694
Base 4	20.00	1.450	0.700	0.709
Base 5	20.00	1.575	0.973	0.973
Base 6	20.00	0.375	0.147	0.147
Average	**20.00**	**1.492**	**0.589**	**0.590**
L. Cost 1	15.00	1.533	0.582	0.582
L. Cost 2	15.00	1.667	0.878	0.891
L. Cost 3	15.00	1.333	0.412	0.412
L. Cost 4	15.00	5.000	0.639	0.642
L. Cost 5	15.00	1.900	1.170	1.170
L. Cost 6	15.00	1.000	0.322	0.442
Average	**15.00**	**2.072**	**0.667**	**0.690**
L. Cash 1	20.00	0.450	0.283	0.283
L. Cash 2	20.00	1.500	0.223	0.226
L. Cash 3	20.00	0.300	0.174	0.174
L. Cash 4	20.00	0.450	0.265	0.265
L. Cash 5	20.00	0.250	0.199	0.199
L. Cash 6	20.00	0.240	0.109	0.109
Average	**20.00**	**0.532****	**0.209****	**0.209****

Two-tailed Permutation Results: Asterisks represent significant differences against the baseline treatment, shown in the top band of the table. * p<0.1, **p<0.05, ***p<0.01

Note: Column 2 lists the fundamental value of capital. Column 3 shows the peak deviation. Columns 4 and 5 show GD and GAD measures for each market. Averages listed after treatments are of the market level measures in that treatment.

[a] $Peak\ Deviation\ =\ max\left\{\frac{P_t - FV_t}{FV_t}\right\}$

[b] $Geometric\ Deviation\ =\ \left(\prod_{t=1}^{T}\frac{P_t}{FV}\right)^{\frac{1}{T}} - 1$

[c] $Geometric\ Absolute\ Deviation\ = exp\left(\frac{1}{T}\sum_{t=1}^{T} |\ ln\left(\frac{P_t}{FV}\right)|\right) - 1$

The looser interpretation of testable implication 2 predicts that the geometric deviation for a given market is equally likely to be positive and negative. Table 2.4 shows that for each market the geometric deviation is positive. Using a two tailed binomial test, the odds of this happening by random chance are 7.6294×10^{-6}, implying that at the 99.99% confidence level the null hypothesis that the probability of a positive GD is 0.5 can be rejected. Using two tailed hypothesis testing and a 99% confidence level, the probability of having a positive GD would need to be greater than 0.8467 to fail to reject a null hypothesis that the probability of having a positive GD is this hypothetical value. Since all GDs are observed to be greater than 0, this supports result 2.3.

The fact that price bubbles persist in all treatments, shows that allowing subjects to produce capital does not eliminate price bubbles in experimental asset markets. This finding implies that capital markets may be broadly consistent with equity markets in terms of pricing and speculative behavior. This is significant, because it shows that an increasing marginal cost production function for capital is insufficient to influence prices to trend towards the fundamental value.

While in all treatments prices may deviate from the fundamental value, the nature of this deviation differs across treatments. In addition to the geometric deviation, the peak deviation is used to measure differences in the maximal deviation across treatments, and the geometric *absolute* deviation is used to measure differences in positive and negative deviations. In previous experiments without capital production, the ratio of cash in the market to the fundamental value of assets has been found to be an important predictor of bubbles size (Caginalp et al. 2001). In the absence of the ability to produce new assets, the denominator of this ratio remained constant across markets in these earlier experiments. This is no longer the case, as every time a new capital unit is produced, both the numerator and denominator of the ratio are altered. However, the ratio at initial endowments is held constant within each treatment, and across the baseline and low cost treatments. This allows for the pricing effects of the cash to capital ratio to be compared between the low cash treatment and the pooling of the baseline and low cost treatments.

Result 2.4: Increasing the aggregate cash-to-capital value ratio significantly increases the magnitude of capital price bubbles.

The support for result 2.4 comes from comparing the baseline and low cost treatments to the low cash treatment. As in the support of result 2.2, the data from these treatments are pooled for the support of result 2.4. These pooled data are used to conduct two-tailed permutation tests on the differences in bubble measures (Holt and Sullivan, 2019). At the 99% confidence level, the null hypotheses that GD and GAD are the same for low and high cash-to-capital ratios can be rejected (p-value of 0.0023 for GD and 0.0020 for GAD). The null hypothesis that the peak deviation is the same across cash-to-capital ratios can also be rejected at the 95% confidence level

(p-value = 0.0148).[37] These tests indicate that across all bubble measures, markets with low aggregate cash-to-capital value ratios have smaller bubbles than markets with high ratios.

This is consistent with the findings of Caginalp et al. 2001, and shows that their findings extend to environments where subjects both produce and trade assets (capital in this setting). The Caginalp et al. 2001 finding is reliably reproduced in numerous other studies of asset markets without production.[38] The story behind this result is frequently presented as more cash in the market, relative to the number of assets, gives subjects a greater ability to speculate and attempt to outbid each other for assets. Such speculation and intensified bidding naturally drives up the price of the asset. With the added ability to produce assets, it was possible that subjects would use the excess cash to produce more assets, and not bid up prices. Combining results 1 and 4, shows that increasing the cash-to-capital ratio increase both prices *and* production. This implies that subjects are using the excess cash to produce more capital units, but they are still using some of the excess cash to speculate and bid up market prices for existing capital.

When comparing production differences between the baseline and low cost treatments, there were significant differences in overall (MPD) and absolute (AMPD) deviations, but no differences in absolute deviations from the optimal level. However, this pattern of differences is not the case when comparing price deviations, as is seen in result 2.5.

Result 2.5: There is no significant difference in the size of capital price bubbles between high and low production cost markets, holding relative cash levels constant.

For the peak deviation, geometric deviation, and geometric absolute deviation, the null hypothesis that there is no difference in bubble size between the baseline and low cost treatments cannot be rejected at the 90% confidence level. This indicates that, relative to the fundamental value of capital, subjects do not price capital differently when marginal costs and fundamental value change. Their under or over pricing proportionately scales with the fundamental value of capital. Additionally, given the general consistency between the GD and GAD, the price deviations are almost always in the direction of overpricing.

---

[37] When comparing only the baseline and low cash treatments, these results hold at the 95% confidence level. The p-values are 0.0292 for peak deviation, 0.0119 for GD, and 0.0130 for GAD.

[38] For a complete description of this result and related work see Palan (2013) and Nuzzo and Morone (2017).

IV.B. Rates of Optimal Decision Making

IV.B.1. Treatment Averages

Testable implications 4 and 5 relate to the effects of individual and aggregate cash holdings on production decisions. Some of these effects are seen in the aggregate production differences discussed above. However, these aggregate differences may be consistent with q-theory if they are the result of subjects optimally responding to their price expectations as defined in lemma 1. If subjects expect prices to be higher than the fundamental value of capital, then it is privately optimal for them to produce more than the first best level. Accounting for these differing price expectations, testable implications 4 and 5 can be evaluated from the perspective of adherence to the optimal production levels predicted by lemma 1. From this perspective, these testable implications predict that cash will not have an effect on the rate at which subjects make privately optimal production decisions.

Lemma 1 defines a privately optimal production decision as a subject producing capital at the point where the marginal cost of capital is equal to their price expectation, assuming they are unconstrained. When the cash-in-advance constraint is binding for a subject, their production is optimal if they spend all of their cash on production. In the theoretical model, agents can produce any positive real number of capital units. This allows them to produce exactly at the point where marginal cost equals their price expectation, or at the point where all of their cash is used in production. In the experiment, subjects are restricted to producing integer quantities of capital. This requires me to refine the definition of optimality from lemma 1 to account for integer production of capital. An unconstrained subject's production decision, $x_{t,i}$ is optimal if $q^E_{t,i} \geq 1$ and $\frac{E_i[P_t|\mathcal{I}_{t-1}]}{C'(x_{t,i}+1)} < 1$. That is, it is optimal if the marginal cost of their production is less than or equal to their price expectation, and producing an additional unit would have a marginal cost greater than their price expectation. Furthermore, an unconstrained subject is underproducing if $\frac{E_i[P_t|\mathcal{I}_{t-1}]}{C'(x_{t,i}+1)} > 1$, and overproducing if $q^E_{t,i} < 1$. A constrained subject's production decision is optimal if $\mathrm{C}(\mathrm{x}_{\mathrm{t,i}}) < (1+r)b_{t-1,i} + Dk_{t-1,i} < C\left({C'}^{-1}(\boldsymbol{E_i}[P_t|\mathcal{I}_{t-1}])\right)$ and $(1+r)b_{t-1,i} +$

$Dk_{t-1,i} < \mathrm{C}(\mathrm{x}_{\mathrm{t,i}} + 1) \leq C\left(C'^{-1}(\boldsymbol{E_i}[P_t|\mathcal{I}_{t-1}])\right)$.[39] In words, their production decision is optimal if they cannot afford to produce an additional unit of capital even though it would be optimal to do so if unconstrained.

Using this refined definition for production optimality under the constraints of the experiment, I measure the proportion of optimal production decisions overall, and for each treatment. These results are reported in figure 2.4. The first grouping of columns in figure one represents the proportion of optimal decisions across all 2,880 production decisions made by subjects in the experiment. The first bar is the rate for all decisions, and the second and third columns are for the 1,440 decisions made by subjects with low (2nd bar) and high (3rd bar) individual cash endowments. Overall, 48.22% of production decisions meet the definition of private optimality; the 95% confidence interval for this rate is 46.39% to 50.05%. Conditioning the overall optimality on subjects' cash endowments shows a slight difference in the rate of optimal decisions between high and low cash endowment subjects. The 95% confidence intervals for these rates are 48.32% to 53.51% for low cash subjects and 42.97% to 48.12% for high cash subjects. This result indicates that at the 95% confidence level, there is a difference in the rate at which subjects with low and high initial cash endowments make optimal decisions.

[39] Across all markets and decisions (2,880 production decisions) a subject is only constrained from making the optimal decision 18 times. In all 18 cases, the subject makes the constrained optimal decision according to this definition. These 18 production decisions are counted as optimal in figure 2.4.

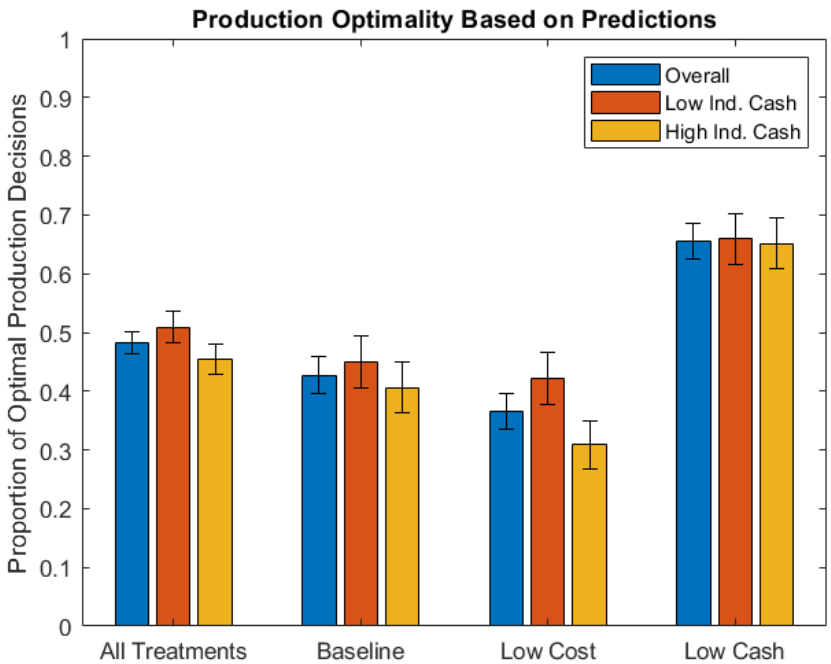


Figure 2.4: Production Optimality Overall and by Treatment.

Note: Each column represents the proportion of optimal production decisions made by subjects in the given treatment. The error bars represent 95% confidence intervals for this rate. The first grouping of bars represents optimality across all treatments, both overall and for subjects with high and low individual cash holdings. The other groupings are for the baseline, low cost, and low cash treatments respectively. Blue bars represent optimality for all subjects in the grouping. Orange bars and gold bars represent optimality for subjects with low and high individual cash holdings.

This overall difference in the rate of optimal production decisions between subjects with high and low cash endowments is seemingly a contradiction of testable implication 4. This testable implication predicts no difference in the rate of optimal decisions for subjects with different cash endowments. However, this may overstate the case against testable implication 4. When comparing differences across initial cash endowments at the market treatment level, the differences only persist in the low cost treatment. In this treatment, the 95% confidence intervals for the rate of optimal decisions are 37.66% to 46.50% and 26.76% to 45.02% for subjects with low and high individual cash endowments respectively. Thus, at the 95% confidence interval, subjects in the low cost treatment with a lower initial cash endowment more frequently make optimal production decisions than those with a high cash endowment. In both the baseline and low cash treatments there is no significant difference in the optimality rate of subjects with different cash endowments. This indicates that the overall difference in the rate of privately optimal production decisions between high and low cash endowment subjects is driven primarily by the low cost treatment. This supports the sixth result.

Result 2.6: In markets with a lower marginal production cost, subjects with low individual cash endowments make privately optimal production decisions at a higher rate than subjects with high individual cash endowments.

Result 2.6 summarizes that individual cash only effects the rate at which subjects make optimal decisions in some market treatments. This indicates that testable implication 4 may hold in some environments and not others. These individual cash effects are only one component of cash in the experiment. The other is aggregate cash in a market. Testable implication 5 predicts that the rate at which subjects make optimal production decisions is unaffected by the amount of aggregate cash in the market. Comparing the rate of optimal decision making in the baseline and low cash treatments is the clearest test of this prediction. The overall optimality rate of production decisions in the baseline treatment has a 99% confidence interval of 38.61% to 46.89%. In the low cash treatment, this 99% confidence interval is 61.53% to 69.49%. The significant difference in the rate of optimal production decisions between the baseline and low cash treatment refutes the prediction of testable implication 5. Not only do subjects produce more in higher aggregate cash environments (result 2.1), but they also make privately optimal production decisions at a lower rate. These significant differences form the basis of result 2.7.

Result 2.7: Holding all other initial conditions constant, decreasing the amount of aggregate cash in a market significantly increases the rate at which subjects in that market make privately optimal production decisions.

Results 6 and 7 focus on the rate at which subjects make privately optimal production decisions. However, it is also important to consider what happens when subjects do not make privately optimal production decisions – i.e., whether they tend to over or under produce. Two treatments with similar proportions of optimal decisions can have very different production quantities and outcomes if in one treatment subjects tend to overproduce and in the other they tend to underproduce. Figure 2.5 shows the rates at which subjects over and underproduce both overall and for each market and cash endowment treatment.

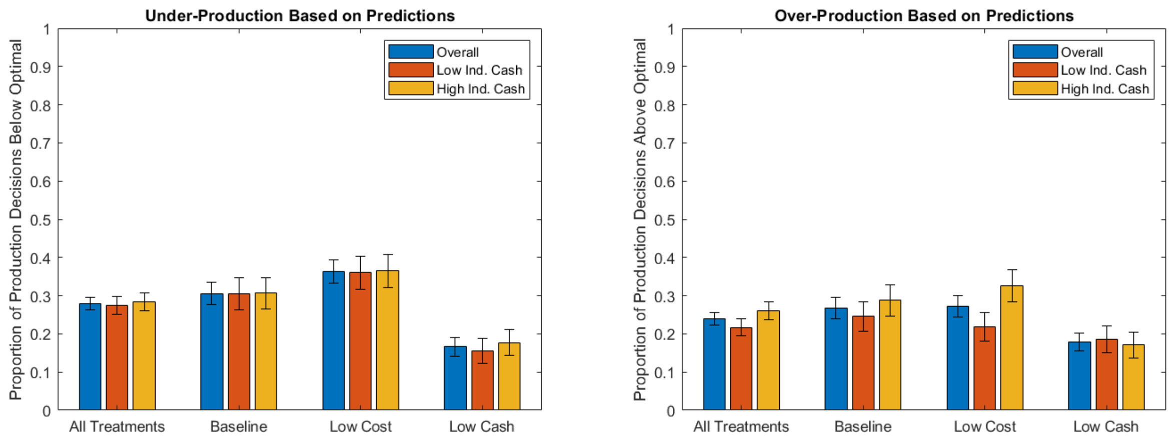


Figure 2.5: Overproduction and underproduction rates.

Note: The lefthand panel of figure 2 shows the rates of underproduction overall and for each treatment. The righthand panel shows the rates of overproduction overall and for each treatment. The error bars represent 95% confidence intervals for the rate of over or under production. In both panels, the first grouping of bars represents the rate across all treatments, both overall and for subjects with high and low individual cash holdings. The other groupings are for the baseline, low cost, and low cash treatments respectively. Blue bars represent optimality for all subjects in the grouping. Orange bars and gold bars represent optimality for subjects with low and high individual cash holdings respectively.

For market level treatments, there is no significant difference in the overall rate of over or underproduction between subjects in the baseline and low cost treatments. Subjects in the low cash treatment make significantly less decisions to over and underproduce relative to subjects in the other two market level treatments. This difference between the low cash treatment and other treatments is expected given the high rate of optimal decision-making in the low cash treatment. When comparing differences in over and underproduction rates between subjects with low and high individual cash endowments, the only significant differences occur in the low cost treatment. In this treatment, subjects with high and low individual cash holdings underproduce at rates that do not statistically differ. However, the rate at which subjects chose to overproduce does significantly differ between those with high and low cash endowments. In the low cost treatment, the 95% confidence interval for the overproduction rate of subjects with low cash endowments is 18.17% to 25.58%. For subjects with high cash endowments this interval is 28.37% to 36.77%. This difference mirrors the difference in optimal decision making rates. Recall that there is no difference in underproduction rates across cash endowments in the low cost treatment. These results show that the additional non-optimal decisions made by subjects with high cash endowments in the low cost treatment are almost exclusively decisions to overproduce.

IV.B.2. Modeling Individual Production Decisions

The results in the previous subsection discuss differences in the unconditional averages of the rate of optimal production making across treatments. While some of these differences are significant, they may be explained by other underlying market conditions than just the treatments themselves. To better understand such affects I use a Probit model to understand the factors influencing the optimality of subject's individual production decisions. In this model I include market and individual cash endowment treatments along with the price deviation in the previous period, the optimality of a subject's previous production decision, and subjects' risk aversion scores. Factors such as the previous period price deviation and optimality of a subject's decision in the previous period may be correlated with the experimental treatments. The Probit model helps to understand how these factors and the treatments independently effect subjects' production choices. The following equation gives the specification of this Probit model, where $\lambda_{t,i}$ is a vector of a subject's treatments, and production decision in period t.

$$\mathbb{1}_{Optimal}(\lambda_{t,i}) = \Phi\Big(\beta_0 + \beta_1 \mathbb{1}_{Low\,Cost}(\lambda_{t,i}) + \beta_2 \mathbb{1}_{Low\,Cash}(\lambda_{t,i}) + \beta_3 \mathbb{1}_{High\,Ind.\,Cash}(\lambda_{t,i}) + \beta_4 \mathbb{1}_{High\,Ind.\,Cash}(\lambda_{t,i}) * \mathbb{1}_{Low\,Cost}(\lambda_{t,i}) + \beta_5 \mathbb{1}_{High\,Ind.\,Cash}(\lambda_{t,i}) * \mathbb{1}_{Low\,Cash}(\lambda_{t,i}) + \beta_6 \frac{P_{t-1} - FV}{FV} + \beta_7 \mathbb{1}_{Optimal}(\lambda_{t-1,i}) + \beta_8 \mathbb{1}_{Overproduce}(\lambda_{t-1,i}) + \beta_9 RA_i + \varepsilon_{t,i}\Big)$$

The previous period price deviation is included in the Probit model as $\frac{P_{t-1}-FV}{FV}$. While subjects are not explicitly told the fundamental value of capital, they are told all information necessary to calculate it, including the redemption value. This means that subjects have sufficient information to know when the price deviates from the fundamental value. Even if they are tracking differences from the redemption value, rather than the fundamental value, they will still get the same result since the experiment is designed for these values to be equal. When subjects see prices moving above the fundamental value, this might create some uncertainty as to why this is happening. A price bubble also might create an alternative focal point for subjects' attention. In either case, subjects might make less privately optimal decisions as they attempt to either ride the bubble, or become confused about market conditions. These effects are important to control for in understanding the treatment effects, because price bubbles differ significantly across treatments.

Subject's previous production decisions are represented in the model through the inclusion of indicators for if a given subject produced optimally or overproduced in the previous period. Including these indicators for past behavior allows the model to estimate the persistence of subjects ability to make optimal decisions. Some subjects may inherently be prone to over or under production, while others may consistently make optimal production choices. Any persistence of optimal production decisions could be a sign that subjects are learning to make optimal decisions after making one optimal decision and experiencing a more profitable outcome that period. To avoid multicollinearity, I only include indicators for an optimal decision and a decision to overproduce in the previous period. Controlling for these previous decisions acts as a proxy for a subjects inherent tendencies to overproduce, underproduce, or produce optimally.

The final control added to the Probit model is a subject's risk aversion, represented in the equation by RA_i. This is the coefficient of constant relative risk aversion implied by a subject's choices in the BRET task. Although the production choice is an intratemporal decision, and is thus not affected by risk aversion if utility is isoelastic, risk aversion my still have an effect on subject's decisions. Fellner and Maciejovsky (2007) find that a subject's risk aversion significantly affects their trading decisions in asset market experiments without production. They find that more risk averse subjects are less active in the market. This effect on trading decisions may still be present in this experiment with production, and risk aversion could potentially affect production decisions as well as trading decisions.

The Probit model specified above is used to analyze the optimality of subjects' production decisions. To fully understand the effects of the treatments and control variables on production choices, I use the model to predict the likelihood of a subjects making optimal production decisions, overproducing, and underproducing. The results of these regressions are included in Table 2.5. In the table, treatment effects are shown as the total effect of each treatment, rather than the separate effects of the market and cash endowments.

Table 2.5: Probit Model Regression Coefficients for Optimal Decisions, Overproduction, and Underproduction.

Market Treatment	Individual Cash Treatment	Control Variable	Optimal Production	Under-production	Over-production
		Intercept	-0.2080**	-0.1442	-1.2059***
			(0.0914)	(0.0942)	(0.1039)
Baseline	Low		--	--	--
			(--)	(--)	(--)
	High		-0.1109	-0.0506	0.1666*
			(0.0912)	(0.0984)	(0.0990)
Low Cost	Low		-0.0369	-0.0196	0.0403
			(0.0911)	(0.0972)	(0.1010)
	High		-0.2280**	0.0655	0.1775*
			(0.9037)	(0.0987)	(0.0995)
Low Cash	Low		0.1723*	-0.0646	-0.2527**
			(0.0947)	(0.1070)	(0.1082)
	High		0.1480	-0.0448	-0.2503***
			(0.0938)	(0.1022)	(0.1074)
		$\frac{P_{t-1} - FV}{FV}$	-0.5509***	0.5740***	-0.0540
			(0.0588)	(0.0567)	(0.0556)
		$\mathbb{1}_{Optimal}(x_{t-1,i})$	0.9496***	-1.1759***	0.2465***
			(0.0658)	(0.0677)	(0.0809)
		$\mathbb{1}_{Overproduce}(x_{t-1,i})$	-0.0170	-1.2890***	1.3906***
			(0.0749)	(0.0788)	(0.0814)
		Risk Aversion	0.0991**	0.1176**	-0.1866***
			(0.0456)	(0.0589)	(0.0476)

Note: The values in the fourth through sixth columns show the probit regression coefficient estimates for dependent indicator variables for optimal production, overproduction, and underproduction, respectively. Numbers in parentheses are estimated standard errors. Treatment effects reported are the total effect of the treatment and corresponding standard error. Significance levels: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

After accounting for these additional control variables, the effects of the aggregate cash on the rate of optimal decision making are reduced. In the case of underproduction the effects are altogether eliminated. The regression results presented in Table 2.5, compare the optimality (or under or over production) of decisions in each market and individual treatment to the combined treatment of being in the baseline market with a low individual cash endowment. In the low cash treatment, subjects with low individual cash levels are slightly more likely to make optimal decisions than their counterparts in the baseline treatment, at the 90% confidence level. To understand this difference in probabilities, assume that the decisions are made by a risk neutral subject after a period in which there was no price deviation. If the subject underproduced in the previous period, the probability of an optimal decision would be 41.76% under the baseline treatment, and 48.58% under the low cash treatment. An increase of 6.82%. This is a considerably lower difference than in the unconditional estimates. Subjects with high individual cash endowments in the low cash treatment are not significantly more likely to make optimal decisions than those with low individual cash endowments in either the baseline or low cash treatments. However, comparing the rate of optimality for subjects with high individual cash endowments across the baseline and low cash treatment, there is a significant difference. At the 99% confidence level, moving a subject with a high individual cash endowment from the baseline treatment to the low cash treatment will increase their likelihood of making an optimal production decision. The point estimate of this Probit coefficient change is 0.2589. In percentage terms, the subject's probability making of an optimal decision will increase from 37.49% to 47.61%, assuming that the subject is risk neutral, underproduced in the previous period, and the previous period price deviation was zero. This shows that the control variables do not account for all of the effects of aggregate cash on the likelihood of subjects making optimal production decisions, but that the control variables explain part of the difference observed in the unconditional averages.

Result 2.8: The effects of aggregate cash on the rate of optimal production decisions are reduced after controlling for price deviations, the optimality of a subject's previous decisions, and risk aversion.

Result 2.8 summarizes the findings on how the inclusion of the control variables alters the effects of aggregate cash. The weakening of aggregate cash effects on the rates of optimal production decisions brings the results closer to the predictions of testable implication 5. This result applies to the rate of optimal production decisions. Using these control variables, I also model decisions to over and underproduce. I find that the market treatment effects on the likelihood of over and underproduction are also altered.

In the case of underproduction, the effects of aggregate cash are altogether eliminated by the control variables. In the Probit model there is no significant difference between the estimated effects of any of the treatments. For overproduction, aggregate cash still significantly reduces the likelihood of overproduction after accounting for the control variables. At the 99% confidence level, subjects in the low cash treatment are less likely to overproduce than subjects with their same cash endowment in the baseline treatment. Using the same set of assumptions on the control variables as in the above optimality rate discussion, the likelihood of overproducing decreases from 11.39% to 7.23% for subjects with low individual cash endowments, and from 14.93% to 7.27% for subjects with high cash endowments. If I change the assumptions to assume that the hypothetical subjects overproduced in the previous period, these differences become 57.33% to 47.29% and 63.73% to 47.38% for low and high individual cash endowments respectively. These persistent differences imply the control variables do not fully explain varying tendencies to overproduce across market treatments.

The reduction in the treatment differences after including these control variables indicates that these controls are important in explaining the likelihood of subjects making optimal production decisions, or decisions to over or underproduce. The Probit models show that the optimality (or lack thereof) of a subject's production decision in a previous period is significant in predicting the optimality of their current period decision. When making a production decision, subjects are more likely to make a privately optimal decision if their decision in the previous period was optimal. This result is significant at the 99% confidence level. In percentage terms, in a period following a price deviation of zero, a risk neutral subject, with a low individual cash endowment, in the baseline treatment, is 35.33% more likely to make an optimal production decision if they made an optimal decision in the previous period. This is compared to the same subject having made a decision to underproduce in the previous period. Considering the likelihood of over or underproducing, subjects are significantly more likely to overproduce if they overproduced in the previous period, and underproduce if they underproduced in the previous period. At the 99% confidence level, having overproduced in the previous period increases the probability that a subject overproduces in the current period. Taking the same hypothetical subject used to estimate the effects of making an optimal decision, this subject will be 45.94% more likely to overproduce if they overproduced in the previous period. In modeling underproduction I include the same controls as for optimality and overproduction – indicators for optimal production or overproduction in the previous period. Therefore, I do not directly estimate the effect of underproducing in the previous period on underproduction in the current period. However, I do find that at the 99% confidence level, producing optimally, or overproducing, reduces the likelihood of underproducing. These persistence results form the basis for result 2.9.

Result 2.9: Subjects make persistent decisions to produce optimally, overproduce, or underproduce.

This persistence of production decisions shows that subjects tend to be drawn towards optimality, overproducing, or underproducing, and then make similar decisions for several time periods. Given the reduction in aggregate cash differences that come in part from controlling for previous period decisions, some of the unconditional differences across treatments may come from subjects being naturally inclined against optimal production. This may be innate, or induced by the treatment. The experiment is unable to separate how much persistence is innate and how much is a response to both the individual and market treatments. If subject's tendency to produce optimally is entirely innate, then a portion of the difference in unconditional optimality rates across treatments comes from the random distribution of subjects across treatments. Given the magnitude of the persistence effects, it seems unlikely that so many subjects with a bias towards non-optimal production would end up in the high aggregate cash treatments. It is therefore likely that the treatments themselves are inducing some of the observed persistence towards producing optimally, overproducing, and underproducing.

Another of the control variables with statistically significant effects is a subject's risk aversion score. The BRET task results in 12 possible risk aversion score ranging from -10 to 1, one score for each number of boxes selected. Negative numbers represent risk seeking behavior, and positive numbers represent risk averse behavior. Risk neutrality is represented with a 0. Most subjects are risk neutral to risk averse. In the Probit model of making an optimal, increasing a subject's risk aversion increases the probability that they make an optimal production decision, at the 95% confidence level. The same is true in the model of underproduction. However, these point estimates are relatively small compared to those for the other control variables. To understand the size of the effects of risk aversion, consider a hypothetical subject with a low individual cash endowment, in the baseline treatment, who underproduced, and experienced no price deviation in the previous period. Changing this subject's risk aversion score from 0 to 0.5 (a change from selecting 6 to 4 boxes) would increase their likelihood of producing optimally by 1.95% and their likelihood of underproducing by 2.33%. Risk aversion has the opposite effect on overproduction. At the 99% confidence level, more risk averse subjects are less likely to overproduce. For the same hypothetical subject and risk aversion change, the subject's probability of overproducing decreases by 1.70%.

The final control variable included in the Probit models is the previous period price deviation, $\frac{P_{t-1}-FV}{FV}$. The previous period price deviation does not have a significant effect on the likelihood of overproduction, but it has significant and important effects on the likelihood of underproducing and making an optimal decision. At the 99% confidence level, a subject is less likely to make an optimal production decision after experiencing a positive price deviation than after experiencing no price deviation. Similarly, a subject is more likely to underproduce after a positive price deviation, at the 99% confidence level. To illustrate these effects first consider a risk neutral subject with a low individual cash endowment in the baseline treatment. Also, assume that this subject produced optimally in the previous period. If the price deviation in the previous period were to increase from 0.25 to 1.08, the subject would be 16.88% less likely to make an optimal production decision and 11.5% more likely to underproduce. This represents a movement from the average price deviation in the fifth period of the low cash treatment to the fifth period average price deviation of the baseline treatment.

Result 2.10: Increasing the price deviation in a period significantly decreases the likelihood that subjects will make optimal production decisions in the next period.

To better illustrate this result, figure 2.6 shows the average price deviation by period for each treatment and the proportion of optimal decisions made in each period of each treatment. The top two panels show a rough co-movement between price deviations and optimal decisions. When price deviations go up, the proportion of optimal decisions tends to go down. This is particularly clear in the baseline treatment shown in the top right panel, and visible to a lesser extent in the low cost treatment in the top left panel. In the low cash treatment, there does not appear to be a co-movement between price deviations and the proportion of optimal decisions. However, this is unsurprising given the consistently low price deviations and the consistently high proportions of optimal decisions.

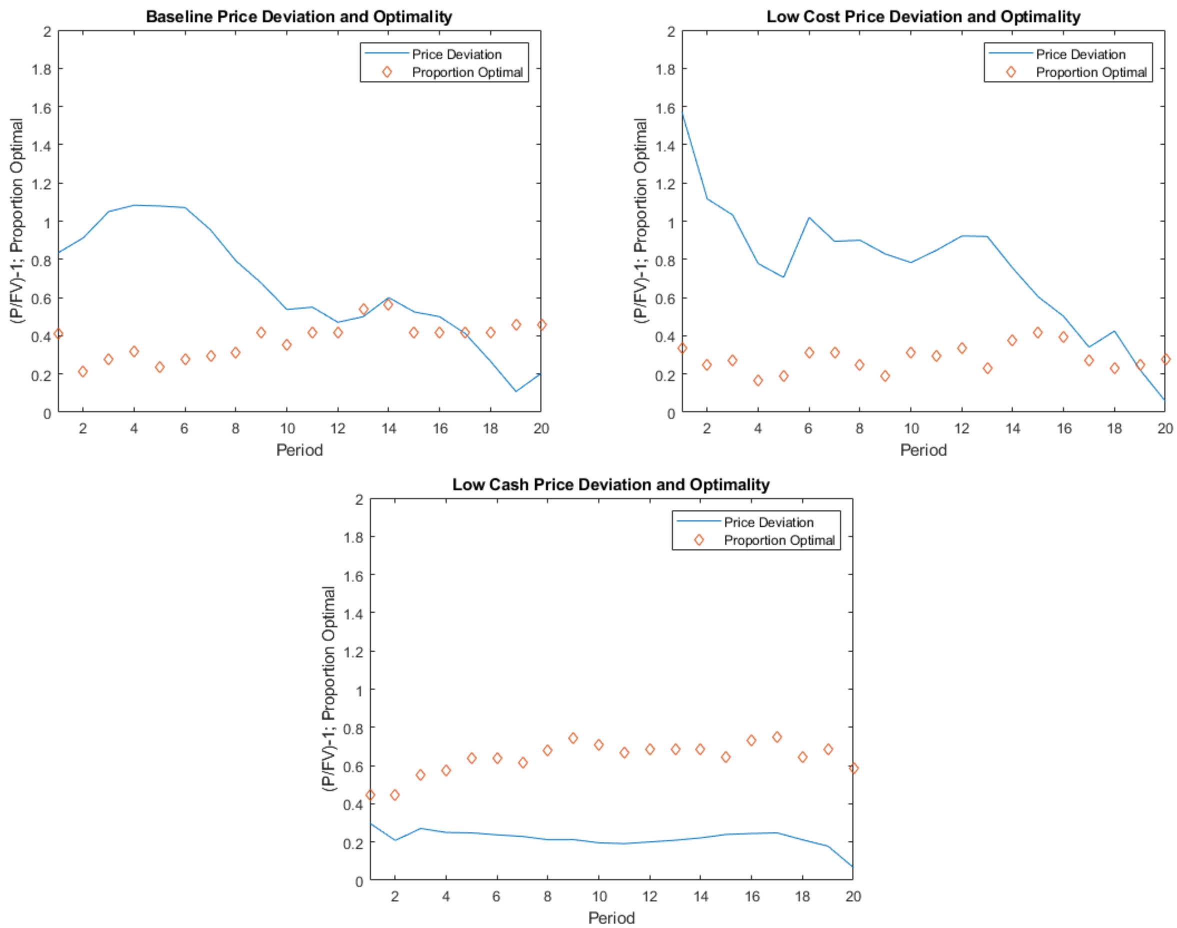


Figure 2.6: Average Price Deviation and Proportion of Optimal Decisions by Period and Treatment.

Note: In each panel, the blue line represents the average capital price deviation from the fundamental value across periods. The orange diamonds show the proportion of production decisions that were optimal in each period. The top right panel shows this for the baseline treatment, the top left shows the low cost treatment, and the bottom shows the low cash treatment.

This tendency of subjects to be less likely to make optimal decisions after a large price deviation is a possible mechanism through which production decision are affected by increased aggregate cash. After accounting for price deviations, persistence, and risk aversion, aggregate cash has a significantly weaker effect than in the unconditional proportions of optimal production decisions. A direct effect of aggregate cash on production, such as that seen in the unconditional proportions, is difficult to explain considering that subjects are not given information on the total amount of cash in the market. However, these results show that aggregate cash may partially be acting through price bubbles to reduce the rate of optimal production decisions, and increase overall production away from the first best level.

In experiments where subjects trade non-producible assets, increasing cash to asset ratios (aggregate cash) increases the magnitude of price bubbles, as is seen in this experiment (Calginalp et al., 2001).[40] Since the relationship between aggregate cash and price bubbles exists in experiments without production, this finding is not a result of introducing production to the market. Increased bubble magnitudes in markets with increased aggregate cash is a more general phenomenon in asset trading markets. In my experiment with production, subjects are less likely to make optimal decisions after experiencing large price deviations. This may be the result of subjects seeing higher price deviations and becoming confused, or diverting their attention to the capital trading market. The observed trends suggest that confusion may be the dominant cause. Production is greater in markets with larger price bubbles, as are average price expectations. This implies the increased production is in part a privately optimal response to higher price expectations. However, subjects are also more likely to underproduce after a large price deviation. This may indicate that they are confused about why the price has increased and are making a less optimal decision. An additional sign of confusion is the strong explanatory effect of previous period decisions on the optimality of subject's production decisions. If subjects are confused by high prices in high aggregate cash markets, then they may be more likely to over or underproduce in their confusion. The persistence of production decisions would make it more likely that they continue over or underproducing, reducing the overall proportion of optimal decisions in the market.

This confusion mechanism is consistent with the results of the experiment, but the experiment is not designed to test this mechanism conclusively. I leave the testing of this to future work. The experiment is designed to study the impact of aggregate cash on production decisions, both in relation to the first best level and the private optimality of decisions. Placing these findings in the context of the existing literature on aggregate cash effects, I can identify the mechanism that increased aggregate cash increases price deviations. These increased price deviations then decrease the likelihood of subject's making optimal production decisions.

---

[40] This result is also seen in Haruvy and Noussair's (2006) asset markets studying short selling, which include an aggregate cash change of similar magnitude to the one used in this experiment, and in Coppock, Harper, and Holt's (2021) asset markets studying the effects of leverage.

IV.C. Subject Root Mean Squared Error

The Probit model above is informative on factors effecting if a subject makes an optimal decision, or if they over or underproduce. However, the magnitude of deviations from optimal production is also important and might differ across treatments. To study this magnitude I measure the root mean squared error (RMSE) of each subject's observed production quantities from their privately optimal quantity based on $q_{t,i}^{E}$, $\mathrm{RMS}E_i = \sqrt{\frac{1}{\mathrm{N}}\sum_{t=1}^{20}\left(Production_{t,i} - Optimal\ Production_{t,i}\right)^2}$. I regress this measure on indicators for the subject's treatment, the geometric deviation in their market, and their risk aversion score.

$$
\begin{aligned}
RMSE_i = \beta_0 &+ \beta_1 \mathbb{1}_{Low\ Cost}(\lambda_i) + \beta_2 \mathbb{1}_{Low\ Cash}(\lambda_i) + \beta_3 \mathbb{1}_{High\ Ind.\ Cash}(\lambda_i) \\
&+ \beta_4 \mathbb{1}_{High\ Ind.\ Cash}(\lambda_i) * \mathbb{1}_{Low\ Cost}(\lambda_i) + \beta_5 \mathbb{1}_{High\ Ind.\ Cash}(\lambda_i) * \mathbb{1}_{Low\ Cash}(\lambda_i) \\
&+ \beta_6 GD_i + \beta_7 RA_i + \varepsilon_i
\end{aligned}
$$

The results of this regression are shown in Table 2.6.

There are multiple significant treatment effects on RMSE. The most striking of these is that subjects in the low cost treatment have significantly higher RMSE than subjects in the baseline or low cost treatments. This difference is significant at the 99% confidence level. The RMSE measures the quantity deviation of production away from the privately optimal level. In the low cash treatment, the optimal production quantity controls for the reduced marginal cost, but the measure of deviation does not adjust for the higher level of optimal production. Considering this, the higher RMSE in the low cost treatment implies that in an environment where the first best level of production is higher, subjects make greater quantity deviations from the privately optimal production level. However, these quantity deviations are of lower cost than in the baseline and low cash treatments. In relation to testable implication 3, this implies that while production increases when marginal cost decreases, the quantity deviation of production from the privately optimal level also increases.

Table 2.6: OLS Regression Coefficients for RMSE Regression.

Market Treatment	Individual Cash Treatment	Control	Estimated Effect
		Intercept	0.8254***
			(0.1149)
Baseline	Low		--
			(--)
	High		0.1909
			(0.1520)
Low Cost	Low		0.4586***
			(0.1556)
	High		0.8326***
			(0.1570)
Low Cash	Low		-0.3025**
			(0.1485)
	High		-0.1449
			(0.1484)
		Market GD	0.4820**
			(0.2082)
		Risk Aversion	-0.0691
			(0.1051)
	R^2		0.4482

Note: Numbers in parentheses are estimated standard errors of the regression equation specified immediately above, where the dependent variable is the root mean squared error of a subject's decisions from the optimal level. Treatment effects reported are the total effect of the treatment and corresponding standard error. Significance levels: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

The geometric deviation of prices in a subject's market also has a significant effect on the RMSE of the subject's production decisions. At the 95% confidence level, subjects in markets with higher geometric deviations have a higher RMSE. This is consistent with the finding that increasing previous period price deviations decreases the likelihood of a subject making an optimal production decision. This also supports the mechanism that aggregate cash affects capital production decisions through price bubbles. Increasing aggregate cash increases the price geometric deviation. The increased geometric deviation increases the RMSE of production decisions for subjects in that market.

V. Discussion and Conclusion

The base experimental design I develop in this paper is the first to allow all subjects to produce and retrade depreciating capital stock and accumulate cash that can be used across rounds. I use this framework to study *q*-theory in an environment without measurement error or binding financial frictions, and find that subjects frequently make production decisions inconsistent with the predictions of q-theory. The experimental design I develop can also be used to address numerous other questions relating to assets that are not held in fixed supply. An extension of this work on q-theory, would be to allow subjects to borrow funds for capital production or purchase. Such an experiment would test theories of how internal (cash-on-hand and cash earnings) and external (borrowing) sources of funding affect investment decisions. Theoretical work on this question proposes frictions between these sources of funding as a reason for empirical contradictions of neoclassical q-theory (Fazzari et al., 1988; Moyen, 2004; Cao et al. 2019). By allowing the capital return to depend on the number of capital units in the market, the framework can also be extended to study investment cycles, and investment in capital with variable returns. Initial pilot studies on such an experiment show this to be a promising area for future research.

The main finding of my experiment is that in an environment with no measurement error and financially unconstrained subjects, cash and q affect subject's production behavior. Less than half of all production decisions are privately optimal according to q theory. However, decreasing the marginal cost of production increases production levels, as predicted by q-theory. The rate of optimal decision making does not systematically differ across the individual cash holding of subjects. However, the rate of optimal decision making is significantly lower in markets with more aggregate cash. Increasing the amount of aggregate cash in a market increases the magnitude of capital price bubbles, and increases the aggregate amount of capital produced. This increased production results in production being further from the first best. In markets with larger price bubbles, subjects make more deviations from privately optimal production – they are less likely to make optimal decisions, and have a greater RMSE between their actual decisions and privately optimal decisions. This price bubble effect explains part of the decreased optimality of production decisions observed in high aggregate cash markets.

These findings occur in a controlled experimental environment where quantitative measures might not align with those experienced outside of the lab. However, the main findings of the experiment are not in quantitatively measuring the effects of cash and q on investment, but in establishing directional results associated with variations in individual cash, aggregate cash, and q-theory. It is these statistically significant directional findings that apply outside of the lab (Kessler and Vesterlund, 2015). In the related experimental environment of asset markets without production, directional findings are consistent between groups of college students, like the participants in this experiment, and groups of professional traders (Weitzel et al., 2020). This finding in a related environment is a positive indicator for the external validity of the results of this paper. Applying these results outside of the lab would indicate that in economic booms, and periods of large economic stimulus, capital goods prices will rise above their fundamental value and firm investment expenditures will increase. However, this increased investment expenditure may not be entirely socially optimal, or optimal for firm owners.

Chapter 3: Evaluating the Efficient Market Hypothesis in Experimental Asset Markets and Analyzing the Effects of Private Information

I. Introduction

The ability of markets to price assets at their fundamental value has been studied extensively in a variety of experimental settings. Two major settings are experiments where assets are traded in a single period before being redeemed for cash, *non-durable assets*, and experiments where assets are traded and re-traded over multiple periods before being redeemed for cash, *durable assets*. These two settings have starkly different findings for the ability of markets to price assets at the fundamental value. Single period markets are able to disseminate and aggregate private information into the asset price (Plott and Sunder 1982, 1988). Multi-period markets however, frequently experience prices exceeding the fundamental value in cases where traders are all fully informed about the asset's value (Smith et al, 1988). These differing results have opposite implications for the strong and semi-strong forms of the efficient market hypothesis. The strong form of the hypothesis states that "prices accurately summarize all information, private as well as public," whereas the semi-strong form only pertains to "all publicly known information." (Burton and Shah, 2013 pp. 6, 8). The tendency for single period markets to aggregate and disseminate information is consistent with the strong form, while the observed price bubbles in fully informed multi-period markets are a violation of the semi-strong form. This chapter seeks to investigate these differing results by varying the information given to traders and analyzing individual trader behavior within the market.

This chapter is particularly interested in how private information, and explicit knowledge of the existence and form of private information, affects the connection between market price and the fundamental values of *durable assets*. Subjects in the experiment trade shares of a durable asset over several time periods, which is defined to be a market. These shares pay a risky dividend in each period and are redeemed for a pre-determined "redemption value" after the final period. The redemption value represents the long-term payoff of an asset share, and is the basis of private information in the experiment. In each market, some traders, "insiders," are given private information on the precise redemption value of each share, while other traders, "outsiders," are only told a distribution of possible redemption values. This experiment finds the following facts (1) For all numbers of insiders, price bubbles persist, and that the magnitude of the bubble is not affected by the number of insiders. (2) In the final period, prices do not systematically differ from the fundamental value, and are weakly closer to the fundamental value as the number of insiders increases. (3) At the individual trader level, telling a trader they have private information stimulates their demand for shares. (4) Insiders final earnings do not significantly differ from outsiders final earnings.

Empirical tests of the efficient market hypothesis tend to suggest that it does not hold for the stock market as a whole. Early tests focus on the degree of stock price volatility implied by the efficient market hypothesis. Shiller (1981a, 1981b) finds excess volatility in the aggregate stock market.[41] Campbell (1991) decomposes the portions of this excess volatility due to expectations over future dividends (short-term information) and expectations over future returns (long-term information). He finds that much of the excess volatility comes from expectations over future returns. This experiment is focused on future returns and uses the control of a laboratory environment to directly measure how information over future returns affects the market and the expectations of traders.

The efficient market hypothesis predictions, in theory, also apply to markets for non-durable goods, as long as the trading and re-trading evolves within a time period in a manner that permits information dissemination. Such markets have been extensively studied by experimental economists. While Smith's classic 1962 experiment demonstrates that markets are able to reach an efficient outcome with a small number of participants who have differing payoff structures, the informational symmetry of the design does not permit an analysis of the aggregation and dissemination of insider information. Such asymmetries were implemented in a seminal paper by Plott and Sunder (1982), who show that market prices embody private insider information about the true payout value of an asset. These results are extended by Plott and Sunder (1988), who study the aggregation of disparate bits of partial information that must be combined to pin down the end-of-period payout value of an asset. These optimistic findings spurred a large literature investigating aspects of rational expectations in markets for non-durables, [42] including clarification of conditions under which the rational expectations predictions hold (Corgnet et al., 2021). A common feature of these single period markets is heterogeneity over traders' information. In this experiment informational heterogeneity is introduced by giving some traders insider

[41] For a detailed discussion of the empirical test of the efficient market hypothesis and a history of behavioral finance see Shiller (2003) and Shiller (2014).
[42] This literature generally finds that markets price assets consistently with rational expectations predictions and the efficient market hypothesis. For a review of this literature see Isaac (2022).

information over the redemption value. This insider information is similar to the information given in one period markets in that it pertains to the final payout of an asset.

A critical factor that is omitted from these single period experiments is the possibility of cross-period speculative motives for traders to buy at a low price before selling at a higher price in a later period. This speculation could disrupt price discovery, potentially leading to a violation of the strong form of the efficient market hypothesis. Such intertemporal speculation is most likely in multi-period markets, like those first used by Smith et al. (1988), which produced bubble and crash price patterns with inexperienced traders. These durable asset market structures provide an ideal environment to analyze the dissemination of insider information in the shadow of speculation, often fueled by cash accumulation from dividend or interest payments.[43] In the Smith et al. (1988) asset market design, the final-period redemption value is known by all to be zero. In contrast, the experiment in this chapter specifies a final redemption value that, if known, would induce a relatively flat fundamental value that hovers above zero even in the final period. Some traders are informed of the exact redemption value, while others are only told a range of possible redemption values. This information is long-term because it only affects the final payout of the asset, which provides ample opportunity for speculation.

Price bubbles are observed in all experimental asset markets; there is no number of insiders for which price bubbles cease to exist. This means that the market does not fully disseminate the long-term private information provided to some traders, which is a violation of the strong form of the efficient market hypothesis. By increasing the number of insiders, I make the private information more public, creating informational conditions converging from the strong to semi-strong form of the efficient market hypothesis. I find no systematic reduction in the magnitude of price bubbles as the number of insiders increases. While this does not directly reject the semi-strong form of the efficient market hypothesis, it shows that markets struggle to disseminate long-term private information, even when a large majority of traders are informed.

To understand why I find results contradictory to the efficient market hypothesis, I analyze the actions and predictions of insiders to identify possible behavioral biases affecting insiders. I

[43] Caginalp et al. (2001) show that reducing the ratio of cash to the value of assets and deferring the payment of dividends until the end of an experiment reduces the size of price bubbles. Both of these treatments act to limit trader's ability to speculate in the asset market. These findings are reinforced by Kirchler et al. (2012) and Stöckl et al. (2015) who use low cash-to-asset ratios and dividends with zero expected value to eliminate bubbles in asset market experiments.

decompose the effects of market and individual characteristics of traders' decisions to attempt to buy or sale assets. This decomposition reveals that having inside information induces behavioral biases stimulating insiders' demand for assets. I also examine the effect of insider information on the formation of traders' price beliefs. During periods at the peak of price bubbles, insiders do have beliefs that are closer to the fundamental value, although they are significantly higher than this value. These biases (stimulated insider asset demand and upward-biased beliefs) may inhibit the ability of the markets to incorporate insider information into asset prices.

The focus of this chapter is on long-term insider information, and on the differences between insider and outsider trading and price forecasts. Experiments with a small number of periods (e.g., Forsythe et al. 1982) tend to produce positive results for rational expectations and the efficient market hypothesis, which are similar to the results found in the one-period markets discussed above. However, when experiments have a larger (8+) number of periods for trading a durable asset, the results are more mixed. Experiments using insider information in the Smith et al. (1988) framework find that bubbles persist when there is insider information in the market, but insider information tends to abate the size of these bubbles (Sutter et al., 2012, Halim and Riyanto, 2020). As the strength of the insider information is weakened through trading restrictions, the ability of this information to abate bubbles is reduced (Halim and Riyanto, 2020). Sutter et al. (2012) and Halim and Riyanto (2020) provide insiders with information about uncertain dividend payments each period for assets that have no final redemption value. The private information in these experiments is short-term information about the current or next period dividend. In contrast, the experiment in this chapter is focused on the dissemination of long-term private information, which allows a greater scope for speculation. In addition, it varies the number of insiders, while holding their information constant.

To better understand the effects of insiders on the supply and demand of assets, I analyze traders' limit order decisions. Sutter et al. (2012) analyze the numbers of bids and asks posted or accepted in double auction trading. They report that more orders are posted by outsiders and accepted by insiders. By using a call market, I have more complete information on traders' preferences to buy and sell asset shares. All trade is conducted via limit order so the experiment records the maximum (minimum) a trader is willing to pay (accept) for a share, without the truncation observed when accepting an open order. I find that insiders are more likely than outsiders to submit a buy order. As a result, increasing the number of insiders in a market tends to stimulate demand for asset shares. Another novel contribution of this chapter is the analysis of the effects of private information on traders' price predictions. Previously, Marquardt et al. (2019) investigated adherence of prices to rational expectations in a durable goods market, but they used public information and their results are consistent with the semi-strong form of the efficient market hypothesis. In this chapter, price predictions are elicited for a 3-period horizon for both insiders and outsiders, which allows me to determine the effects of insider information on prediction data. In periods where price bubbles are most intense, traders with private inside information make predictions closer to the fundamental value than traders without private information. Differences in insider and outsider predictions over time measure how much information has been disseminated by the market. The experiment also measures cognitive ability to find that traders with higher cognitive ability make predictions closer to the fundamental value, a pattern that was also reported by Marquart et al. (2019).

The next section explains the experimental design and methodology. The third section presents the results based on market level data. The final sections focus on comparing the behavior of insiders and outsiders in terms of trading activity, price predictions, and earnings.

II. **Procedures**

The experiment is based on a between-subjects design in which groups of 9 subjects were endowed with 6 asset "shares" each. Shares could be bought or sold using a call market in a sequence of 15 periods. After the 15th period shares were redeemed for a value that was drawn randomly from a uniform distribution on the interval [\$21, \$35]. Subjects were told the range of potential redemption values and the number of insiders who were informed of the actual redemption value. A reminder of this information structure was provided after trading in each period. Outsiders were only told the upper and lower limits of the value range, with the actual value being revealed after the final period. The between-subjects design involved separate sessions, with either 1, 3, 6, 8, or 9 insiders, so there was complete public information in the 9-insider treatment.

Prior to the first round of trading, subjects received a \$70 endowment of lab cash, which was supplemented with an income of \$30 at the start of each of the 15 periods. A period begins with traders submitting limit orders to buy or sell, with each order specifying a number of shares and the most one is willing to pay (for a bid) or the least one is willing to accept (for an ask). The cash-in-advance constraint required that the total amount of a bid (shares time price limit) must not exceed the person's cash holdings. Similarly, the number of shares offered for sale could not exceed the subjects' share holdings – i.e., short selling was not permitted. Subjects could submit a bid, an ask, neither, or both (but in that case the sell order price was required to be above the buy order price to prevent self-trading). After all orders were submitted, the bid and ask arrays would be crossed in a standard "call market" procedure to determine a single market-clearing price, with ties at the clearing price decided at random.

After trading in a period was finalized, shares held paid a random dividend of either $1.20 or $1.60, which are equally likely and the same for all shares. Cash held after trading (but before dividends or final redemption payments) earned an interest payment of 5 percent. Simultaneously with submitting limit orders, traders submitted predictions for the current period, next period, and two periods ahead share price. Traders received a $1.00 bonus per prediction that was within +/- $2.50 of the actual share price. This bonus was paid after interest and dividends were paid in the period being predicted, as shown in figure 3.1. After the final period, all shares were redeemed and lab cash balances were converted at a rate of 1 US dollar of take home pay per 100 lab dollars.

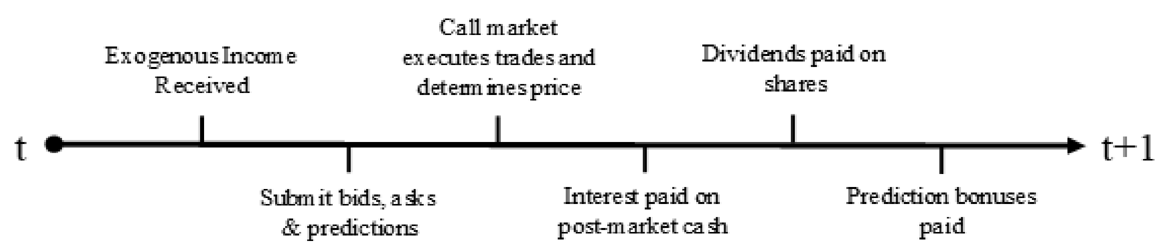


Figure 3.1: Timeline of a Period

The announced range of possible share redemption values, [$21, $35] was selected so that the midpoint of $28 would result in a flat fundamental value of $28 for each period, based on the expected dividend payment, *D,* of $1.40 (average of $1.20 and $1.60). The intuition is that the 5% interest, *i*, on the cash needed to purchase at $28 would equal the expected dividend, *D*, of $1.40. Therefore, a risk neutral person expecting a flat $28 price trajectory equal to *D*/*i*, would be indifferent between holding cash or shares in each period. A formal proof can be based on calculations at the beginning of each period of the present value of the remaining expected dividends and a final redemption value of *D*/*i*. Such a formal proof is shown in Section III of

Chapter 1. The final redemption value can be increased or decreased relative to D/i, which produces an increasing or decreasing series of asset fundamental values (Giusti, et al., 2016).[44] This experiment uses pre-drawn redemption values that are low ($22.90), medium ($28), or high ($33.11), which produces decreasing, flat, or increasing patterns of fundamental values. For each of the 5 insider treatments (1, 3, 6, 8, or 9), there are 3 sessions, one each with a low, medium, or high redemption value.

In addition to the trading process, subjects completed a risk aversion measure done prior to the end of the first trading period, and a cognitive response test done after the final period. The risk aversion measure was based on Crosetto and Filippin's (2013) "bomb" task: subjects could choose to open between 0 and 12 boxes, each of which contained $1.00, but one of the boxes also contained a hidden "ink bomb" which would destroy the money in all boxes. If the trader selected the box with the ink bomb, they received $0 from the task; otherwise they received $1.00 per open box. All boxes are opened before the location of the bomb is revealed. A risk neutral trader will open half of the boxes (6), a risk seeking trader will open more than half, and a risk averse trader will open less than half. These earnings were not revealed until after the final trading period, and these ink bomb earnings were paid at a 1:1 conversion ratio into USD. The cognitive response test consisted of three un-incentivized questions used to measure cognitive abilities.[45]

Subjects were recruited from the University of Virginia student population in groups of 9 for each market. There were 15 sessions, with 3 redemption values (low, medium, or high) for each of the 5 insider treatments.[46] Subjects received a $6 payment for their participation, plus earnings

---

[44] Bostian, Goeree, and Holt (2005) used this present value logic to run an experiment with a flat fundamental value. Teaching present value consideration is always difficult, and this insight was incorporated into a teaching paper in Bostian and Holt (2009). An alternative approach to paying interest on cash is based on the insight that a dividend today is worth less than an equal dividend tomorrow if the asset might self-destruct in the meantime. Ball and Holt (1998) used a random stopping technique to induce a flat fundamental asset value share, which equaled the *expected value* of subsequent dividends. These flat-value designs are based on a present-value structure, in contrast to other papers that induce a flat asset value by deferring dividend payments or by paying a random dividend with a zero expected value.

[45] The cognitive response test is the same test used by Holt at al. (2017) to measure cognitive ability in an asset trading experiment. The questions used are available in the Experimental Instructions Appendix.

[46] Of these 15 sessions, 8 were conducted in-person, and 7 were conducted online (itam7-13 in table 3.1). The in-person sessions were conducted in a computer lab with cash payment. The online sessions were conducted over Zoom with payment via payment apps. Participants in online sessions were required to have their camera on for the duration of the session, and the experimenter read the instructions out loud in both the online and in-person sessions. I test for differences in the relative deviation (Stöckl et al., 2010) between online and in-person sessions. To control for potential effects from the number of insiders I use a 2-tailed stratified permutation test on the 9 sessions with 3,6, and 9 insiders, where each number of insiders is a stratum (Holt and Sullivan, 2019). The mean relative deviation is almost identical (at 0.17) for online and in-person sessions combined, and the small difference is not statistically significant in the stratified test.

from the ink bomb task and market trading. Each person's market-based earnings were scaled down by dividing by 100. Total earnings averaged about $26 (USD) (including the participation and ink bomb risk payoffs) for sessions that lasted about ninety minutes. The experiment was run using the Leveraged Asset Market program on the publicly available V*e*conlab platform, which generates instructions that implement the parameter selections for this experiment. These instructions are provided in the Experimental Instructions Appendix.

III. Market Level Results

Table 3.1 lists the 15 sessions sorted by the number of insiders, each with low, medium, or high redemption values seen by insider(s), shown in the third column. Recall that the fundamental value has a downward trend when the redemption value is low and an upward trend when it is high. The fourth column lists the peak deviation of price from fundamental value over all 15 periods of each session.[47] The peak price deviation is positive for all sessions, and the treatment average peak deviation ranges from $9.49 for sessions with 6 insiders to $23.19 for sessions with 1 insider.

Although the peak price is above the fundamental value in all cases, a more nuanced view of the efficient market hypothesis allows for some price variability around the fundamental value, which should not show a persistent bias. A measure of such a bias is the Relative Deviation (Stöckl et al., 2010), which is the average of all deviations of price (P_t) from fundamental value (FV_t), normalized by the fundamental value: $RD = \frac{1}{T}\sum_{t=1}^{T}\frac{P_t - FV_t}{FV_t}$, where *T* is the number of periods. If prices were fluctuating randomly around fundamental value, these relative deviation measures should be positive for some markets and negative for others. In fact, the *RD* measures for the 15 market sequences are all positive, ranging from 0.038 to 0.392, as shown in the fifth column of Table 3.1. Therefore, the null hypothesis that positive and negative deviations are equally likely can be rejected with a two-tailed binomial test ($p < 0.001$), which justifies the first result:

Result 3.1: Asset markets do not reliably disseminate insider information as predicted by the strong form of the efficient market hypothesis.

[47] Peak deviation is the maximum difference between the share price and the fundamental value. Peak deviation is used instead of peak price to control for differences in fundamental value trajectories induced by the redemption value.

Table 3.1: Summary of Bubble Measures

Session	Number Insiders	Redemption Value	Peak Deviation[a]	RD[b]	RAD[c]	Average Cognitive
itam11	1	$22.90	$18.20	0.273	0.401	1.889
itam7	1	$28.00	$17.00	0.226	0.300	1.556
itam10	1	$33.11	$34.37	0.319	0.468	1.444
Average	**1**	**$28.00**	**$23.19**	**0.273**	**0.390**	**1.630**
itam9	3	$22.90	$7.00	0.114	0.172	1.333
itam5	3	$28.00	$30.00	0.392	0.435	1.444
itam2	3	$33.11	$19.37	0.061	0.391	1.444
Average	**3**	**$28.00**	**$18.79**	**0.189**	**0.333**	**1.407**
itam3	6	$22.90	$6.62	0.119	0.146	1.333
itam6	6	$28.00	$8.00	0.062	0.214	1.444
itam8	6	$33.11	$13.86	0.208	0.232	1.667
Average	**6**	**$28.00**	**$9.49**	**0.130**	**0.197**	**1.481**
itam16	8	$22.90	$15.87	0.339	0.389	1.889
itam14	8	$28.00	$22.00	0.302	0.321	1.889
itam15	8	$33.11	$12.00	0.183	0.191	1.889
Average	**8**	**$28.00**	**$16.62**	**0.275**	**0.300**	**1.889**
itam13	9	$22.90	$23.20	0.324	0.387	1.222
itam4	9	$28.00	$17.00	0.191	0.419	1.444
itam12	9	$33.11	$3.09	0.038	0.074	2.111
Average	**9**	**$28.00**	**$14.43**	**0.184**	**0.293**	**1.592**

Note: Sessions are organized in bands by number of insiders present in the market. Within each band, the markets are listed by decreasing, flat, and increasing fundamental value. There are no significant effects on peak deviation, RD, or RAD between markets with varying number of insiders.

[a] $\text{Peak Deviation} = \max_t \mathrm{P_t} - \mathrm{FV_t}$

[b] $Relative\ Deviation\ = \frac{1}{T}\sum_{t=1}^{T}\frac{P_t - FV_t}{FV_t}$

[c] $Relative\ Absolute\ Deviation\ = \frac{1}{T}\sum_{t=1}^{T}\frac{|P_t - FV_t|}{FV_t}$

Figure 3.2 shows the time paths of asset average prices for each insider treatment (top-left panel) and separately for individual market sessions (other panels). The dark straight line in each panel is the fundamental value, defined as the net present value of expected dividends and the asset's redemption value (known only to insiders). The top-left panel shows the average price sequence for each insider treatment (1, 3, 6, 8, 9), each of which consists of one session done with a flat fundamental value, one with a decreasing value, and one with an increasing value. The average fundamental value line in the top left panel is the average of these three value lines, which is flat at 28. The price sequences for individual sessions are shown in the other three panels of figure 3.2, for the three cases of flat, decreasing, or increasing value. Note that share prices deviate from fundamental values in every case. Such a deviation is inconsistent with the predictions of rational expectations and the strong form of the efficient market hypothesis, which predict that even with one insider, the price should eventually track the fundamental value.

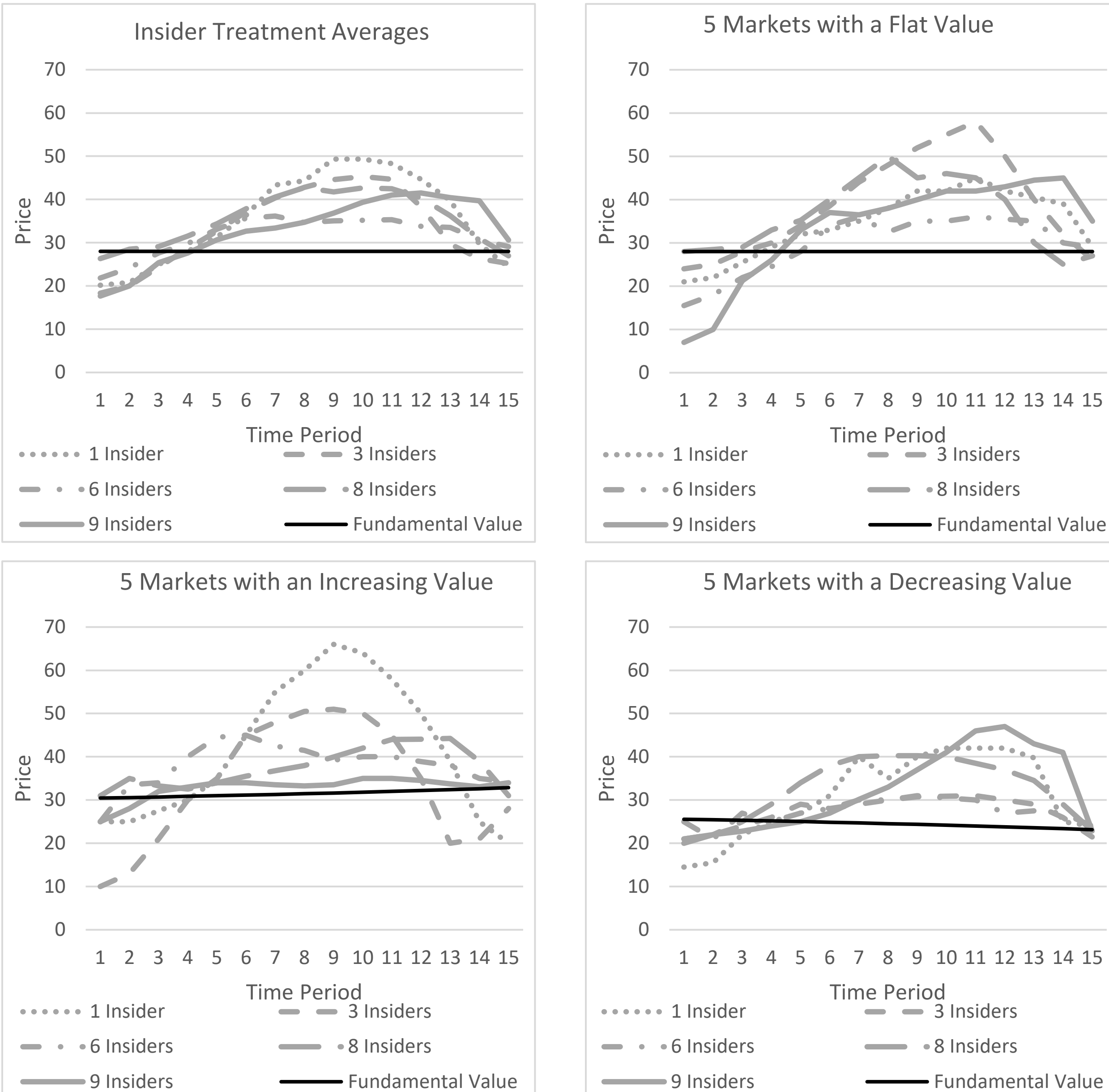


Figure 3.2. Asset Price Patterns by Insider Treatment (Top-Left Panel)
and by Fundamental Value Trajectory (Other Panels)

Correlations

The panels in figure 3.2 indicate that price patterns exhibit autocorrelation and trends, so a more systematic analysis of fundamental value effects is begun with a simple time-series regression for the asset price P_t using data from all periods in all 15 markets:

$$P_t = \beta_0 + \beta_1 P_{t-1} + \beta_2(P_{t-1} - P_{t-2}) + \beta_3 FV_t + \varepsilon_t \tag{1}$$

$$\underset{1.28\,(2.20)}{} \quad \underset{0.79^{***}(0.03)}{} \quad \underset{0.65^{***}(0.06)}{} \quad \underset{0.21^{***}(0.08)}{}$$

with $R^2 = 0.86$, where the standard errors are shown in parentheses and the asterisks indicate significance (*** for $p < 0.01$). Therefore, the lagged price, the trend (change in price), and the fundamental value are all significant factors in the subsequent evolution of asset prices.

A strict interpretation of the efficient market hypothesis stipulates that asset prices are equal to the fundamental value. A looser interpretation, which I test, allows for prices to have some random deviations from the fundamental value. Such an interpretation would predict that the coefficient on fundamental value should equal 1. In contrast, the coefficient estimate for fundamental value is 0.21, which is less than the estimated coefficient on lagged price. While this effect is non-zero and significant, I also reject the null hypothesis (at the 99% confidence level) that the coefficient is equal to one, as would be predicted by the strong form of the efficient market hypothesis.

Insider Trading Effects

The time series regression in (1) did not include a measure of the proportion of insiders, which could be justified if even a single insider would be sufficient to push prices to the fundamental value, as suggested by the strong form of the efficient market hypothesis. Figure 3.2 suggests a different story: that there is no relationship between the number of insiders and the size of the bubble. The experimental design varies the number of insiders from 1 to 9 insiders in each period to test if increasing the amount of private information in the market aids in the dissemination of information. The top left panel of figure 3.2 shows the average price trajectory for each number of insiders. There is no clear pattern in these lines. The lines for 1 (dotted grey line), 3 (short dashed grey line) and 8 (long dashed grey line) insiders appear to follow roughly the same trajectory, while the line for 9 insiders (solid grey line) shows a smaller bubble, and the line for 6 insiders (grey dash-dot line) shows an even smaller bubble. This lack of a clear pattern can also be observed in the other three panels of figure 3.2, which separate the sessions by fundamental value trajectory.

Bubble Magnitudes

In order to compare bubble magnitudes across insider trading treatments, the average of normalized *absolute values* of price deviations from fundamental value is used, as proposed by

Stöckl et al. (2010). This Relative Absolute Deviation is calculated: $RAD = \frac{1}{T}\sum_{t=1}^{T}\frac{|P_t - FV_t|}{FV_t}$. In this experiment, the insider information is perfect knowledge of an otherwise uncertain final redemption value. When paired with the common information about dividends and interest, this is sufficient for an insider to calculate the fundamental value of an asset for each period. Thus, the strong form of the efficient market hypothesis predicts that asset shares will trade at their fundamental value each period. With this as the benchmark, both positive and negative deviations count equally against the efficient market hypothesis prediction. The absolute value bubble measure, *RAD*, weighs positive and negative deviations equally, in contrast with the peak deviation that only indicates the maximum positive deviation and is insensitive to the duration of the deviation. The *strong form* of the efficient market hypothesis predicts that all private information will be incorporated into the price of an asset. This implies that information will be disseminated for any number of insiders, and is contradicted by the experiment's first result. In contrast, the *semi-strong form* of the efficient market hypothesis does not pertain to private information but is only concerned with public information. As the number of insiders is increased, the private information becomes more public, increasing the relevance of the semi-strong form. Therefore, as by increasing the number of insiders, this experiment is testing an implication of the semi-strong form. Note that increasing the number of insiders, while holding constant the type of insider information, increases the amount of insider information. With more insider information in the market, this information can become a more powerful force in determining the equilibrium price and quantity.

To evaluate this hypothesis, a Jonckheere test is used with a null hypothesis that *RAD* (or Peak Deviation) is equal across the number of insiders in a market, against a directional alternative that bubble size is decreasing in the number of insiders. The null hypothesis of no effect cannot be rejected ($p = 0.1468$ for RAD and $p = 0.2274$ for peak deviation), which leads to the second result:

Result 3.2: Increasing the number of insiders in a market does not reduce the magnitude of bubbles in the market.

These insider treatment results stand in contrast to the Plott and Sunder (1982) finding that markets are able to integrate insider information as predicted by rational expectations theory, irrespective of the number of insiders in the market. The key difference between this experiment and Plott and Sundaer (1982) is that in this experimend markets last for multiple time periods and involve *durable* assets. Note that the final period of the experiment in this chapter is similar to the single-period setting in the Plott and Sunder setup. In the final period, the asset is essentially a one-period asset over which some traders have insider information on the redemption value and others do not. The primary difference is that the traders in these sessions have had 14 previous periods influencing their decisions, whereas traders in the Plott and Sunder experiment must confine any speculation to buying or selling decisions made during a double auction period. The final-period price deviations are shown in Table 3.2 below. This table shows the final period price, final period decision, $P_{15} - FV_{15}$, and relative deviation in the final period, $\frac{P_{15}-FV_{15}}{FV_{15}}$.

Table 3.2: Period 15 Price Deviations

Session	Number of Insiders	Redemption Value	Final Price	Final Deviation[a]	Final Relative Deviation[b]	Sign
itam11	1	$22.90	$24.00	$1.10	0.0480	+
itam7	1	$28.00	$29.00	$1.00	0.0357	+
itam10	1	$33.11	$20.00	$13.11	0.3960	-
Average	**1**	**$28.00**	**$24.33**	**$3.67**	**0.1041**	**-**
itam9	3	$22.90	$21.50	$1.40	0.0611	-
itam5	3	$28.00	$26.00	$2.00	0.0714	-
itam2	3	$33.11	$28.00	$5.11	0.1543	-
Average	**3**	**$28.00**	**$25.17**	**$2.84**	**0.0956**	**-**
itam3	6	$22.90	$24.00	$1.10	0.0480	+
itam6	6	$28.00	$29.00	$1.00	0.0357	+
itam8	6	$33.11	$34.20	$1.09	0.0329	+
Average	**6**	**$28.00**	**$29.07**	**$3.19**	**0.0389**	**+**
itam16	8	$22.90	$22.91	$0.01	0.0004	+
itam14	8	$28.00	$27.00	$1.00	0.0357	-
itam15	8	$33.11	$31.00	$2.11	0.0637	-
Average	**8**	**$28.00**	**$30.63**	**$1.03**	**0.0330**	**-**
itam13	9	$22.90	$22.89	$0.01	0.0004	-
itam4	9	$28.00	$35.00	$7.00	0.2500	+
itam12	9	$33.11	$34.00	$0.89	0.0269	+
Average	**9**	**$28.00**	**$30.63**	**$2.63**	**0.0922**	**+**

Note: Sessions are organized in bands by number of insiders present in the market. Within each band, the markets are listed by decreasing, flat, and increasing fundamental value. At the 90% confidence level, final deviation and final relative deviation decrease as the number of insiders increases.

[a] Final Deviation $= P_{15} - \mathrm{FV}_{15}$

[b] $Final\ Relative\ Deviation = \frac{P_{15}-FV_{15}}{FV_{15}}$.

An examination of final-period prices in this experiment indicates that prices do not tend to deviate systematically from the fundamental value.[48] There is also marginally significant evidence that final period prices are closer (in absolute terms) to the fundamental value as the number of insiders increases.[49] This observation about final-period prices in our sessions is consistent with the Plott and Sunder finding that pricing is consistent with rational expectations theory in markets for *non-durable* assets. The fact that prices are consistent with the efficient market hypothesis in the final period, when speculation is no longer possible, suggests that speculation plays an important role in the deviations observed in earlier periods.

When assets are durable and can be bought today and sold tomorrow, there is greater scope to speculate on the future price of an asset share. This speculation may be the driving force behind the presence of asset bubbles in markets with insiders, as insiders may pay less attention to their insider information, and instead choose to speculate. To better understand how the number of insiders affects the market, the next sections look at individual characteristics of traders, and how insider status effects trader decisions.

IV. Comparisons of Insiders and Outsiders: Bid and Ask Behavior

The observed market level deviations from the efficient market hypothesis are the result of individual level decisions that differ from those predicted by rational expectations theory. One decision that is potentially subject to behavioral biases is a trader's decision to attempt to buy or sell assets. Since assets are traded using a call market, traders do not know the current period price when submitting limit orders. However, they have some expectation over this price, and the next period price. Any interior solution of a risk neutral trader's optimization problem requires indifference between 1) earning interest on the proceeds of selling a share at the current price and 2) keeping a share to earn dividends and sell in a subsequent period.

$$E_t[(1+r)P_t] = E_t[P_{t+1} + D_t]$$

Letting $Bid_{i,t}$ and $Ask_{i,t}$ act as indicators for trader i submitting a bid or an ask in period t, the following functions can be derived for when a trader should submit bid or ask orders to maximize profits based on their beliefs.

---

[48] A binomial test is used with the null hypothesis that final period prices are equally likely to be above and below the fundamental value. The deviation is positive in 8 sessions and negative in 7 sessions. This gives a p-value of 1.000.

[49] A Jonckheere test is used to test the null hypothesis of no difference in final period deviations across the number of insiders against an alternative hypothesis that the magnitude of final period deviation increases as the number of insiders decreases. The p-value of this test is 0.0874, which is significant at the 90% confidence level.

$$Bid_{i,t} = \begin{cases} 1, & E_{i,t}[(1+r)P_t] < E_{i,t}[P_{t+1} + D_t] \\ 0, & E_{i,t}[(1+r)P_t] \geq E_{i,t}[P_{t+1} + D_t] \end{cases} \tag{2}$$

$$Ask_{i,t} = \begin{cases} 0, & E_{i,t}[(1+r)P_t] \leq E_{i,t}[P_{t+1} + D_t] \\ 1, & E_{i,t}[(1+r)P_t] > E_{i,t}[P_{t+1} + D_t] \end{cases} \tag{3}$$

These functions imply that a subject should attempt to buy shares in period t if they believe that those shares will give a greater return than cash and sell shares otherwise. The only relevant consideration in submitting a bid or ask is the *sign* of the expected payoff differences in equations (2) and (3). Even if the expected gain is only \$0.01, a profit maximizing trader should submit a bid or ask order to realize this gain. It is possible that other factors affect traders' decisions to attempt to buy or sell shares, e.g., insider or outsider status, and cognitive ability. These factors could lead to misestimations or overconfidence. Additionally, traders' valuations of the shares' future returns could be influenced by risk preferences (aversion or attraction).

I am particularly interested in how insider and outsider status influences traders' bid and ask decisions. These effects may help to explain why insider information is not disseminated by the market, and why increasing the proportion of insiders does not reduce bubble size. The experimental design specifically highlights that traders are either insiders or outsiders. This is true even in the 9 insider sessions when all subjects are insiders. Explicit knowledge of either status may affect how a trader makes decisions. To identify the effects of each status, traders' decisions must be compared to a set of decisions made by traders in markets that only differ in the structure of private information. The ten 15-period markets in section 4 of Holt et al. (2017) substantively satisfy this criterion.[50] These markets act as a control for the behavior of traders who are informed of the redemption value, but have not been treated with the insider/outsider framing. I will refer to traders from these markets as the control group.

To model the effect of traders' beliefs and characteristics on the decision to attempt to buy or sale shares, I estimate the following regressions in which the indicator functions implement the

[50] These 10 markets have the same sequence of cash endowments, initial share endowments, dividend structure, and interest rate as the markets in this experiment. The redemption value for the assets in Holt et al. (2017) corresponds to this chapter's flat redemption value treatment. Current period, period ahead, and two period ahead price predictions were elicited in both experiments with the same incentive structure. All traders were informed of the redemption value, and there was no insider vs. outsider framing in the instructions. Holt et al. (2017) investigates gender differences in bubble formation, and finds no significant difference. Thus, 5 of the markets had all male traders and 5 had all female traders, rather than the mixed gender markets of this chapter. The all-male and all-female sessions were conducted at the same time, so that traders were not aware that they were only grouped with traders of the same gender. Moreover, the null results for gender differences implies that this should not affect the ability to use these markets as identifying controls.

decisions implied by the expected payoff differences in equations (2) and (3). I include the fundamental value trajectory as a fixed effect to control for any differences induced by changes in the redemption value. A control for risk aversion is not included, because the data from Holt et al. (2017) uses a different measure of risk aversion than the experiment in this chapter.[51] The prices used in the estimation are each individual trader's price expectations for the current period price and the next period price. This estimation includes periods 1-14, but excludes period 15 in which there was not a "next-period" price prediction.

$$\begin{aligned} Bid_{i,t} &= \beta_0 + \beta_1 \mathbf{1}\{E_{i,t}[(1+r)P_t] < E_{i,t}[P_{t+1} + D_t]\} + \beta_2 \mathbf{1}\{Insider_i\} \\ &\quad + \beta_3 \mathbf{1}\{Outsider_i\} + \beta_4 Cog.Score_i + \beta_5 \mathbf{1}\{Increasing\ FV_i\} \\ &\quad + \beta_6 \mathbf{1}\{Decreasing\ FV_i\} + \varepsilon_{i,t} \qquad (4) \end{aligned}$$

$$\begin{aligned} Ask_{i,t} &= \beta_0 + \beta_1 \mathbf{1}\{E_{i,t}[(1+r)P_t] > E_{i,t}[P_{t+1} + D_t]\} + \beta_2 \mathbf{1}\{Insider_i\} \\ &\quad + \beta_3 \mathbf{1}\{Outsider_i\} + \beta_4 Cog.Score_i + \beta_5 \mathbf{1}\{Increasing\ FV_i\} \\ &\quad + \beta_6 \mathbf{1}\{Decreasing\ FV_i\} + \varepsilon_{i,t} \qquad (5) \end{aligned}$$

In these equations, $Bid_{i,t}$ and $Ask_{i,t}$ are now indicator variables for if a trader submitted a bid (or ask) order in period *t*. In estimating these equations, it is assumed that subjects have no heterogeneity over their beliefs on the interest rate and dividends, and that their expectations align with the common information on interest and dividends. The interest rate is common knowledge and fixed, as is the fact that the dividend has two possible values with equal probabilities.

The use of linear regression to estimate the binomial variables of $Bid_{i,t}$ and $Ask_{i,t}$ follows Chang et al. (2016) and Frydman and Wang (2020). These papers estimate the disposition effect using linear regression on the binomial variable of whether a trader sold assets in a given time period. In their cases, and in this case, the use of linear regression allows for a clearer theoretical interpretation of the coefficients than a logit model.

The second column of table 3.3 reports estimates of the coefficients in equation 4, which models traders' decisions to submit bid orders. I find that a trader from the control group, with a cognitive score of zero, will submit a bid order 71.13% of the time when they expect no gain from owning an asset. I reject the null hypothesis that this intercept term is zero at the 99% confidence

---

[51] The chapter's experiment use the bomb task described in section 2. Holt et al. (2017) uses the Eckel and Grossman (2002,2008) risk aversion measure.

level. When accounting for increasing or decreasing fundamental value trajectory, this estimate of bid probability is unchanged. The fixed effects for both of these trajectories are not significantly different from zero at any conventional significance level.

Table 3.3: Regression Coefficients for Decision to Bid or Ask

Coefficient	Decision to Bid (equation 4)	Decision to Ask (equation 5)
Intercept	0.7113***	0.5410***
	(0.0175)	(0.0187)
Sign of Expected Gain	0.1189***	0.0709***
	(0.0149)	(0.0180)
Insider	0.0614***	-0.0139
	(0.0214)	(0.0257)
Outsider	-0.0039	0.0218
	(0.0231)	(0.0277)
Cognitive Score	-0.0100	0.0065
	(0.0065)	(0.0077)
Increasing FV	0.0010	-0.0251
	(0.0231)	(0.0278)
Decreasing FV	-0.0176	0.0439
	(0.0231)	(0.0277)
R^2	0.0260	0.0902

Note: The second column shows the linear regression coefficients for the dependent variable of the probability of a subject deciding to bid in a given period. The third column shows the coefficients for the dependent variable of the probability a subject decides to submit and ask order in a given period. Values in parentheses are estimated standard errors. Significance levels: ***p<0.01, **p<0.05, *p<0.1

Theory predicts that the most important determinant in submitting a bid is an expected gain. I find that traders are 11.89 percentage points more likely to submit a bid when they expect a positive return on purchasing a share. While I reject the null hypothesis that this effect is zero at the 99% confidence level, I also reject, at the 99% confidence level, the null hypothesis that this is the only significant factor in placing a bid. This implies that the existence of a positive expected gain does increase the odds of a trader submitting a bid order, but not solely, as predicted for a profit maximizing trader.

The primary interest is on the effects of insider and outsider status on the decision to submit a bid. Traders in this experiment were given an information treatment that clearly labeled them as insiders or outsiders, and this treatment was emphasized throughout the experiment. I find that traders receiving the insider treatment were 6.14 percentage points more likely to submit a bid order than traders in the control group. A result that is significant at the 99% confidence level.

For outsiders, the point estimate indicates that they have a slightly lower probability of submitting a bid order than insiders. However, this finding is not significant at any traditional confidence level. Together these results show that giving a trader insider information, and highlighting this fact, increases the trader's probability of submitting a bid order.

The third column of Table 3.3 reports estimates of the coefficients in equation 5, which models traders' decisions to submit ask orders. At the 99% confidence level I reject the null hypothesis that the intercept term of this equation is zero. The point estimate indicates that there is a 54.10% chance a trader in the control group, with a cognitive score of zero, will attempt to sell shares in a period with no expected loss from shares in the next period. I additionally find that the existence of an expected loss has a significant effect on traders' decisions to submit an ask order at the 99% confidence level. The point estimate of this effect is a 7.09 percentage point increase in the likelihood of submitting an ask order when there is a negative expected gain. An increased probability of submitting an ask order when there is an expected loss is consistent with the theoretical predictions.

For the main variables of interest, insider and outsider status, I find no effect on the probability to submit an ask order. The point estimates of these effects show that insiders are slightly less likely than the control group to submit an ask order, and outsiders are slightly more likely. However, neither of these estimates is significant at any traditional confidence level. This implies that decisions to submit an ask order are not affected by insider or outsider information treatments. To summarize:

Result 3.3: Giving a trader explicit insider information increases the probability that they submit a bid order in any given period.

The regressions modeling traders' decisions to submit limit orders show the potential for the insider information treatment to affect the market demand for asset shares. Being treated with insider information makes a trader more likely to submit a bid order than the control, but does not affect the likelihood of submitting an ask order. Neither the likelihood of submitting a bid or ask order is affected for traders treated with the outsider information treatment. This implies that as the number of insiders is increased, the expected number of traders submitting a buy order in any given period is also increased. If the orders submitted by insiders are for similar, or greater, quantities and prices, then insiders' greater probability of submitting orders will increase demand.

Although there is no difference in insiders' and outsiders' probabilities of submitting an ask order, it is still possible that increasing the number of insiders in the market affects the supply curve, if there are differences in the type of ask orders submitted by insiders and outsiders. It is to these differences in the type of limit orders submitted that I now turn.

I measure the intensity of a trader's bid as the proportion of their cash placed at risk by the bid.

$$Bid\ Intensity_{i,t} = \frac{P_{i,t}^{B} \times Q_{i,t}^{B}}{Cash_{i,t}}$$

In this expression, $P_{i,t}^{B}$ is the limit order bid price, $Q_{i,t}^{B}$ is the bid quantity, and $Cash_{i,t}$ is the cash holdings of trader *i* in period *t*. Thus, the bid intensity is the proportion of a trader's cash holdings they would spend on shares and were able to purchase $Q_{i,t}^{B}$ shares at their bid price. I measure the intensity of a trader's ask as the proportion of their shares they are willing to sale with their ask.

$$Ask\ Intensity_{i,t} = \frac{Q_{i,t}^{A}}{Q_{i,t}}$$

In this expression, $Q_{i,t}^{A}$ is the ask quantity and $Q_{i,t}$ is the quantity of shares owned by trader *i* in period *t*.

To decompose factors that affect traders' intensities decisions, I estimate the following two regression equations on traders' intensities, conditional on a bid or ask being made.

$$\begin{aligned} &Bid\ Intensity_{i,t} \\ &\quad = \beta_0 + \beta_1 \mathbf{1}\{E_{i,t}[(1+r)P_t] < E_{i,t}[P_{t+1} + D_t]\} + \beta_2 \mathbf{1}\{Insider_i\} \\ &\quad + \beta_3 \mathbf{1}\{Outsider_i\} + \beta_4 Cog.Score_i + \beta_5 \mathbf{1}\{Increasing\ FV_i\} \\ &\quad + \beta_6 \mathbf{1}\{Decreasing\ FV_i\} + \varepsilon_{i,t} \end{aligned} \tag{6}$$

$$\begin{aligned} &Ask\ Intensity_{i,t} \\ &\quad = \beta_0 + \beta_1 \mathbf{1}\{E_{i,t}[(1+r)P_t] > E_{i,t}[P_{t+1} + D_t]\} + \beta_2 \mathbf{1}\{Insider_i\} \\ &\quad + \beta_3 \mathbf{1}\{Outsider_i\} + \beta_4 Cog.Score_i + \beta_5 \mathbf{1}\{Increasing\ FV_i\} \\ &\quad + \beta_6 \mathbf{1}\{Decreasing\ FV_i\} + \varepsilon_{i,t} \end{aligned} \tag{7}$$

These equations are estimated using only trader and period combinations for which the trader submitted a bid or ask order. The results of these regressions are reported in table 3.4.

Table 3.4: Regression Coefficients for Estimates of Bid and Ask Intensity

Coefficient	Intensity of Bid[a] (equation 6)	Intensity of Ask[b] (equation 7)
Intercept	0.3137***	0.4197***
	(0.0132)	(0.0156)
Sign of Expected Gain	-0.0146	0.0807***
	(0.0111)	(0.0145)
Insider	-0.0108	0.0237
	(0.0158)	(0.0210)
Outsider	0.0008	0.0112
	(0.0169)	(0.0224)
Cognitive Score	0.0439***	0.0092
	(0.0048)	(0.0064)
Increasing FV	-0.0112	-0.0227
	(0.0170)	(0.0228)
Decreasing FV	-0.0783***	-0.0503**
	(0.0169)	(0.0221)
R^2	0.0490	0.0222
N	2458	1839

Note: The second column shows the regression coefficients for the dependent variable of the intensity of a subject's bid order. The third column shows the coefficients for the dependent variable of the intensity of a subject's ask order. Data in these regressions are conditional on a subject having submitted a bid or ask order. Values in parentheses are estimated standard errors. Significance levels: ***p<0.01, **p<0.05, *p<0.1

[a] $Bid\ Intensity_{i,t} = \frac{P^B_{i,t} \times Q^B_{i,t}}{Cash_{i,t}}$

[b] $Ask\ Intensity_{i,t} = \frac{Q^A_{i,t}}{Q_{i,t}}$

For both regressions I find the intercept is significantly different from zero at the 99% confidence level. This is not surprising since I estimate the regressions conditional on a bid or ask being made. The intercepts represent the bid (ask) intensity of a bid (ask) order made by a risk neutral outsider, with cognitive score zero, when they have an expected gain (loss) of zero. Given that a bid (ask) is being made, this coefficient cannot be zero. Of more interest are the estimates of the effects of the insider and outsider information treatments.

When submitting bid orders, I find that the insider information treatment does not affect the proportion of a traders' cash they put at stake with the order, neither does the outsider information treatment. In both cases, I am unable to reject the null hypothesis of no difference at any traditional significance level. This implies that when submitting bids, there are no substantive differences between the bids of insiders and outsiders. Thus, insiders' greater likelihood of submitting bids is stimulating demand for assets, because these bids are of the same intensity as outsiders' bids.

On the other side of the market, I also estimate the intensity of traders' ask orders. As with bid order intensity, I find no significant difference between the intensity of ask orders submitted by insiders and outsiders. Also, their ask order intensity is not significantly different than that of traders in the control group. I do find that the existence of an expected loss significantly increases the intensity of all traders ask orders (at the 99% confidence level) by 8.07% of the shares they own. The lack of difference in the probability of submitting an ask order, and the ask intensity, between insiders and outsiders indicates that increasing the number of insiders in the market does not affect the asset supply curve.

Result 3.4: Neither bid nor ask order intensity are affected by a trader receiving the insider or outsider information.

Combining the analysis of traders' decisions to submit limit orders, and the intensity of those orders, I find that increasing the number of insiders affects the demand side of the market. Treating a trader with insider information increases the likelihood that they will submit a bid order in any given period. However, the intensity of that bid order does not differ significantly from the bid order of an outsider. Taken together these facts imply that increasing the number of insiders in a market increases the demand for assets in any given period in that market. For ask orders, neither the decision to submit an order nor the intensity of the order are affected by a trader being an insider or an outsider. Therefore, the insider and outsider information treatments do not affect the supply side of the market, and supply curves are unchanged as the number of insiders is increased. Since increasing the number of insiders increases demand, but does not increase supply, the increase applies upward pressure on market prices. This upward pressure could be the reason I find bubble magnitudes do not decrease with more insiders in the market, as is predicted by the efficient market hypothesis.

V. Comparisons of Insiders and Outsiders: Asset Price Predictions

In each period of the market, traders are asked to predict the asset price in the current period, the next period, and two periods ahead. Correct predictions are rewarded with a monetary incentive, which should yield unbiased modal predictions. The insider information treatment provides sufficient information for an insider to know the fundamental value of the asset in each period, which may influence their price predictions. At the same time, when a price bubble is forming, elicited predictions may reflect their expectations of the trajectory of the bubble. Traders should make trading decisions based on beliefs about the current period and future asset prices. Through this payoff maximizing behavior, traders' beliefs about the price, as expressed in their predictions, can affect the market price. If there are several traders who have bullish beliefs, they may attempt to purchase as many asset shares as possible, pushing up the price. Similarly, if insiders' beliefs are more anchored to the fundamental value, because of their private information, they will act on that information and submit trading decisions more consistent with pricing at the fundamental value. This behavior would imply that as the number of insiders increases, more traders' beliefs are influenced by the fundamental value, and the price will correspondingly be closer to the fundamental value.

To evaluate this beliefs-based mechanism, I conduct two sets of regressions using data from all 15 sessions shown in table 3.1. The dependent variables are the normalized absolute values of differences between a trader's price prediction *P** (indexed by *i* and *t*) and the fundamental value (FV) of the asset for period *t*: $\frac{|P^*_{i,t}-FV_t|}{FV_t}$. I first consider a simple specification, with an indicator for the trader's insider information status, risk aversion score (*RA*), cognitive score, and controls for market fixed effects.

$$\frac{|P^*_{i,t} - FV_t|}{FV_t} = \beta_0 + \beta_1 \mathbf{1}_{Insider}(i) + \beta_2 RA_i + \beta_3 Cog.Score_i + Fixed\ Effects + \varepsilon_{i,t} \quad (8)$$

This regression expression is considered separately for current-period, next-, and two-period-ahead predictions. The cognitive score control is particularly important, as the FV is never directly presented to traders, they must compute it themselves. Traders with high cognitive scores are more likely to identify the FV, and more closely consider it in their predictions. Risk aversion controls are used because the share dividends are risky, and this risk lowers the fundamental value from the perspective of risk averse traders and increases the fundamental value from the perspective of risk seeking traders. This regression is used for current period, next period, and two period ahead prediction data. In the cases of next period and two period ahead predictions, the time period indicators correspond to the period in which the prediction was made.

The prediction regression results are shown in table 3.5. The intercept terms of regressions 1-3 represent the average percent deviation of a risk-neutral outsider with a cognitive score of zero, not accounting for market fixed effects. For example, the intercept term for regression 1 is 0.5522. This can be interpreted as an average deviation from the FV of 55.22% for risk neutral outsiders with a cognitive score of zero. After accounting for market-level fixed effects, I reject the null hypothesis that there is a 0% deviation in predicted price from the *FV* at all prediction horizons at a minimum of a 99% confidence level for each market.[52] Put differently, I am 99% confident that the predictions of risk neutral outsiders with a cognitive score of zero have some degree of deviation from the *FV*.

Table 3.5: Asset Price Prediction Regression Results, Dependent Variable is Normalized Absolute Value Differences

Prediction Horizon	(1) Current Period	(2) Next Period	(3) Two Periods Ahead	(4) Current Period	(5) Next Period	(6) Two Periods Ahead
Intercept	0.5522*** (0.0294)	0.5857*** (0.0317)	0.6128*** (0.0364)	0.4155*** (0.0321)	0.4170*** (0.0336)	0.4237*** (0.0381)
Insider Status	-0.0253 (0.0199)	-0.0319 (0.0215)	-0.0367 (0.0246)	0.0027 (0.0274)	0.0128 (0.0283)	0.0313 (0.0315)
Risk Aversion	-0.0249*** (0.0057)	-0.0325*** (0.0062)	-0.0414*** (0.0071)	-0.0249*** (0.0055)	-0.0325*** (0.0059)	-0.0414*** (0.0067)
Cognitive Score	-0.0396*** (0.0063)	-0.0439*** (0.0068)	-0.0496*** (0.0078)	-0.0396*** (0.0060)	-0.0439*** (0.0064)	-0.0496*** (0.0073)
Periods 6-10				0.2285*** (0.0263)	0.2871*** (0.0270)	0.3271*** (0.0298)
Periods 11- 15				0.1816*** (0.0263)	0.2315*** (0.0286)	0.2741*** (0.0344)
Insider Status x Periods 6-10				-0.0949*** (0.0340)	-0.1233*** (0.0348)	-0.1506*** (0.0444)
Insider Status x Periods 11-15				0.0108 (0.0340)	-0.0024 (0.0369)	-0.0437 (0.0459)
$\mathbf{R^2}$	0.1328	0.1527	0.1578	0.2000	0.2464	0.2518

Note: Values in parentheses are estimated standard errors. ***p<0.01, **p<0.05, *p<0.1

The prediction equations discussed thus far (on the left side of table 3.4) do not support the hypothesis that insiders dampen bubbles because their beliefs are more anchored to fundamental value than those of outsiders. It is possible, however, that insider status might have a larger dampening effect during the upward price surge in the middle periods of the trading sequences. This is investigated by adding indicator variables for whether the prediction was made in the middle 5 periods (periods 6-10), or the final 5 periods (periods 11-15). Additionally, these later-

[52] This hypothesis is tested for each market by using a *F*-test to test that the addition of the intercept term and the market fixed effect term are not equal to zero.

period indicators are interacted with insider status. These interaction variables account for differences in predictions between insiders and outsiders in different phases of the market.

The regressions 4, 5, and 6 on the right side of table 3.5 show that insiders' predictions in the first five periods, and the final periods are not significantly different from the predictions of outsiders. However, in the middle periods, insiders make predictions that are closer to the fundamental value. An F-test of the sum of the insider status coefficient and interaction term for the middle periods rejects (at the 99% confidence level) the null hypothesis that insiders' and outsiders' predictions are equally close to the fundamental value. That is, insiders' predictions are closer to the fundamental value than outsiders' predictions in periods 6 through 10. These findings support the fifth result:

Result 3.5: For all prediction horizons, insiders' predictions made in the middle periods (6-10) are closer to the fundamental value than the predictions of outsiders.

It is privately optimal for a trader to make bids and asks based on their current and future period price beliefs, i.e., their predictions. Given that insider's predictions are closer to the fundamental value in periods of peak bubble activity, it can be infered that their market actions more closely reflect the fundamental value. Therefore, as the number of insiders increases, the market is more heavily weighted towards the fundamental value.

The baseline for the regressions in table 3.4 is a trader with a cognitive score of zero. For all prediction horizons, the coefficient on cognitive score is negative, and different from zero at the 99% confidence level, which supports our sixth result.

Result 3.6: Traders with higher cognitive scores tend to make price predictions that are closer to the fundamental value.

VI. Comparisons of Insiders and Outsiders: Final Earnings Results

To summarize, insiders generally predict prices to be closer to the fundamental value during the middle (boom) periods, and in all periods traders with higher cognitive scores make predictions that are closer to the fundamental value. These differences could result in differences in final earnings if traders are able to successfully act on these differences in the market.[53] To estimate the effects of a trader's characteristics on their final earnings, the following regression is used, where each trader is indexed by i.

$$Final\ Earnings_i = \beta_0 + \beta_1 \mathbf{1}_{Insider}(i) + \beta_2 Cog.Score_i + \beta_3 RA_i + Fixed\ Effects + \varepsilon_i \quad (9)$$

Since there are three different redemption values for the asset (\$22.90, \$28.00, and \$33.11), fixed effects are included for high and low redemption values. These fixed effects account for the fact that lower (higher) redemption values will systematically reduce (increase) the final earnings of traders in those markets. This regression specification is estimated twice, using all markets and using only markets with both insiders and outsiders, as shown in table 3.6. As a baseline for interpreting these results, a subject in the flat fundamental value treatment who never engaged in trading shares would have had final earnings of \$1,176.65.

Table 3.6. Determinants of Final Earnings

Markets Included	Intercept	Insider Status	Cognitive Score	Risk Aversion	R^2
All 15 Markets	1102.34*** (37.14)	-0.8594 (31.08)	45.78*** (13.14)	-0.61 (11.68)	0.1139
Markets with 1-8 Insiders	1107.99*** (38.96)	-6.05 (33.03)	39.00*** (14.46)	2.66 (11.69)	0.0976

Note: Regression coefficient estimates for regressions with the dependent variable a subject's final earnings from the market task in lab dollars. The first row includes all markets. The second row includes only markets with some degree of information asymmetry. Values in parentheses are estimated standard errors. ***p<0.01, **p<0.05, *p<0.1

The final earnings regression in the bottom row of table 3.5, using only data from markets with both insiders and outsiders, is useful in determining whether insiders experience higher earnings than outsiders in the same market. The markets with all insiders are excluded from this regression because the lack of an information asymmetry means there is no informational advantage insiders can use to enhance their earnings at the expense of outsiders. It is estimated that, on average, insiders earn \$6.05 less (in lab dollars) than outsiders. However, this effect is not significant at the 90% confidence level, so the null hypothesis that insider status has no effect on earnings cannot be rejected. This null result is further reinforced by a non-parametric test of insiders' versus outsiders' earnings. I use a 2-tailed stratified permutation test (stratifying by

[53] Final earnings are calculated as the sum of a trader's cash holdings after the final interest and dividend payments at the end of period 15, and the redemption value of their asset shares held at the end of period 15.

market) to test the null hypothesis that insiders and outsiders have the same earnings and are unable to reject the null hypothesis (p-value = 0.8871). It seems to be the case that any advantage of insider information does not translate into higher earnings from correctly timed sales prior to the end of a price bubble.

Result 3.7: Insiders do not tend to have higher final earnings than outsiders.

Another factor that could influence earnings is cognitive ability. Recall the prior result 3.6, which shows that traders with higher cognitive scores tend to make price predictions that are more influenced by the fundamental value. It is no longer necessary to exclude markets with all insiders, as the effects of cognitive score are assumed to be independent from the effects of insider status. The estimated coefficient of cognitive score is significant and positive in the All Markets row of table 3.6. The coefficient estimate of 45.78 means that for each additional cognitive score point a trader's expected final earnings in lab dollars increase by $45.78. This supports the final result:

Result 3.8: Traders with higher cognitive scores tend to have higher final earnings than traders with lower cognitive scores.

VII. Conclusion

This chapter finds that in markets for durable assets, private information about the final payout (redemption value) is not incorporated into the price until the final trading period. This is a violation of the strong form of the efficient market hypothesis, and of rational expectations models, which imply that private information should immediately be reflected in the asset price. Observed prices differ substantially from the dividends-based fundamental values for most periods of the trading process. Moreover, these price deviations are not in a direction that could be explained by risk aversion. Additionally, as the proportion of traders with private information is increased (i.e., the information is made more public) there is no observed systematic change in deviations from the fundamental value. These observations suggest that either insiders or outsiders behave in such a way as to cancel out the theoretical gains from more information. To understand this, I analyze the behavior of insiders and outsiders in submitting limit orders and making price predictions.

In the analysis of traders' limit order decisions, I find that insiders are more likely to submit bid orders (to buy shares) than outsiders, and that these orders do not involve fewer shares than those of outsiders. Together, these findings indicate that increasing the number of insiders in a market will increase demand for shares in that market. On the supply side (ask orders) differences between insiders and outsiders are less clear, and could imply a weak increase or decrease in supply. These demand and supply shifts provide a possible path for behavioral differences between insiders and outsiders to counteract any potential bubble reducing effects of increasing the number of insiders.

Incentivized price predictions are used to evaluate how traders utilize private information. On average, traders who receive private information believe that asset prices will be closer to the prices predicted by theory. It is in traders' best interest to act on their beliefs when submitting limit orders. While more informed traders exhibit smaller deviations in their price predictions, I do not find any differences in the final earnings of traders with and without private information. These findings suggest we should be skeptical about the private information content of market prices for assets such as stocks and long-term bonds. Participants in these markets who have private information are likely using this information to form their beliefs, but it is unclear that this information increases their earnings. Moreover, the crosswinds of speculation during price surges for durable assets tend to blur the effects of private information.

Proofs Appendix

Proposition 1 *An allocation* $\left\{\left\{x_{t,i}\right\}_{i\in\Phi}\right\}_{t\in\{1,\ldots,\mathrm{T}\}}$ *is a first best allocation iff*

(a) $\mathrm{C}'\left(\mathrm{x}_{\mathrm{t,i}}\right) = FV_t$ *and* $C\left(x_{t,i}\right) \leq (FV_t)x_{t,i}\ \forall t, i$ **OR**

(b) $x_{t,i} = 0\ \forall\ t, i$ *and* $\nexists \left\{\left\{x_{t,i}\right\}_{i\in\Phi}\right\}_{t\in\{1,\ \ldots,T\}}$ *such that* $x_{t,i} > 0$, $C'\left(x_{t,i}\right) = FV_t$, *and* $C\left(x_{t,i}\right) \leq (FV_t)x_{t,i}\ \forall t, i$

Where $FV_t = \left(\frac{1-\delta}{1+\mathrm{r}}\right)^{\mathrm{T}+1-\mathrm{t}} \Upsilon + \frac{1}{1+r}\sum_{i=1}^{T-t}\left(\frac{1-\delta}{1+r}\right)^{i} D$

Proof Given that utility is linear over final portfolio values for all agents, the social planner will achieve their optimal allocation for any set of welfare weights, $\{\alpha_i\}_{i\in\Phi}$, by maximizing the total amount of resources in the economy. This implies that they seek to maximize the aggregate value of all agents' final portfolios. This maximization is subject to resource constraints on cash and capital.

$$\max_{\left\{\{b_{t,i}\}_{i\in\Phi},\{k_{t,i}\}_{i\in\Phi},\{x\}_{i\in\Phi}\right\}_{t\in\{1,\ldots,\mathrm{T}\}}} \sum_{i\in\Phi}(1+r)b_{T,i} + \left((1-\delta)\Upsilon + D\right)k_{T,i}$$

$$s.t. \quad \sum_{i\in\Phi} b_{t,i} + \sum_{i\in\Phi} C\left(x_{t,i}\right) = (1+r)\sum_{i\in\Phi} b_{t-1,i} + D\sum_{i\in\Phi} k_{t-1,i} \quad \forall t$$

$$\sum_{i\in\Phi} k_{t,i} = (1-\delta)\sum_{i\in\Phi} k_{t-1,i} + \sum_{i\in\Phi} x_{t,i} \quad \forall t$$

$$x_{t,i} \geq 0 \quad \forall t, i$$

Since utility is linear, the first order conditions of this optimization problem give the following single condition on capital production, assuming the production non-negativity constraint is not binding.

$$\mathrm{C}'\left(\mathrm{x}_{\mathrm{t,i}}\right) = FV_t\ \forall t, i \tag{4}$$

In equation 4, $FV_t = \left(\frac{1-\delta}{1+\mathrm{r}}\right)^{\mathrm{T}+1-\mathrm{t}} \Upsilon + \frac{1}{1+r}\sum_{i=1}^{T-t}\left(\frac{1-\delta}{1+r}\right)^{i} D$, which is the fundamental value of capital. For the production non-negativity constraint to be slack, it must be the case that the present value of all capital units produced exceed (or are equal to) the total cost of production. Therefore, the production non-negativity constraint will not bind if $C\left(x_{t,i}\right) \leq (FV_t)x_{t,i}$.

If the production non-negativity constraint is binding (including just binding), then the planner's problem will have a corner solution at $x_{t,i} = 0\ \forall i,\ t$. In this case the socially optimal production level will be to produce no capital, or $x_{t,i} = 0\ \forall i,\ t$.

□

Proposition 2: Stationary State: *If* $K_0 = \overline{K}$, $\Upsilon = \frac{D}{r+\delta}$, $C'\left(\delta\frac{\overline{K}}{N}\right) = \Upsilon$, $\mathrm{C}\left(\delta\frac{\overline{\mathrm{K}}}{\mathrm{N}}\right) \leq \delta\frac{\overline{\mathrm{K}}}{\mathrm{N}}\Upsilon$, $r \geq 0$, $\delta > 0$, *and* $\mathrm{r}b_{0,i} + \mathrm{Dk}_{0,\mathrm{i}} \geq C\left(\delta\frac{\overline{K}}{N}\right)\ \forall i$, *then the rational expectations equilibrium will be stationary and will entail* $FV_t = P_t = \Upsilon$, $K_t = \overline{K}$, *and* $x_{t,i} = \delta\frac{\overline{K}}{N}\ \forall t, i$.

Proof Assume $\Upsilon = \frac{D}{r+\delta}$, then $\Upsilon = \frac{1}{1+r}\sum_{j=0}^{\infty}\left(\frac{1-\delta}{1+r}\right)^j D$. In all time periods, the fundamental value of capital is:

$$\mathrm{FV}_\mathrm{t} = \frac{1}{1+r}\sum_{j=0}^{\mathrm{T-t}}\left(\frac{1-\delta}{1+r}\right)^j D + \left(\frac{1-\delta}{1+r}\right)^{T+1-t}\Upsilon = \frac{1}{1+r}\sum_{j=0}^{\infty}\left(\frac{1-\delta}{1+r}\right)^j D = \Upsilon$$

So $\forall t$, $FV_t = \Upsilon$.

Assume agents form rational expectations, $C'\left(\delta\frac{\overline{K}}{N}\right) = \Upsilon$, and $\mathrm{r}b_{0,i} + \mathrm{Dk}_{0,\mathrm{i}} \geq C\left(\delta\frac{\overline{K}}{N}\right)\ \forall i$. Also, assume that the borrowing constraint, $b_{t,i} \geq 0$, nor the cash-in-advance constraint, $(1+r)b_{t-1,i} + Dk_{t-1,i} \geq C(x_{t,i})$, is ever binding for any agent.

In period T, $E_i[P_{T+1}|\mathcal{I}_{T-1}] = \Upsilon\ \forall i$ because capital is redeemed for Υ and not traded in period T. The capital pricing equation for each agent is then:

$$P_T = \frac{(1-\delta)\Upsilon + D}{1+r} + \mu_{T,i} = \Upsilon + \mu_{T,i}\ \forall i$$

Assume that for agent *j*, the no short sale constraint is binding, $k_{T,j} = 0$ and $\mu_{T,j} > 0$. Then, $P_T > \Upsilon$. At such a P_T, all agents will want to sell all of their capital in period T, because the price $P_T > \Upsilon$ gives them a greater return than holding capital until it is redeemed in the next period. However, this is a contradiction as all agents selling all of their capital is a violation of the market clearing condition. Therefore, $P_T = \Upsilon$ and $\mu_{T,i} = 0\ \forall i$.

Since expectations are rational, this implies $E_{t,i}[P_T|\mathcal{I}_{t-1}] = \Upsilon\ \forall t, i$. Therefore, in period T-1,

$$P_{T-1} = \frac{(1-\delta)\Upsilon + D}{1+r} + \mu_{T-1,i} = \Upsilon + \mu_{T-1,i}\ \forall i$$

By the same contradiction as in period T, $P_{T-1} = \Upsilon$. Iterating backwards, $P_t = \Upsilon\ \forall t$ and $\mathrm{E_i}[\mathrm{P_t}|\mathcal{I}_{\tau-1}] = \Upsilon\ \forall \tau < \mathrm{t}, \mathrm{t}, \mathrm{i}$.

Given that $\mathrm{E_i}[\mathrm{P_t}|\mathcal{I}_{t-1}] = \Upsilon\ \forall \mathrm{t}, \mathrm{i}$, equation (3) becomes $\Upsilon = C'(\mathrm{x_{t,i}})$. Since $C(\cdot)$ is strictly increasing and convex, and $C'\left(\delta\frac{\bar{K}}{N}\right) = \Upsilon$, this implies that $x_{t,i} = \delta\frac{\bar{K}}{N}\ \forall t, i$ if it is optimal for agents to produce. It will be optimal for agents to produce if the total cost of production is less than or equal to the total value of the assets produced, $\mathrm{C}\left(\delta\frac{\bar{\mathrm{K}}}{\mathrm{N}}\right) \leq \delta\frac{\bar{\mathrm{K}}}{\mathrm{N}}\Upsilon$. This is assumed to be the case, so it is optimal for $x_{t,i} = \delta\frac{\bar{K}}{N}\ \forall t, i$.

At this production and price combination, each agent will be indifferent over holding capital, as its return is equal to the return on cash, but will produce $x_{t,i} = \delta\frac{\bar{K}}{N}$. This production occurs because at lower production levels, there is an arbitrage gain from slightly increasing production and selling the capital at a price higher than the marginal cost. Therefore, an agent's borrowing constraint and cash-in-advance constraint will not be binding if they can afford this optimal production level.

By assumption $\mathrm{r}b_{0,i} + \mathrm{Dk_{0,i}} \geq C\left(\delta\frac{\bar{K}}{N}\right)\ \forall i$, which implies that all agents can afford to produce $x_{1,i} = \delta\frac{\bar{K}}{N}$ in the first period, using the returns from their endowment. In periods after the first period agents will endogenously choose to hold some combination of assets and cash, including the possibility of holding all assets and all cash. If agents meet the cash-in-advance constraint for $x_{t,i} = \delta\frac{\bar{K}}{N}$ when holding all cash or all assets, then the constraint will be met for any combination of cash and assets.

First assume that a given agent *j* choses to hold only cash – i.e. they sell all of their initial endowment of assets and any assets they produce. It is already shown they can afford to produce $x_{1,j} = \delta\frac{\bar{K}}{N}$. Selling these assets yields $\delta\frac{\bar{K}}{N}\Upsilon$ in cash, which will be carried into period 2 with interest. Since $\mathrm{C}\left(\delta\frac{\bar{\mathrm{K}}}{\mathrm{N}}\right) \leq \delta\frac{\bar{\mathrm{K}}}{\mathrm{N}}\Upsilon$, they will satisfy the cash-in-advance constraint in period 2, and any period in which they sold $\delta\frac{\bar{K}}{N}$ assets in the previous period. Thus, agents following an always sell strategy will satisfy the cash-in-advance constraint to produce $x_{t,i} = \delta\frac{\bar{K}}{N}$ in all periods.

Now assume that a given agent *j* chooses to hold only assets – i.e. anytime they have cash after production they use it to purchase assets. For this agent to satisfy the cash-in-advance their dividend payments must be sufficient to finance production in every period. In period 2, they will receive $Dk_{1,j}$ in dividends.

$$k_{1,j} = (1-\delta)k_{0,i} + \delta\frac{\overline{K}}{N} + \frac{\varepsilon_{1,j}}{\Upsilon} \;\; where$$

$$\varepsilon_{1,j} = (1+r)b_{0,j} + Dk_{0,j} - \mathrm{C}\left(\delta\frac{\overline{\mathrm{K}}}{\mathrm{N}}\right) \geq (1+r)b_{0,j} + Dk_{0,j} - \delta\frac{\overline{\mathrm{K}}}{\mathrm{N}}\Upsilon$$

$$\Rightarrow \mathrm{Dk}_{1,\mathrm{j}} \geq (1+\mathrm{r})\mathrm{Dk}_{0,\mathrm{j}} + (1+\mathrm{r})(r+\delta)b_{0,j} \geq \mathrm{r}b_{0,j} + \mathrm{Dk}_{0,\mathrm{j}} \geq C\left(\delta\frac{\overline{K}}{N}\right)$$

Thus, in period 2, agent *j* satisfies the cash-in-advance constraint to produce $x_{2,j} = \delta\frac{\overline{K}}{N}$. In period 3, they will receive $Dk_{2,j}$ in dividends.

$$k_{2,j} = (1-\delta)k_{1,i} + \delta\frac{\overline{K}}{N} + \frac{\varepsilon_{2,j}}{\Upsilon} \;\; where$$

$$\varepsilon_{2,j} = Dk_{1,j} - \mathrm{C}\left(\delta\frac{\overline{\mathrm{K}}}{\mathrm{N}}\right) \geq Dk_{1,j} - \delta\frac{\overline{\mathrm{K}}}{\mathrm{N}}\Upsilon$$

$$\Rightarrow \mathrm{Dk}_{2,\mathrm{j}} \geq (1+\mathrm{r})\mathrm{Dk}_{1,\mathrm{j}} \geq C\left(\delta\frac{\overline{K}}{N}\right)$$

Thus, in period 3, agent *j* satisfies the cash-in-advance constraint to produce $x_{3,j} = \delta\frac{\overline{K}}{N}$. This logic iterates forward through period *T*. Therefore, agents following a strategy to only hold assets, no cash, satisfy the cash-in-advance constraint to produce $x_{t,i} = \delta\frac{\overline{K}}{N}$ in all periods.

Since agents following both an all cash and an all asset strategy will satisfy the cash-in-advance constraint in all periods, agents holding a mix of cash and assets will also satisfy the constraint. Thus, the cash-in-advance constraint is always satisfied for production $x_{t,i} = \delta\frac{\overline{K}}{N}$.

Applying this optimal production level, $x_{t,i} = \delta\frac{\overline{K}}{N}$, to the market clearing condition gives:

$$K_t = (1-\delta)K_{t-1} + \sum_{i\in\Phi}\delta\frac{\overline{K}}{N} = (1-\delta)K_{t-1} + \delta\overline{K}$$

Forward iterating this expression from $K_0 = \overline{K}$, gives $K_t = \overline{K} \;\; \forall t$.

□

Lemma 1: Individually Optimal Production *If agent* i *has the price expectation* $E_i[P_t|\mathcal{I}_{t-1}]$ *and*

(c) $(1+r)b_{t-1,i} + Dk_{t-1,i} \geq C\left(C'^{-1}(\boldsymbol{E_i}[P_t|\mathcal{I}_{t-1}])\right)$*, then their optimal production decision is* $x_{t,i} = C'^{-1}(\boldsymbol{E_i}[P_t|\mathcal{I}_{t-1}])$ *and* $q^E_{t,i} = 1$.

(d) $(1+r)b_{t-1,i} + Dk_{t-1,i} < C\left(C'^{-1}(\boldsymbol{E_i}[P_t|\mathcal{I}_{t-1}])\right)$*, then their optimal production decision is* $x_{t,i} = C'^{-1}\left((1+r)b_{t-1,i} + Dk_{t-1,i}\right)$ *and* $q^E_{t,i} > 1$.

Proof Let agent i have the price expectation $E_i[P_t|\mathcal{I}_{t-1}]$.

(a) Also assume that $(1+r)b_{t-1,i} + Dk_{t-1,i} \geq C\left(C'^{-1}(\boldsymbol{E_i}[P_t|\mathcal{I}_{t-1}])\right)$. Then, the cash-in-advance constraint is not binding for $x_{t,i} = C'^{-1}(\boldsymbol{E_i}[P_t|\mathcal{I}_{t-1}])$, or $E_{t,i}[P_i|\mathcal{I}_{t-1}] = \mathrm{C}'(\mathrm{x_{t,i}})$. From equation (3) this is the optimal production decision when the cash-in-advance constraint does not bind. At this point, $q^E_{t,i} = 1$.

(b) Also assume that $(1+r)b_{t-1,i} + Dk_{t-1,i} < C\left(C'^{-1}(\boldsymbol{E_i}[P_t|\mathcal{I}_{t-1}])\right)$. From equation (3) the optimal production decision for $E_i[P_t|\mathcal{I}_{t-1}]$ is $x_{t,i} = C'^{-1}(\boldsymbol{E_i}[P_t|\mathcal{I}_{t-1}])$, when the cash-in advance constraint does not bind. However, the cash-in-advance constraint is binding by assumption. Therefore, optimal production will occur by spending all cash on production. This is because there is an expected arbitrage gain available to the agent by producing at a lower marginal cost than the market price of capital. Thus, $x_{t,i} = C'^{-1}\left((1+r)b_{t-1,i} + Dk_{t-1,i}\right) < C'^{-1}(\boldsymbol{E_i}[P_t|\mathcal{I}_{t-1}])$. Since $C'(\cdot) > 0$, $E_i\left[P_{t,i}|\mathcal{I}_{t-1}\right] > \mathrm{C}'(\mathrm{x_{t,i}})$, so $q^E_{t,i} > 1$.

□

Lemma 2: Socially Optimal Production *If* $\Upsilon = \frac{D}{r+\delta}$*,* $C'\left(\delta\frac{\bar{K}}{N}\right) = \Upsilon$*, and* $C\left(\delta\frac{\bar{K}}{N}\right) = \delta\frac{\bar{K}}{N}\Upsilon$*, then any solution to a social planner's problem will require* $x_{t,i} = \delta\frac{\bar{K}}{N}\ \forall t, i$.

Proof Assume $\Upsilon = \frac{D}{r+\delta}$, $C'\left(\delta\frac{\bar{K}}{N}\right)$, and $C\left(\delta\frac{\bar{K}}{N}\right) = \delta\frac{\bar{K}}{N}\Upsilon$, . From proposition 2, $\Upsilon = \frac{D}{r+\delta}$ implies that $FV_t = \Upsilon\ \forall t$. From proposition 1, an allocation is first best if $C'\left(x_{t,i}\right) = FV_t$ and $C\left(x_{t,i}\right) < FV_t x_{i,t}$. At $x_{i,t} = \delta\frac{\bar{K}}{N}$, $C'\left(x_{t,i}\right) = \Upsilon = FV_t$ and $C\left(x_{t,i}\right) < \Upsilon x_{i,t}$. Thus, $x_{i,t} = \delta\frac{\bar{K}}{N}$ is the unique solution to the social planners problem.

□

Experimental Instructions Appendix

Chapter 1 Instructions (for $10 income, easy-credit treatment with predictions)

Page 1 of 6:

- **Market Setup:** There will be 12 participants in this market. Each person is endowed with **$10.00** in cash and **6** shares of a durable asset that can be bought or sold.
- **Dividends and Interest:** All asset shares owned at the end of each trading period will pay a dividend (explained below). Each dollar in retained cash (from the endowment, from income, or obtained from asset share sales) will earn a fixed interest rate. The dividends may not be known in advance, but the interest rate will be known.
- **Periods:** The market consists of exactly **20 trading periods** or "rounds". All asset shares that you own (from endowment or purchases) at the end of the final trading period (after dividends are paid) will be redeemed for **$28.00** each.
- **Income:** You will receive an income of **$10.00** at the start of each round.
- **Earnings:** In addition to cash receipts from income, interest, and dividends, your cash balance will be altered as you buy and/or sell shares. Transactions will be executed for you based on "limit orders" to buy or sell that you may submit at the beginning of a trading period, as explained below.

Page 2 of 6:

- **Earnings on Investments:** Dividends will be paid on all shares owned after trading in a round is complete. Interest is paid at a rate of 5% on any outstanding loans obtained to purchase shares. Conversely, interest is received at a rate of 5% on any end-of-round cash balances.
- **Dividends:** Each share held at the end of a trading period will pay a dividend that depends on the outcome of a random process. The computer will select a random number from 1 to 10, with each integer in this interval being equally likely. This random "state" determines which column of the Dividend Table (below) is relevant. Thus each of the dividend amounts listed in the bottom row of the table are equally likely to be earned on each share that you own.

Random Determination of Dividends per Share

Random State	1	2	3	4	5	6	7	8	9	10

Share Dividend	\$1.20	\$1.20	\$1.20	\$1.20	\$1.20	\$1.60	\$1.60	\$1.60	\$1.60	\$1.60

- **Interest:** After share purchases and loan payments (if any) for a round have been made, each dollar of cash held (prior to the payment of dividends) will earn \$0.05 in interest, so the interest rate is **5%**.
- **Note:** Note that dividends are random, whereas interest payments are known in advance. Another difference is that interest is paid on **each dollar**, whereas dividends are paid on **each share**, the price of which is determined in the trading process, as explained next.

Page 3 of 6:

- **Limit Orders to Buy or Sell:** At the beginning of a trading period, those with cash who wish to purchase shares will indicate the number of shares desired and the maximum or "limit" price that they are willing to pay. Similarly, those who wish to sell shares will indicate the number of shares offered and the minimum "limit" price that they are willing to accept.
- **Buy and Sell Orders:** The same person may offer to buy and sell shares, but the **buy price** or "bid" must be below the **sell price** or "ask," so you cannot sell to yourself.
- **Loans and Purchase Constraints:** Purchase orders may be placed by anyone who has enough cash to cover at least **\$0.20** for each dollar spent (the rest may be borrowed). A bid will specify the amount that is to be paid in cash and the amount (if any) to be borrowed at an interest rate of **5%**, paid each round on the unpaid balance for that loan. You will not be allowed to borrow additional sums if the total interest payments would exceed your income each period.
- **Loans Payoffs and Forced Sales:** Outstanding loan amounts will be taken out of cash balances in the final round. In addition, the lender will require that you sell any shares for which the previous period's market price was lower than the original loan amount, these sales offers will be entered automatically to sell "at the best available market price."
- **Current Equity:** At the start of each round, you will see a list of the shares that you own, along with information about what price you paid, how much (if any) that you borrowed to purchase the share, and what is the current equity for that share, which is calculated as

the difference between the most recent sales price per share and the amount that you borrowed. You will be forced to sell shares with negative current equity.

Page 4 of 6:

- **Arranging Trades:** Trades are possible if some of the sell order prices (asks) are below some of the buy order prices (bids). The market maker is a computer program that will organize the buy and sell orders and use these to determine a market-clearing price. Ask prices that are too high (above the clearing price) and bid prices that are too low (below the clearing price) will be rejected.
- **Market Clearing:** All transactions will be at the **same** "market-clearing" price. This will be a price such that the number of shares that traders wish to buy is equal to the number of shares that traders wish to sell. In other words, the number of shares with limit sell prices (asks) at or below this clearing price is equal to the number of shares with limit buy prices (bids) at or above this clearing price. Thus, those who are willing to pay the most will buy from those who are willing to sell for the least, but all trades will be at the same price.
- **Loan Paybacks:** If you sell a share that was purchased with borrowed funds, you will have to pay back the loan to the extent that your cash at that point permits. Remaining loan amounts are paid back after the final round 20.

Page 5 of 6:

- **Example 1:** Suppose that a person begins a round with **$20** in cash and **3 shares**. If this person makes no purchases or sales , then the interest earnings would be **$0.05** on each dollar in cash, i.e. $20 x 0.05 = **$1.00** in interest. If the randomly determined dividend turned out to be **$1.20**, then the total dividend income would be 3 x $1.20 = **$3.60**. Similarly, if the randomly determined dividend turned out to be **$1.60**, then the total dividend income would be 3 x 1.60 = **$4.80**.
- **Example 1 (continued):** Suppose that a person started the round with 3 shares, $20 in cash, $10.00 in income, and outstanding loan amounts of $L, with an interest obligation of 0.05*$L. If that person were to purchase a share for $P in the trading period without borrowing any additional money, then this person would earn interest on:
  $20 + $10.00 **-** $P **-** 0.05*$L, and would earn a dividend on 4 shares, and these 4 shares

would make up the person's asset portfolio at the start of the next period. The amount of cash carried over to the next period would be:

$20 (initial cash)
+ $10.00 (income)
- $P (cost of share purchase)
- 0.05*$L (interest paid on loans)
+ 0.05*($20 + $10.00 - $P - 0.05*$L) (interest earned on remaining cash)
+ 4* (dividends on 4 shares).

- **Price Predictions:** Finally, at the start of each round, you will also be asked to predict what the market clearing price will be in future rounds. You will receive **$1.00** if your **current round** prediction is within +- **$1.00** of the subsequent share price, you will receive **$1.00** if your **1 round** prediction is within +- **$1.00** of the subsequent share price, and you will receive **$1.00** if your **2 round** prediction is within +- **$0.00** of the subsequent share price.

Instructions Summary:

- You will begin with an initial cash account of **$*.**** and with **** shares** of a stock with dividends determined by a randomly generated number as shown above, with each of the 10 columns in the dividend table being equally likely.
- In addition, you will receive a regular income of **$10.00** at the beginning of each round.
- Shares can be bought or sold by placing limit orders, which are executed at a single market-clearing price selected to equalize the number of shares demanded (with bids above the price) and the number of shared offered (with asks below the price).
- Purchase orders may be placed by anyone who has enough cash to cover at least **$0.20** for each dollar spent (the rest may be borrowed). A bid will specify the amount that is to be paid in cash and the amount to be borrowed at an interest rate of **5%**. You will not be permitted to incur loans for which the total interest paid is higher than your income of $10.00 per round.
- The lender will require that you sell any shares for which the previous period's market price was lower than the original loan amount.

- Each share owned at the end of a period (after trades have been executed) will pay a randomly determined dividend, and each dollar in retained cash (from the endowment or obtained from stock sales) will earn a fixed interest of **$0.05**.
- You will receive additional payments (**$1.00**, **$1.00**, or **$1.00**) for each prediction (current round, 1 round, and 2 round) that is within a specified range around the subsequent share price.
- Your cash balance will decrease if you purchase shares, pay interest on loans, or pay off outstanding loans, and it will increase as you earn interest on cash balances and receive dividends, and make accurate predictions. All outstanding loans must be paid off in the final round. The computer will keep track of your cash and share accounts, and your final earnings will equal your cash balance in the final period after any shares you have are redeemed.
- This experiment consists of exactly **20 trading periods**, and all shares owned at the end of the final trading period (from your endowment or obtained by purchase) will be redeemed for **$28.00** each.
- **Cash Conversion:** Each **$50.00** in earnings for the experiment will be converted into **$1.00** in cash payments to you at the end.

Chapter 2 Instructions (For Baseline Treatment, Low Cash Type)

Page 1 of 6

- **Market Setup:** There will be 8 participants in this market. Each person is endowed with an initial cash amount and one or more units of a durable asset that can be bought or sold. Moreover, you will have the opportunity to produce more asset units at the start of each period, with production costs to be explained subsequently.
- **Endowments:** All participants are assigned to be one of 2 "types", which will have different cash and asset unit endowments (details to follow). Your initial cash endowent is **$1,200.00** and your initial unit endowment is **9 units**.
- **Dividends and Interest:** All asset units owned at the end of each trading period will pay an earnings amount per unit, which is analogous to a dividend, as explained below. Each

dollar in retained cash will earn a fixed interest rate. Asset unit earnings will be the same in all periods and will be announced in advance. The interest rate will also be known.

- **Periods:** The market consists of exactly **20 trading periods** or "rounds". All asset units that you own (from endowment or purchases or production) at the end of the final trading period (after unit earnings or dividends are paid) will be redeemed for **$20.00** each.
- **Asset unit Purchase Requirements:** Anyone with asset units at the start of a round can offer to sell them, and anyone with sufficient cash can offer to buy units. In order to buy an asset unit, you must have the cash to make the full payment.
- **Earnings:** In addition to cash receipts from interest and asset unit earnings (dividends), your cash balance will be altered as you buy and/or sell units. Transactions will be executed for you based on "limit orders" to buy or sell that you may submit at the beginning of a trading period, as explained below.

Page 2 of 6

- **Earnings on Investments:** Asset unit earnings (dividends) will be paid on all units owned after trading in a round is complete. Interest is received for cash balances owned after trading has taken place in a round (but before asset unit earnings are received).
- **Dividends:** Each asset unit held at the end of a trading period will earn an amount **$2.40** for each asset unit that you own.
- **Interest:** Each dollar of cash held after trading for the round is complete, but prior to the payment of asset unit earnings (dividends), will earn an amount of interest that is **$0.02**.
- **Note:** Interest is paid on **each dollar** not used to purchase units, whereas asset unit earnings (dividends) are paid on **each asset unit**, the price of which is determined in the trading process, as explained next.

Page 3 of 6

- **Limit Orders to Buy or Sell:** At the beginning of a trading period, those with cash who wish to purchase asset units will indicate the number of units desired and the maximum or "limit" price that they are willing to pay per unit. Similarly, those who wish to sell units will indicate the number of units offered and the minimum "limit" price that they are willing to accept per unit sold.
- **Buy and Sell Orders:** The same person may offer to buy and sell units, but the **buy price** or "bid" must be below the **sell price** or "ask," so you cannot sell to yourself.

- **Production of New Units:** In addition to purchasing units in the market, you have the option of producing one or more units at the start of each period. The total costs incurred for each possible number of units produced are shown in the bottom row of the table that follows. Notice that costs increase at an increasing rate, e.g. the cost of producing 2 units, \$50.00, is more than twice as high as the cost of producing only 1 unit, which is only \$20.00.

Production Costs:

Number of Asset units Produced:	**1 unit**	**2 units**	**3 units**	**4 units**	**5 units**
Total Cost:	**\$20.00**	**\$50.00**	**\$100.00**	**\$170.00**	**\$260.00**

Page 4 of 6

- **Arranging Trades:** Trades are possible if some of the sell order prices (asks) are below some of the buy order prices (bids). The market maker is a computer program that will organize the buy and sell orders and use these to determine a market-clearing price. Ask prices that are too high (above the clearing price) and bid prices that are too low (below the clearing price) will be rejected.
- **Market Clearing:** All transactions will be at the **same** "market-clearing" price. This will be a price such that the number of asset units that traders wish to buy is equal to the number of asset units that traders wish to sell. In other words, the number of units with limit sell prices (asks) at or below this clearing price is equal to the number of units with limit buy prices (bids) at or above this clearing price. Thus, those who are willing to pay the most will buy from those who are willing to sell for the least, but all trades will be at the same price.

Page 5 of 6

- **Example 1:** Suppose that a person begins a round with **\$150** in cash and **3 asset units**. If this person makes no purchases or sales and does not produce any new asset units, then the interest earnings would be **\$0.02** on each dollar in cash, i.e. \$150 x 0.02 = **\$3.00** in interest. The dividend earnings per asset unit would be **\$2.40**. In this case, the person who is holding 3 asset units would receive a total dividend earnings of 3 x \$2.40 = **\$7.2**.
- **Example 1 (continued):** Suppose that a person who started with 3 units and \$150 in cash purchased **1 unit** for \$P in the trading period and also produced **2 additional units** for a

total cost of $C. Then this person would earn interest on $150 **-** $P **-** $C and would receive asset unit earnings (dividends) on 6 units (6 = 3 initial + 1 purchased + 2 produced). These 6 units would make up the person's asset portfolio at the end of the period. The amount of cash carried over to the next period would be the initial cash $150, minus the cost of the purchase, minus the cost of production, plus the interest in cash remaining, plus the asset unit earnings on the 6 units.

- **Asset Depreciation:** Asset units are like capital equipment that wears down and becomes less valuable over time in a process of "depreciation". The depreciation rate is **0.1**, so that K units at the end of the period are reduced to only K*(0.9) units at the start of the next period. In the example, the person who ends up with 6 units at the end of one period would lose 0.6 units due to depreciation, and therefore would begin with only 5.4 units at the start of the next period.
- **Price Predictions:** Finally, at the start of each round, you will also be asked to predict what the market clearing price will be in future rounds. There are 3 predictions to be made, for current round, 1 round, and 2 round horizons. In each case, you will receive **$1.00** if your prediction is within +- **$2.50** of the subsequent asset unit price, so your earnings for a round could be increased by as much as $3.00 if all three are accurate.

Page 6 of 6

- You will begin with an initial cash account of **$1,200.00** and with **9 units** of an asset with earnings payments (dividends) of **$2.40** in each period.
- Asset units can be bought or sold by placing limit orders, which are executed at a single market-clearing price selected to equalize the number of asset units demanded and the number of asset units offered.
- In addition to purchasing units in the market, you may produce units at the start of each period. The total cost incurred for each production quantity is shown in the table at the bottom of the page. Notice that costs increase at an increasing rate as you produce more units. It is possible to sell units produced in the same period that they are produced.
- Each asset unit owned at the end of a period (after trades have been executed) will pay an amount **$2.40**. Each dollar in retained cash will earn a fixed interest of **$0.02**.
- You will receive **$1.00** for each prediction (current round, 1 round, and 2 round) that is within +- **$2.50** of the subsequent asset price.

- Your cash balance will decrease if you purchase asset units, and it will increase as you earn interest and cash payments (dividends) on asset units, and make accurate predictions, and as you sell asset units or redeem them in the final period. The computer will keep track of your cash and asset shares accounts.
- This experiment consists of exactly **20 trading periods**, and all asset units owned at the end of the final trading period, from your endowment or obtained by purchase or production, will (after depreciation) be redeemed for **$20.00** each (lab dollars).
- **Cash Conversion:** Each **$100.00** in earnings for the experiment will be converted into **$1.00** in cash payments to you at the end.
- **Additional Task:** There will also be a short task in which you can check one or more "boxes" to pick up cash that is paid AFTER the end of the last round of trading. This final cash payment will **NOT** be converted down, it will be paid dollar for dollar at the end of the experiment, and will NOT affect your earnings from the market trading in any way. Instructions for this task will be provided when you come to it.

Production Costs:

Number of Asset units Produced:	**1 shares**	**2 units**	**3 units**	**4 units**	**5 units**
Total Cost:	**$20.00**	**$50.00**	**$100.00**	**$170.00**	**$260.00**

Chapter 3 Instructions

Asset Market

Page 1 of 6:

- **Market Setup:** There will be 9 participants in this market. Each person is endowed with **$70.00** in cash and **6** shares of a durable asset that can be bought or sold.
- **Dividends and Interest:** All asset shares owned at the end of each trading period will pay a dividend (explained below). Each dollar in retained cash (from the endowment, from income, or obtained from asset share sales) will earn a fixed interest rate. The dividends may not be known in advance, but the interest rate will be known.
- **Periods:** The market consists of exactly **15 trading periods** or "rounds", and each asset share that you own at the end of the final trading period (from your endowment or obtained

by purchase) will be redeemed for an unknown and randomly determined **redemption value**, which is between **$21.00** and **$35.00** per share.

- **Income:** You will receive an income of **$30.00** at the start of each round.
- **Traders:** There are 9 traders in this market. One or more of them ("insiders") will be informed of the exact redemption value, which was randomly determined, and others will not receive any additional information, as explained below.
- **Earnings:** In addition to cash receipts from income, interest, and dividends, your cash balance will be altered as you buy and/or sell shares. Transactions will be executed for you based on "limit orders" to buy or sell that you may submit at the beginning of a trading period, as explained below.

Page 2 of 6:

- **Earnings on Investments:** Dividends will be paid on all shares owned after trading in a round is complete. Interest is received on cash balances owned after trading has taken place in a round (but before dividends are paid).
- **Dividends:** Each share held at the end of a trading period will pay a dividend that depends on the outcome of a random process. The computer will select a random number from 1 to 10, with each integer in this interval being equally likely. This random "state" determines which column of the Dividend Table (below) is relevant. Thus each of the dividend amounts listed in the bottom row of the table are equally likely to be earned on each share that you own.

Random Determination of Dividends per Share

Random State:	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Share Dividend:	**$1.20**	**$1.20**	**$1.20**	**$1.20**	**$1.20**	**$1.60**	**$1.60**	**$1.60**	**$1.60**	**$1.60**

- **Interest:** Each dollar of cash held after trading for the round is complete (but prior to the payment of dividends) will earn an amount of interest that is **$0.05**.
- **Note:** Note that dividends are random, whereas interest payments are known in advance. Another difference is that interest is paid on **each dollar** not used to purchase shares, whereas dividends are paid on **each share**, the price of which is determined in the trading process, as explained next.

Page 3 of 6:

- **Limit Orders to Buy or Sell:** At the beginning of a trading period, those with cash who wish to purchase shares will indicate the number of shares desired and the maximum or "limit" price that they are willing to pay. Similarly, those who wish to sell shares will indicate the number of shares offered and the minimum "limit" price that they are willing to accept.
- **Buy and Sell Orders:** The same person may offer to buy and sell shares, but the **buy price** or "bid" must be below the **sell price** or "ask," so you cannot sell to yourself.

Page 4 of 6:

- **Arranging Trades:** Trades are possible if some of the sell order prices (asks) are below some of the buy order prices (bids). The market maker is a computer program that will organize the buy and sell orders and use these to determine a market-clearing price. Ask prices that are too high (above the clearing price) and bid prices that are too low (below the clearing price) will be rejected.
- **Market Clearing:** All transactions will be at the **same** "market-clearing" price. This will be a price such that the number of shares that traders wish to buy is equal to the number of shares that traders wish to sell. In other words, the number of shares with limit sell prices (asks) at or below this clearing price is equal to the number of shares with limit buy prices (bids) at or above this clearing price. Thus, those who are willing to pay the most will buy from those who are willing to sell for the least, but all trades will be at the same price.

Page 5 of 6:

Random Determination of Dividends per Share

Random State:	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Share Dividend:	**\$1.20**	**\$1.20**	**\$1.20**	**\$1.20**	**\$1.20**	**\$1.60**	**\$1.60**	**\$1.60**	**\$1.60**	**\$1.60**

- **Example 1:** Suppose that a person begins a round with **\$20** in cash and **3 shares**. If this person makes no purchases or sales , then the interest earnings would be **\$0.05** on each dollar in cash, i.e. \$20 x 0.05 = **\$1.00** in interest. If the randomly determined dividend turned out to be **\$1.20**, then the total dividend income would be 3 x \$1.20 = **\$3.60**. Similarly, if the randomly determined dividend turned out to be **\$1.60**, then the total dividend income would be 3 x 1.60 = **\$4.80**.

- **Example 1 (continued):** If the person who started with 3 shares and $20 were to purchase a share for $P in the trading period, then this person would earn interest on $20 **-** $P and would earn a dividend on 4 shares, and these 4 shares would make up the person's asset portfolio at the start of the next period. The amount of cash carried over to the next period would be the initial cash $20, minus the cost of the purchase plus the interest on cash remaining, plus the dividends on the 4 shares.
- **Price Predictions:** Finally, at the start of each round, you will also be asked to predict what the market clearing price will be in future rounds. There are 3 predictions to be made, for current round, 1 round, and 2 round horizons. In each case, you will receive **$1.00** if your prediction is within +- **$2.50** of the subsequent share price, so your earnings for a round could be increased by as much as $3.00 if all three are accurate.

Page 6 of 6

- **Final Redemption Value** This market will continue for **15 periods of trade** or "rounds". At the beginning of the first round, the computer will select a **randomly determined** redemption value that will be the same for all shares owned by all traders. However, you will not find out this redemption value until after the end of the final round, i.e. **round 15**. This common final redemption value may be any penny amount between and including **$21.00** and **$35.00**, with each amount in this interval being equally likely to be chosen. Imagine a roulette wheel with the stops labeled as $21.00, $21.01, ... $34.99, $35.00. Then a hard spin of the wheel would make each of these amounts equally likely. All shares have the same common redemption value, so it is as if we spin the wheel once for the market as a whole.
- **Insider Information:** There are **9 traders** in the market, and of these, only **6** will be told the exact value of the final redemption value. The others will not receive any additional information about the randomly determined final redemption value. You **(will, will not)** be an insider and you **(will, will not)** be told the final redemption value.

Instructions Summary

Random Determination of Dividends per Share

Random State:	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Share Dividend:	**$1.20**	**$1.20**	**$1.20**	**$1.20**	**$1.20**	**$1.60**	**$1.60**	**$1.60**	**$1.60**	**$1.60**

- You will begin with an initial cash account of **$*.**** and with **** shares** of a stock with dividends determined by a randomly generated number as shown above, with each of the 10 columns in the dividend table being equally likely.
- In addition, you will receive a regular income of **$30.00** at the beginning of each round.
- Shares can be bought or sold by placing limit orders, which are executed at a single market-clearing price selected to equalize the number of shares demanded (with bids above the price) and the number of shared offered (with asks below the price).
- After trading is complete in the final round 15, all shares owned at that point will be redeemed for a randomly determined amount. This final redemption value is on the interval from **$21.00** and **$35.00**, with any amount in this interval being equally likely.
- You **(will, will not)** be told the exact value of the final redemption value. There will be 6 traders who will each be told the true redemption value. The total number of traders in the market is 9, and the number of insiders who receive exact redemption value information is 6.
- Each share owned at the end of a period (after trades have been executed) will pay a randomly determined dividend, and each dollar in retained cash (from the endowment or obtained from stock sales) will earn a fixed interest of **$0.05**.
- You will receive **$1.00** for each prediction (current round, 1 round, and 2 round) that is within +- **$2.50** of the subsequent share price.
- Your cash balance will decrease if you purchase shares, and it will increase as you earn interest and dividends, and make accurate predictions, and as you sell shares or redeem them in the final period. The computer will keep track of your cash and share accounts. and your final earnings will equal your cash balance in the final period after any shares you have are redeemed. and after final dividend and interest payments have been made.
- This experiment consists of exactly **15 trading periods**, and all shares owned at the end of the final trading period (from your endowment or obtained by purchase) will be redeemed for a randomly determined **final redemption value**.

- **Cash Conversion:** Each **$100.00** in earnings for the experiment will be converted into **$1.00** in cash payments to you at the end.
- **Final Task:** There will also be a short task in which you can check one or more "boxes" to pick up cash that is paid AFTER the end of the last round of trading. This final cash payment will **NOT** be converted down, it will be paid dollar for dollar at the end of the experiment, and will NOT affect your earnings from the market trading in any way. Instructions for this task will be provided when you come to it.

Finished with Instructions

Ink Bomb Task Instructions (Chapters 2 and 3)

Each of the 12 boxes shown below contains $1.

One of the boxes contains a hidden ink bomb.

The location of the ink bomb has been pre-determined randomly in a manner that is equivalent to throwing a 12-sided die, with each box being equally likely to be selected. This random location has been done independently for each person.

You may now choose the boxes from which to extract $1, but if you mark the box in which the ink bomb is located, then your earnings will be $0 for this task.

If you do not encounter the ink bomb, your earnings from the task will be a dollar for each box checked. You may mark as many or as few boxes as you wish.

While in the process of marking boxes, you will not find out whether or not you have encountered the ink bomb. If you mark NO boxes at all, you will earn $0. If you mark ALL 12 boxes, you will encounter the ink bomb and earn $0 for sure.

Earnings from this task will be withheld and announced later after the final period. Box task earnings will be paid dollar for dollar and will NOT be scaled down.

Please indicate which boxes you wish to mark.

$1	**$1**	**$1**	**$1**	**$1**	**$1**	**$1**	**$1**	**$1**	**$1**	**$1**	**$1**
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Cognitive Score Questionnaire (Chapter 3)

- This questionnaire consists of 4 brief questions, and it will take less than 10 minutes to complete.
- Please enter your answers in the box provided; careful answers will help us in our research.
- Your responses are confidential and your name will not be used.

1. True or False: On the street where you grew up, most of the neighbors knew each other.
2. A hockey stick and puck cost 110 Canadian dollars in total. The stick costs 100 more than the puck. How much does the puck cost? _____ Canadian dollars (no symbols or decimals please)
3. In a lake, there is a patch of lilly pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? _____ days (no symbols or decimals please)
4. A person drives 60 kilometers at 60 kilometers per hour, and then turns abound and drives back to the starting point at 20 kilometers per hour. What was the average speed? (Answer choices available on drop down menu: 20 KM per hour, 30 KM per hour, 40 KM per hour, 50 KM per hour, 60 KM per hour)

Note: Questions 2-4 were used to determine a trader's cognitive score, which was the number of questions answered correctly. The first question was included to make the questionnaire seem less like a test. Traders were presented the questions as a questionnaire with no additional context given (the bullets at the top are all the information on the questionnaire provided to traders).

References

Abel, A.B., 2018. The effects of q and cash flow on investment in the presence of measurement error. *Journal of Financial Economics.* 128:363-377.

Ackert, L. F., Charupat, N., Deaves, R., and Kluger, B.D., 2009. Probability judgement error and speculation in laboratory asset markets. *Journal of Financial and Quantitative Analysis* 44:719–744.

Ball, S.B., and Holt C.A., 1998. Classroom games: Bubbles in an asset market. *Journal of Economic Perspectives.* 12:207-218.

Bernanke, B., Gertler, M., and Gilchrist, S., 1999. The financial accelerator in a quantitative business cycle framework. In Taylor, J. B. and Woodford, M., editors, *Handbook of Macroeconomics 1c,* 1341-1393. Elsevier.

Blanchar, O.J., Lopez-de-Silanes, F., and Shleifer, A. 1994. What do firms do with cash windfalls? *Journal of Financial Economics.* 36:337-360.

Bosch-Rosa, C., Meissner, T., and Bosch-Domènech, A., 2018. Cognitive bubbles. *Experimental Economics.* 21:132-153.

Bostian, A.J., Goeree, J.K., and Holt, C.A., 2005. Price bubbles in an asset market experiment with a flat fundamental value. Discussion Paper, University of Virginia.

Bostian, A.J. and Holt, C.A., 2009. Bubbles in an asset market. *Journal of Economic Education.* 40:27-37.

Burton, Edwin T. and Shah, Sunit N. (2013). *Behavioral finance: Understanding the social, cognitive, and economic debates.* John Wiley and Sons, Inc.

Caginalp, G., Porter, D., Smith, V.L., 2001. Financial bubbles: Excess cash, momentum, and incomplete information. *Journal of Psychology and Financial Markets*. 2:80-99.

Campbell, John Y. (1991). "A variance decomposition for stock returns." *Economic Journal.* 101:157-179

Cao, D., Lorenzoni, G., Walentin, K. 2019. Financial frictions, investment, and Tobin's q. *Journal of Monetary Economics*. 103:105-122.

Chalak, K. and Kim, D. 2020. Measurement error in multiple equations: Tobin's q and corporate investment, saving, and debt. *Journal of Econometrics.* 214:413-432.

Chang, Tom Y., Solomon, David H., and Westerfield, Mark M. (2016) "Looking for someone to blame: Delegation, cognitive dissonance, and the disposition effect," *Journal of Finance.* 71(1):267-302.

Cheung, S. L., and Palan, S., 2012. Two heads are less bubbly than one: Team decision-making in an experimental asset market. *Experimental Economics.* 15:373–397.

Cipriani, M., Fostel, A., and Houser, D., 2018. Collateral constraints and the law of one price: An experiment. *The Journal of Finance.* 73:2757-2786.

Coppock, L.A., Harper, D.Q., and Holt, C.A., 2021. Capital constraints and asset bubbles: An experimental study. *Journal of Economic Behavior and Organization.* 183: 75-88.

Corgnet, Brice, Deck, Cary, DeSantis, Mark, Hampton, Kyle, and Kimbrough, Erick O. (2021). "When do security markets aggregate dispersed information?" *Working Paper.*

Corgnet, B., Kujal, P., and Porter, D., 2010. Uninformative announcements and asset trading behavior. *Journal of Economic Behavior and Organization.* 16:224-266.

Crosetto, Paolo, and Filippin, Antonio (2013). "The "bomb" risk elicitation task." *Journal of Risk and Uncertainty*. 47:31-65.

Cyert, R.M., DeGroot, M.H., and Holt, C.A., 1979. Capital allocation within a firm. *Systems Research and Behavioral Science.* 24:287-265.

Deck, C., Servάtka, M., and Tucker, S., 2019. Designing call auction institutions to eliminate price bubbles: Is English Dutch the best? University of Alabama, forthcoming in *American Economic Review Insights*.

Dickinson, D. L., Chaudhuri, A., Greenaway-McGrevy, R., 2017. Trading while sleepy? Circadian Mismatch and excess volatility in a global experimental asset market. *IZA Discussion Paper 10984*.

Dufwenberg, M., Lindqvist, T., and Moore, E., 2005. Bubbles and experience: An experiment. *American Economic Review.* 95:1731-1737.

Eckel, C. C. and Füllbrunn, S.C., 2015. Thar SHE blows? Gender competition, and bubbles in experimental asset markets. *American Economic Review.* 105:905-920.

Eckel, C. C. and Füllbrunn, S.C., 2017. Hidden vs. known gender effects in experimental asset markets. *Economics Letters.* 156:7-9.

Eckel, C. C. and Grossman, P.J., 2002. Sex differences and statistical stereotyping in attitudes towards financial risk. *Evolutionary Human Behavior.* 23:281-295.

Eckel, C. C. and Grossman, P.J., 2008. Forcasting risk attitudes: an experimental study using actual and forecast gamble choices. *Journal of Economics Behavior and Organization*. 68: 1-17.

Erickson, T. and Whited, T.M., 2000. Measurement error and the relationship between investment and *q*. *Journal of Political Economy.* 108(5):1027-1057.

Erickson, T. and Whited, T.M., 2012. Treating measurement error in Tobin's q. *The Review of Financial Studies*. 25(4):1286-1329.

Fazzari, S.M., Hubbard, R.G., Petersen, B.C., Blinder, A.S., and Poterba, J.M., 1988. Financing constraints and corporate investment. *Brookings Papers on Economic Activity.* 1988(1):141-206.

Fenig, G., Mileva, M., and Petersen, L., 2018. Deflating asset price bubbles with leverage constraints and monetary policy. *Journal of Economic Behavior and Organization.* 155:1-27.

Fellner, G., and Maciejovsky, B., 2007. Risk attitude and market behavior: Evidence from experimental asset markets. *Journal of Economic Psychology*. 28(3):338-350.

Forsythe, Robert, Palfrey, Thomas R., and Plott, Charles R. (1982). "Asset valuation in an experimental market." *Econometrica.* 50(3):537-567.

Fostel, A. and Geanakoplos, J., 2008. Leverage cycles and the anxious economy. *American Economic Review*. 98:1211-1244.

Fostel, A. and Geanakoplos, J., 2014. Endogenous collateral constraints and the leverage cycle. *Annual Review of Economics.* 6:771-799.

Frydman, Cary and Wang, Baolian. (2020) "The impact of salience on investor behavior: Evidence from a natural experiment," *Journal of Finance.* 75(1):229-276.

Füllbrunn, S. and Neugebauer, T., 2013. Deflating bubbles in experimental asset markets: Comparative statics of margin regulations. *Financial Management.* 38(3):603-630.

Geanakoplos, J., 2003. Liquidity, default, and crashes, Endogenous contracts in general equilibrium. In: Dewabtripont, M., Hansen, L.P., and Turnovsky, S.J. (Eds.). Advances in Economics and Econometrics: Theory and Applications, Eighth World Conference, Volume II, Econometric Society Monographs. 170-205

Geanakoplos, J. and Zame, W., 2014. Collateral equilibrium, I: a basic framework. *Economic Theory*. 56:443-492

Giusti, G., Jiang, J.H., and Xu, Y., 2016 Interest on cash, fundamental value process and bubble formation. *Journal of Behavioral and Experimental Finance.* 11:44-50.

Gjerstad, S. D. and Smith, V.L., 2014. *Rethinking Housing Bubbles*, Princeton NJ: Princeton University Press.

Gortner, P. and Massenot, B., 2020. Leverage and Bubbles: Experimental Evidence. *SAFE Working Paper Series,* (239).

Halim, Edward and Riyanto, Yohanes E. (2020). "Asset markets with insider trading disclosure rule and reselling constraint: an experimental analysis." *Journal of Economic Dynamics and Control.* 110:1-23.

Haruvy, E., and Noussair, C.N., 2006. The effect of short selling on bubbles and crashes in experimental spot asset markets. *Journal of Finance.* 61:1119-1157.

Hayashi, F., 1982. Tobin's marginal q and average q: A neoclassical interpretation. *Econometrica*. 50(1):213-224.

Holt, C. A., 2019. Markets, Games and Strategic Behavior: A First Course in Experimental Economics. Princeton NJ: Princeton University Press.

Holt, C. A., Porzio, M., and Song, M.Y., 2017. Price bubbles, gender, and expectations in experimental asset markets. *European Economic Review.* 100:72-94.

Holt, C. A. and Sullivan, S.P., 2019. Permutation tests for experimental data. Discussion Paper presented at the University of Virginia Quantitative Collaborative.

Hommes, C. H., Sonnemans, J., Tuinstra, J., and van de Velden, H., 2005. Coordination of expectations in asset pricing experiments. *Review of Financial Studies.* 18:955–980.

Hubbard, R.G., 1998. Capital-market imperfections and investment. *Journal of Economic Literature.* 36(1):93-225.

Hussam, R., Porter, D., and Smith, V.L., 2008. Thar she blows: Can bubbles be rekindled with experienced subjects? *American Economic Review.* 98:924-937.

Isaac, Mark (2022), review of the reprint of "Rational Expectations and the Aggregation of Diverse Information in Laboratory Securities Markets" by Charles R. Plott and Shyam Sunder. in Gary Charness and Mark A. Pingle, eds., *The Art of Experimental Economics: Top 20 Papers Reviewed*. Routledge.

Jonckheere, A.R. (1954) "A distribution free k-sample test against ordered alternatives." *Biometricka.* 41(1/2):133-145.

Jordà, Ò., Schularick, M., and Taylor, A.M., 2013. When credit bites back: Leverage, business cycles, and crises. *Journal of Money, Credit, and Banking*. 45:3–28.

Jordà, Ò., Schularick, M., and Taylor, A.M., 2015. Leveraged bubbles. *Journal of Monetary Economics*. 76(Supplement):S1-S20.

Kessler, J.B. and Vesterlund, L., 2015. The external validity of laboratory experiments: The misleading emphasis on quantitative effects. In G.R. Fréchette and A. Schotter (Eds.), *Handbook of Experimental Economic Methodology* pp. 391-406

Keynes, J. M., 1965 (originally 1936). *The General Theory of Employment, Interest, and Money.* New York: Harcourt, Brace & World.

King, R., Smith, V., and Van Boening, M., 1993. The robustness of bubbles and crashes in experimental stock markets. In: Prigogine, I., Pay, R., and Chen, P., (Eds*.). Nonlinear Dynamics and Evolutionary Economics*, Oxford: Oxford University Press.

Kirchler, M., Huber, J., and Stöckl, T., 2012. Thar she bursts: Reducing confusion reduces bubbles. *American Economic Review.* 102:865-883.

Kiyotaki, N. and Moore, J., 1997. Credit cycles. *Journal of Political Economy.* 105:211-248.

Kopányi-Peuker, A. and Weber, M., 2021. Experience does not eliminate bubbles: Experimental evidence. *The Review of Financial Studies.* 34(9):4450-4485.

Lei, V. and Noussair, C., 2002. An experimental test of an optimal growth model. *American Economic Review.* 92(3):549-570.

Lucas, R.E. and Prescott, E.C., 1971. Investment under uncertainty. *Econometrica.* 39(5):659-681.

Marquardt, Philipp, Noussair, Charles N., and Weber, Martin (2019). "Rational expectations in an experimental asset market with shocks to market trends." *European Economic Review.* 114:116-140.

Meissner, T., 2016. Intertemporal consumption and debt aversion: an experimental study. *Experimental Economics.* 19:281-298.

Moyen, N., 2004. Investment-cash low sensitivities: Constrained versus unconstrained firms. *The Journal of Finance.* 59(5):2061-2092.

Nadler, A., Jiao, P., Alexander, V., Zak, P.J., and Johnson, C.J., 2015. Testosterone and trading: A biological driver of asset mispricing. SSRN.

Noussair, C. N., Robin, S., and Ruffieux, B., 2001. Price bubbles in laboratory asset markets with constant fundamental values, *Experimental Economics.* 4:87-105.

Noussair, C.N. and Tucker, S.J., 2005. Futures markets and bubble formation in experimental asset markets. *Pacific Economic Journal.* 11:167-184.

Noussair, C.N. and Tucker, S.J., 2016. Cash inflows and bubbles in asset markets with constant fundamental values. *Economic Inquiry.* 54; 1596-1606.

Nuzzo, S. and Morone, A., 2017. Asset markets in the lab: A literature review. *Journal of Behavioral and Experimental Finance.* 13:42-50.

Oechssler, J., 2010. Searching beyond the lamppost: Let's focus on economically relevant questions. *Journal of Economic Behavior and Organization.* 73:65-67.

Palan, S., 2013. A review of bubbles and crashes in experimental asset markets. *Journal of Economic Surveys.* 27:570–88.

Plott, Charles R., and Sunder, Shyam (1982). "Efficiency of experimental security markets with insider information: an application of rational-expectations models." *Journal of Political Economy*. 90(4): 663-698.

Plott, Charles R., and Sunder, Shyman (1988). "Rational expectations and the aggregation of diverse information in laboratory security markets." *Econometrica*. 56(5):1085-1118.

Porter, D. and Smith, V.L., 1995. Futures contracting and dividend uncertainty in experimental asset markets. *Journal of Business.* 68:509-541.

Powell, O., 2016. Numeraire independence and he measurement of mispricing in experimental asset markets. *Journal of Behavioral and Experimental Finance.* 9:56-62.

Rajan, R. and Ramcharan, R., 2015. The anatomy of a credit crisis: The boom and bust in farm land prices in the United States in the 1920s. *American Economic Review.* 105:1439-1477.

Reinhart, C.M. and Rogoff, K.S., 2009. *This time is different: Eight centuries of financial folly*. Princeton NJ: Princeton University Press.

Richardson, S., 2006. Over-investment of free cash flow. *Review of Accounting Studies*. 11:159-189.

Schularick, M., and Taylor, A.M., 2012. Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870–2008. *American Economic Review.* 102:1029–61.

Sengul, M., Costa, A.A, and Gimeno, J., 2019. The allocation of capital within firms. *Academy of Management Annals.* 13(1):43-83.

Shiller, Robert J. (1981a). "Do stock prices move too much to be justified by subsequent changes in dividends." *American Economic Review.* 71(3): 421-436.

Shiller, Robert J. (1981b). “The uses of volatility measures in assessing market efficiency.” *Journal of Finance*. 36:291-304.

Shiller, Robert J. (2003). “From efficient markets theory to behavioral finance.” *Journal of Economic Perspectives.* 17(1): 83-104.

Shiller, Robert J. (2014). “Speculative asset prices.” *American Economic Review.* 104(6): 1486-1517.

Smith, Vernon L. (1962). “An experimental study of competitive market behavior.” *Journal of Political Economy.* 70(2):111-137.

Smith, V. L., Suchanek, G.L., and Williams, A.W., 1988. Bubbles, crashes, and endogenous expectations in experimental spot asset markets. *Econometrica.* 56:1119–1151.

Stöckl, Thomas, Huber, Jürgen, and Kirchler, Michael (2010). “Bubble measures in experimental asset markets.” *Experimental Economics.* 13:284-298.

Stöckl, Thomas, Huber, Jürgen, and Kirchler, Michael (2015). “Multi-period experimental asset markets with distinct fundamental value regimes.” *Experimental Economics.* 18:314-334.

Sutter, Matthias, Huber, Jürgen, and Kirchler, Michael (2012). “Bubbles and information: an experiment.” *Management Science.* 58(2):384-393.

Tobin, J., 1969. A general equilibrium approach to monetary theory. *Journal of Money, Credit, and Banking*. 1(1):15-29.

Tobin, J., 1989. Review of *Stabilizing an Unstable Economy*. By Minsky, H.P.. Journal of Economic Literature 27, 105-108.

Van Boening, M., Smith, V.L., and Wellford, C.P., 2000. Dividend timing and behavior in laboratory asset markets. *Economic Theory.* 16:567-583.

Van Boening, M., Williams, A.W., and LaMaster, S., 1993. Price bubbles and crashes in experimental call markets. *Economics Letters.* 41:179-185.

Wang, J., Houser, D.E. and Xu, H., 2017. Do females always generate small bubbles? Experimental evidence from U.S. and China. ISES, George Mason University.

Weitzel, U., Huber, C., Huber, J., Kirchler, M., Lindner, F., and Rose, J., 2020. Bubbles and financial professionals. *The Revies of Financial Studies*. 33(6): 2659-2696

Williams, A.W., 1987. The formation of price forecasts in experimental markets. *Journal of Money, Credit, and Banking*. 19:1-18.