

2-17-2018

Experimental Evidence on the Cyclicalities of Investment

Cortney S. Rodet
Ohio University

Andrew Smyth
Chapman University, smyth@chapman.edu

Follow this and additional works at: https://digitalcommons.chapman.edu/esi_working_papers



Part of the [Econometrics Commons](#), [Economic Theory Commons](#), and the [Other Economics Commons](#)

Recommended Citation

Rodet, C. S., & Smyth, A. (2018). Experimental evidence on the cyclicalities of investment. ESI Working Paper 18-02. Retrieved from https://digitalcommons.chapman.edu/esi_working_papers/237

This Article is brought to you for free and open access by the Economic Science Institute at Chapman University Digital Commons. It has been accepted for inclusion in ESI Working Papers by an authorized administrator of Chapman University Digital Commons. For more information, please contact laughtin@chapman.edu.

Experimental Evidence on the Cyclicalities of Investment

Comments

ESI Working Paper 18-02

Experimental Evidence on the Cyclicity of Investment^{*}

Cortney S. Rodet[†] Andrew Smyth^{††}

February 17, 2018

Abstract

We report laboratory experiments investigating the cyclicity of investment. In our setting, optimal investment is counter-cyclical because investment costs fall following market downturns. However, we do not observe counter-cyclical investment. Instead, heuristic investment models where firms invest a fixed percentage of their liquidity, or a fixed percentage of anticipated market demand, better fit our data on average than does optimal investment. We also report a control treatment without cost changes and a treatment with asymmetric investment liquidity. Both of these extensions support our main result.

Keywords: investment, business cycles, heuristics, experimental economics

JEL: C90, D22, D25, E22, E32, L16

^{*} For helpful comments we thank Philip Brookins, Stephen Cole, Joy Buchanan, seminar participants at Ohio University, and conference participants at the Economic Science Association and the Southern Economic Association annual meetings. We also thank Megan Luetje for help conducting the experiments, and the Economic Science Institute for funding and for the use of their laboratory. Naturally, any errors are our own.

[†] Department of Economics, Ohio University, Athens, OH 45701, *email: rodet@ohio.edu*

^{††} Department of Economics, Marquette University, Milwaukee, WI 53201, *email: andrew.smyth@marquette.edu*

1 Introduction

For many economists, recessions are the worst of times, they are the best of times. To be sure, they are not desired, yet they are often viewed with a Schumpeterian silver lining as times of cleansing and reorganization. On this outlook, low investment costs and low investment opportunity costs during downturns spur firms to invest counter-cyclically.¹ The business press also lauds counter-cyclical investment, emphasizing the “risk of not investing while the economy is weak” (Ghemawat, 1993) and touting recessions as “one of the finest opportunities an innovation-driven business can have” (Vossoughi, 2012).

In this paper, we report results from laboratory experiments that examine the cyclicity of investment over the business cycle. In our motivating duopoly model, recessions make investing in future profit cheaper so that optimal investment is counter-cyclical, and in our experimental design, investment cost changes are timed to permit clean identification of counter-cyclical investment—if it occurs.

Our research was motivated by the fact that aggregate research and development (R&D) investment is pro-cyclical.² This well-documented result (Barlevy, 2007) belies the Schumpeterian story. Possible explanations include the presence of binding liquidity constraints (Aghion, et al., 2012), of high R&D adjustment costs (Brown and Peterson, 2011), and of the lack of full appropriability of much R&D (Barlevy, 2007). Yet precisely identifying the effect of falling investment costs on investment is challenging since firms face declining market revenues at the same time that their investment costs fall.³

¹Examples of low investment costs include low input good costs and low wages. Investment opportunity costs are low if new investment is less disruptive to current production during recessions than during expansions.

²Zajac and Bazerman (1991) provide additional motivation from the management literature: “[A] competitive decision-making perspective could be used to discuss other current topics in industry and competitor analysis, such as . . . the choice of optimal research and development or advertising levels (e.g., to what extent are levels chosen with competitors in mind?).”

³The former suggests *less* investment, the latter *more*. Identification is even trickier with inter-industry variation in how liquidity hampers R&D investment (Ouyang, 2011).

We examine the cyclical investment in a precise way. By design, our investment cost change is not subtle. We make investment *half* as costly following a recessionary period as after an expansionary period. Still, our participants' response to the cost change is roughly one tenth of that predicted by our model. On average, our participants over-invest during market expansions when investment costs are relatively high and under-invest following recessions when investment costs are relatively low.

We find it striking that we do not observe counter-cyclical investment in our stylized experiment with stark investment cost changes. Our data suggest that many participants exhibit bounded rationality and what Porter (1980) terms a *blind spot*, as they “will either not see the significance of events (such as a strategic move) at all, will perceive them incorrectly, or will perceive them only very slowly.” On average, the rules-of-thumb *invest a fixed percentage of liquidity* and *invest a fixed percentage of the market forecast* fit our data better than the optimal investment path does. These heuristics also well-fit data from a treatment with asymmetric liquidity constraints.

Our paper contributes to several literatures. Our experimental markets are extended and contextualized proportional-prize contests, so it extends the growing experimental contest literature. It also expands behavioral industrial organization research with its results on heuristics in investment competition and is, to the best of our knowledge, the first experimental paper to examine competition in markets with frequent cost changes. Finally, to the extent that our results are externally valid, they contribute to the literature on the cyclical investment.⁴

Our paper is organized as follows. In Section 2, we describe our motivating model. Section 3 conveys our experimental design and procedures and the optimal investment path for our experiments. We report our experimental results in Section 4. Finally, Section 5

⁴We mostly frame our paper in microeconomic terms, but it is related to the burgeoning experimental macroeconomics literature reviewed by Duffy (2016).

concludes.

2 Motivating Model

We present a model that guides our experimental design and which we reference when reporting our experimental results. Our motivating model is stylized, but it incorporates several important features of investment: (1) Investment *today* affects profit *tomorrow*, (2) Market demand and investment costs are inversely related, and (3) Investment liquidity is constrained.

There are two firms in our model, indexed by $i \in \{1, 2\}$, that compete in the same market. Time is finite and composed of periods represented by t , where T is the model's final period. Firms earn revenue $R_t^i = s_t^i M_t$, where s_t^i denotes Firm i 's market share in period t , and M_t is the value of the market in that period. Firm i 's market share is determined according to:

$$s_t^i = \frac{x_{t-1}^i}{x_{t-1}^i + x_{t-1}^{-i}} \quad (1)$$

where x_{t-1}^i is Firm i 's investment in period $t-1$. Thus, each firm's market share is their investment last period divided by the total market investment last period.

Note that revenue is increasing in market share, and thus is increasing in investment. However, firms bear costs associated with their investment. Firm i 's investment cost in period t is $C_t^i = \alpha_t^i (\Delta M_{t-1}) x_t^i$, where $\Delta M_{t-1} = M_{t-1} - M_{t-2}$. To capture counter-cyclical investment costs, we assume that:

$$\alpha_t^i = \begin{cases} \alpha_L & \text{if } \Delta M_{t-1} < 0 \\ \alpha_H & \text{if } \Delta M_{t-1} \geq 0 \end{cases} \quad (2)$$

where $\alpha_L < \alpha_H$. In other words, when $\Delta M_{t-1} < 0$, investing gets cheaper.

Figure 1: Timeline for Investment Cost Change

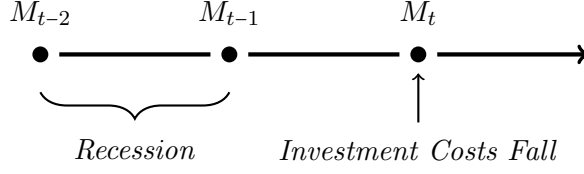


Figure 1 illustrates the timing of the cost change. At the beginning of each period, Firm i observes the value of the economy, M_t , and their investment cost coefficient, $\alpha_t^i(\Delta M_{t-1})$. Both firms then simultaneously make investments $x_t^i \leq \phi_i R_t^i$, where the coefficient ϕ_i captures Firm i 's liquidity. In other words, firms must choose an investment that is less than or equal to their current liquidity-adjusted revenue.

We can write Firm i 's profit maximization problem recursively as:

$$\begin{aligned} \max_{\{x_t^i\}} \quad & \pi_t^i = -\alpha_t^i(\Delta M_{t-1})x_t^i + s_{t+1}^i(x_t^i)\mathbf{E}_t^i[M_{t+1}] + \delta V_{t+1}^i \\ \text{subject to} \quad & x_t^i \leq \phi_i R_t^i \end{aligned} \quad (3)$$

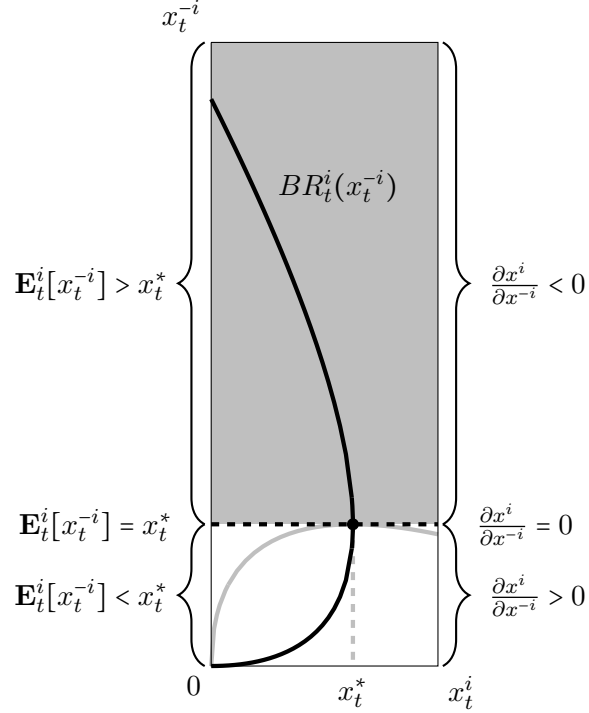
where V_{t+1}^i is the continuation value and δ is the discount factor. Note that investment today affects revenue tomorrow, whereas the cost of the investing is borne today.

The value of the market is assumed to be autoregressive of order 1, $AR(1)$. Its value in period t is $M_t = \mu + \rho M_{t-1} + \epsilon$, where μ and ρ are constants and $\epsilon \sim N(0, \sigma^2)$. Note that because the noise term is mean zero, $\mathbf{E}_t^i[M_{t+1}] = \mu + \rho M_t$.

Differentiating (3) with respect to x_t^i and rearranging yields the following best-response function:

$$BR_t^i(x_t^{-i}) = \sqrt{x_t^{-i} \left[\frac{\mathbf{E}_t^i[M_{t+1}]}{\alpha_t^i(\Delta M_{t-1})} \right]} - x_t^{-i} \quad (4)$$

Figure 2: Best Response Curve



In Appendix I we show that the optimal investment path in our model is defined by:⁵

$$x_t^* = \frac{\mathbf{E}_t^i[M_{t+1}]}{4\alpha_t^i(\Delta M_{t-1})} \quad (5)$$

A representative best-response curve is plotted in Figure 2. There are two distinct regions in the plot that can be thought of in terms of Firm i 's expectations about Firm $-i$'s investment. When a firm anticipates their rival investing above the optimal investment, x_t^* , they should respond in the *opposite* direction. However, when a firm anticipates their rival investing below x_t^* , they should respond in the *same* direction.

⁵We can precisely define “cyclical investment” and “counter-cyclical investment” in our experiment. When $\alpha = 1.0$, optimal investment is positively related to expected market demand (“cyclical”). On the other hand, equation (5) shows that when $\alpha < 1.0$, optimal investment can be negatively related to expected market demand (“counter-cyclical”).

Our model can be viewed as a proportional-prize contest (Long and Vousden, 1987; Cason, et al., 2010). In a standard proportional-prize contest, players compete for a prize by putting forth costly effort. They receive shares of the prize in proportion to their individual effort over the sum of all effort. Our model modifies this canonical structure in light of several “stylized facts” about investment.

To incorporate the fact that investments take time to generate revenue, investment in the current period (t) affects a player’s share of the prize in the *subsequent* period ($t + 1$)—not the current period. Because investment revenue may vary over the course of the business cycle, the contest prize varies period-to-period. To incorporate the fact that the cost of investing varies over the course of the business cycle, the cost of effort varies period-to-period. Finally, because firm liquidity may vary over the course of the business cycle, the maximum possible effort varies period-to-period.

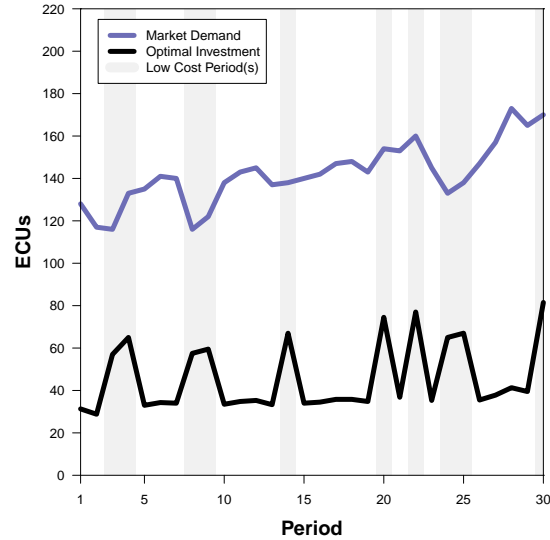
3 Experimental Design and Procedures

We make the following choices to translate our motivating model into an experiment. First, we assume no discounting, $\delta = 1$. We also set the cost parameter so that $\alpha_L = 0.5$ and $\alpha_H = 1.0$. Finally we use the same, pre-drawn market path randomly realized from $M_{t+1} = 10 + 0.9M_t + \epsilon$ with $\epsilon \sim N(0, 10)$ in each of our experimental sessions. Periods 1-30 of this path are shown in Figure 3, along with the optimal investment path. Market demand is presented in experimental currency units (ECUs) and it attains a minimum value of 116 ECUs in Periods 3 and 8 and a maximum value of 173 ECUs in Period 28.⁶ For the thirty periods shown, the market has 19 expansionary and 11 recessionary periods (the latter are shown in gray in Figure 3).

Our experiments were conducted with 166 participants at a mid-sized liberal arts uni-

⁶The exchange rate between ECUs and U.S. dollars was 60 ECUs to \$1.00 in all treatments.

Figure 3: Market Demand and Optimal Investment, by Period



versity. They were run in zTree (Fischbacher, 2007) with our participants recruited via proprietary recruitment software. Each session included approximately 15 minutes of instructions, which are produced in full in Appendix II. On average, across all of our treatments, participants earned \$23.30 (this includes a \$7.00 show-up fee).

We conducted three treatments: *No Cost*, *Cost*, and *Liquidity*. Table 1 provides information on each treatment. We ran each session for as long as possible, conditional on finishing the session within two hours.⁷ There are three *Cost* sessions because *Cost* Session I was relatively short. While we analyze all of our data statistically (except where indicated), our figures only show the first 30 periods as that is the period minima across treatments.

In all three treatments, each participant managed an experimental firm. Our program randomly assigned participants to duopolies prior to the experiment and they remained in

⁷Participants did not know the session length. Because of heterogeneity in the time it took participants to make their investment decisions, we deemed it necessary to conduct each session for as long as possible.

Table 1: Experiment Summary

Treatment	Cost Change	Liquidity	Session	Participants	Markets	Periods
<i>No Cost</i>	No	$\phi_1 = 1.00, \phi_2 = 1.00$	I	22	11	38
	No	$\phi_1 = 1.00, \phi_2 = 1.00$	II	24	12	30
				46	23	
<i>Cost</i>	Yes	$\phi_1 = 1.00, \phi_2 = 1.00$	I	24	12	21
	Yes	$\phi_1 = 1.00, \phi_2 = 1.00$	II	24	12	30
	Yes	$\phi_1 = 1.00, \phi_2 = 1.00$	III	24	12	26
				72	36	
<i>Liquidity</i>	Yes	$\phi_1 = 1.00, \phi_2 = 0.75$	I	24	12	39
	Yes	$\phi_1 = 1.00, \phi_2 = 0.75$	II	24	12	30
				48	24	
Total				166	83	

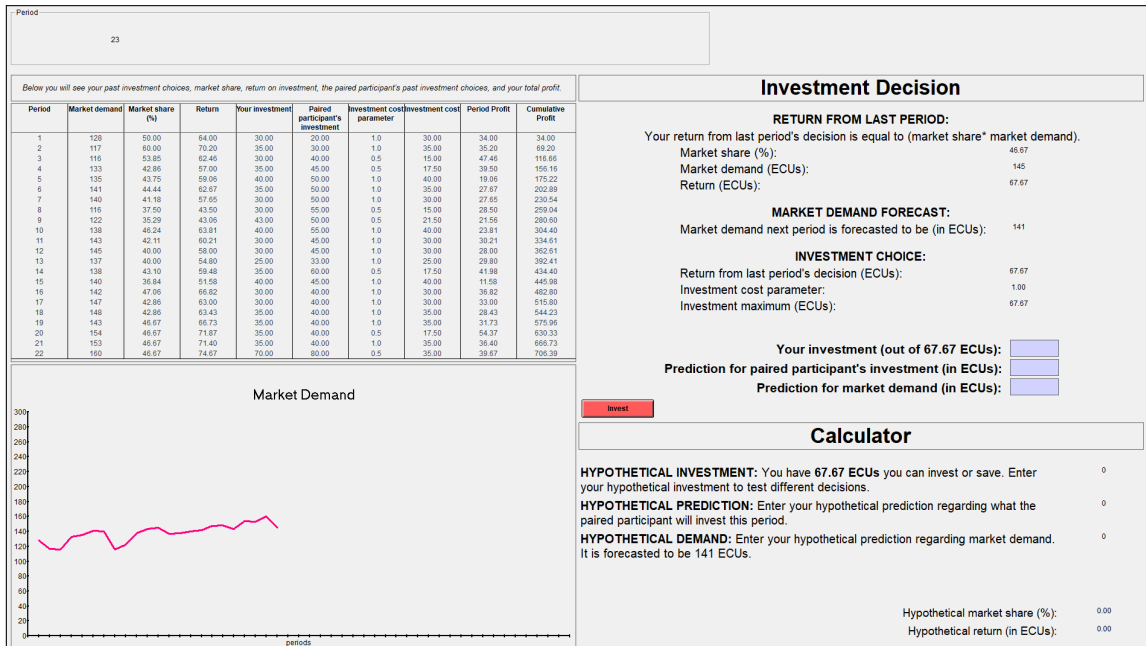
the same duopoly market throughout the experiment. During the experiment, participants could test out investments before making their actual investment decision. They did so by entering a “hypothetical” investment for themselves and their rival and a hypothetical value for market demand into an on screen calculator. The calculator returned a market share and a market return based on the entered values; it did not include a “best response” or similar option.

When participants were ready to make their actual investment, they entered their chosen investment and predictions about the other firm’s investment (“paired participant’s investment”) and about market demand.⁸ The rival investment and market demand predictions were not incentivized. We felt that incorporating an incentive-compatible belief elicitation mechanism into our already complex design would be too taxing on our participants.

Figure 4 is a screenshot of the experimental decision screen. As the figure shows, participants’ screens gave them the complete history of market demand, their market share, their

⁸To avoid “deficit spending,” participants had to invest at least 5 ECUs each period.

Figure 4: Experiment Screenshot



market revenue (“return”), their investment, their rival’s investment (“paired participant’s investment”), past cost parameters, investment costs, period profits, and their cumulative profit.

We exogenously vary the cost parameter, α_t^i , and the liquidity parameter, ϕ_i , across our three treatments. *No Cost* is our control treatment. It was identical to our other treatments in every respect, except that the cost parameter on investment did not vary with market demand. In other words, α_t was equal to 1.0 in every period.

Cost is our baseline treatment. *Cost* firms had symmetric liquidity, and as described in Section 2, investment costs changed following recessionary periods with a one-period lag. Finally, *Liquidity* is identical to our other treatments expect that one of the firms, Firm 2 say, had $\phi_2 = 0.75$, so that $x_t^2 \leq 0.75R_t^2$. This was not common knowledge. Firm 1, with $\phi_1 = 1.0$, was never told and could only infer that Firm 2 was relatively more liquidity

constrained. In fact, $\phi_1 = 1.0$ firms received *exactly the same* instructions as *Cost* firms.

We test the following hypotheses generated by the model in Section 2:

Hypothesis 1 In *No Cost* and *Cost*, investment will be the optimal investment.

Hypothesis 2 In *Liquidity*, investment and liquidity will be inversely related.

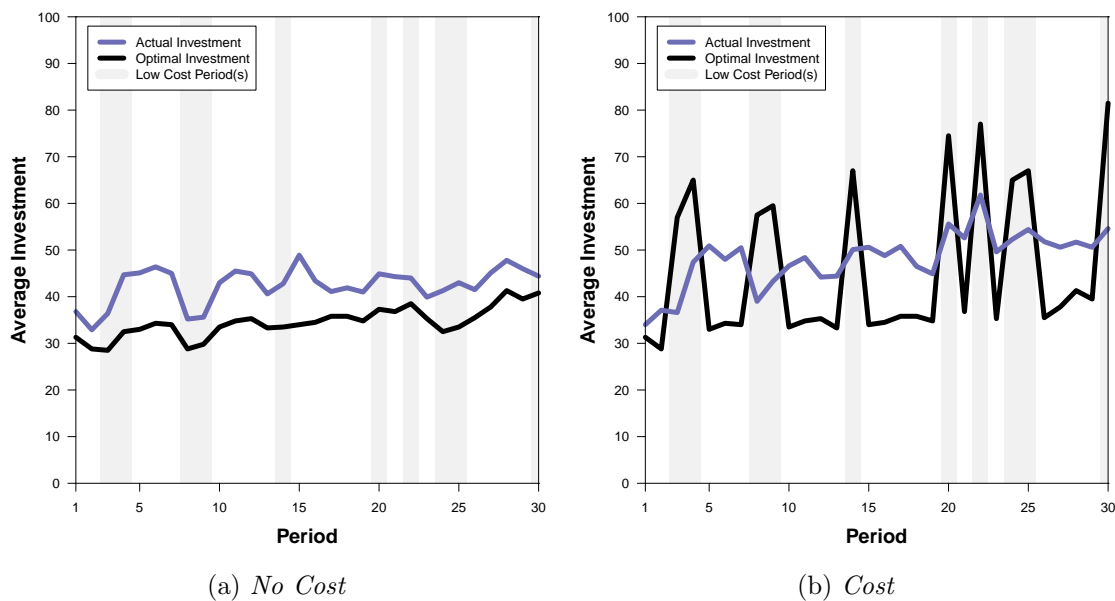
Hypothesis 1 follows directly from our motivating model in Section 2. Specifically, equation 5 implies that investment is pro-cyclical in *No Cost* and counter-cyclical in *Cost*. By comparison, Hypothesis 2 is more general than Hypothesis 1. We intentionally designed *Liquidity* to be as similar as possible to *Cost*. The *only* change across the two treatments is that “100%” was replaced by “75%” in the text of the $\phi = 0.75$ firms’ instructions (See Appendix II). Hypothesis 2 implies that $\phi = 1.00$ firms invest relatively more than $\phi = 0.75$ firms in *Liquidity*. Our participants were not informed about how their own liquidity coefficient stacked up against their rival’s liquidity coefficient, but we expect that they gleaned this information with market feedback.

4 Results

Our presentation of results begins visually. Figure 5 shows the time series of average investment (in ECUs). Panel (a) contains the *No Cost* data and Panel (b) contains the *Cost* data. Vertical gray bars indicate periods where $\alpha_t = 0.5$ in *Cost*, and we include bars in the *No Cost* figure for comparison purposes, even though the investment cost coefficient did not change in *No Cost*.

Figure 5a shows that actual *No Cost* investment was consistently above the optimal investment path, on average. We calculate Pearson correlation coefficients between actual investment and market demand for each *No Cost* participant ($n = 46$). The average such correlation was $\bar{r} = 0.14$, with an average 95% confidence interval of $[-0.14, 0.40]$. For

Figure 5: Average Investment by Period, by Treatment



comparison, if every *No Cost* participant invested optimally in each period, the analogous average correlation *would* have been $\bar{r} = -0.09$, with an average 95% confidence interval of $[-0.48, 0.34]$.

Figure 5b reveals that, on average, actual *Cost* investment was above the optimal investment path in expansions and below the optimal path in recessions. The average correlation between actual investment and market demand for *Cost* participants ($n = 72$) was $\bar{r} = 0.25$, with an average 95% confidence interval of $[-0.09, 0.54]$. By contrast, if every *Cost* participant always invested optimally, it would have been $\bar{r} = 0.37$, with an average 95% confidence interval of $[0.11, 0.61]$.

We now examine *No Cost* and *Cost* investment more rigorously with regression analysis.

Our estimating specification is:⁹

$$\Delta \ln(Invest_{m,t}) = \beta_0 + \beta_1 \Delta \ln(Forecast_t) + \beta_2 \Delta \ln(Cost_t) + Feasible_{m,t} + \epsilon_{m,t} \quad (6)$$

where $Invest_{m,t}$ is average investment at the market level (m indexes duopoly markets), $Forecast_t$ is the exogenous forecast of market demand displayed on each participant's screen, $Cost_t$ is the market-level cost coefficient in period t , $Feasible_{m,t}$ equals 1 if neither firm in market m is so liquidity-constrained that they cannot invest the optimal investment in period t (x_t^*), and equals 0 otherwise, and $\epsilon_{i,t}$ is an error term.

Our experimental design ensures that any two markets are independent, so that $\epsilon_{m,t}$ and $\epsilon_{-m,t}$ are independent. However, autocorrelation is an obvious concern since $\epsilon_{m,t}$ and $\epsilon_{m,t+1}$ are not independent, so we first-difference our specification (note that this removes any time-invariant, unobserved market heterogeneity). However, Wooldridge Tests reject null hypotheses of no autocorrelation for each treatment, so we also employ Driscoll-Kraay standard errors that are robust to heteroskedasticity, cross-sectional correlation, and autocorrelation.

We estimate specification (6) for each treatment by pooled ordinary least squares (OLS) with Driscoll-Kraay standard errors. For the *No Cost* treatment, $\Delta \ln(Cost_t) = 0$ for all periods. Before reporting the regression results, we note that estimating specification (6) with optimal investment (x_t^*) as the dependent variable results in the coefficient estimates $\widehat{\beta}_1^* = 1.00$ and $\widehat{\beta}_2^* = -1.00$.

Table 2 shows regression results for the *No Cost* and *Cost* treatments. All the coefficient estimates on $\Delta \ln(Forecast_t)$ are significantly different from 0, but none are significantly different from 1. Thus, in both *No Cost* and *Cost*, we estimate that a 1% change in the market demand forecast leads to a 1% change in investment, in the same direction.

⁹Standard tests suggest that multicollinearity is not an issue for specification (6) with our data.

Table 2: Regression Results

$\Delta \ln(Invest_{m,t})$	No Cost		Cost		
$\Delta \ln(Forecast_t)$	1.00*** (0.24)	1.02*** (0.24)	1.15*** (0.27)	1.28*** (0.27)	1.34*** (0.26)
$\Delta \ln(Cost_t)$				-0.08** (0.03)	-0.11*** (0.03)
$Feasible_{m,t}$		0.12*** (0.04)			0.05** (0.02)
R^2	0.02	0.04	0.03	0.04	0.05
Observations	755	755	888	888	888

Notes: Pooled OLS coefficient estimates with Driscoll-Kraay standard errors in parenthesis. Statistical significance: *** < 0.01, ** < 0.05, * < 0.10.

For *Cost*, we estimate that lowering investment costs increases investment. However, our estimate of the effect of lowering investment costs by half is only 11% of that predicted by our motivating model ($-0.11 / -1.00$).¹⁰ Not surprisingly, in both *No Cost* and *Cost*, average investment is higher when both firms can investment the optimal investment amount. When both firms can invest the optimal amount, investment is 12% higher in *No Cost* and 5% higher in *Cost* than when one or both firms cannot invest the optimal amount.

From the preceding analysis, we conclude:

Result 1 In *No Cost*, average investment exceeded optimal investment.

Result 2 In *Cost*, average investment exceeded optimal investment when $\alpha = 1.0$ and was less than optimal investment when $\alpha = 0.5$.

Our data clearly do not support Hypothesis 1. We interpret Result 1 as a manifestation of the near ubiquitous “overbidding” phenomenon in experimental contests (Sheremeta, 2013; Dechenaux, et al., 2015). In *Cost*, participants over-invest when $\alpha = 1.0$ as in *No*

¹⁰The effect of lowering investment costs by half is 16% of that predicted by our motivating model when we drop the first 10 periods from our estimating sample.

Cost, but under-invest when $\alpha = 0.5$. Why do the data not support Hypothesis 1?

4.1 Why was investment suboptimal?

We now consider possible explanations for our results: Participants were confused, participants were inexperienced, participants cooperated (or, if you prefer, colluded), participants did not use the “rational” forecast, and participants did not view their investment problem game theoretically but in some other way.

Perhaps participants did not understand that investment costs change, did not understand how costs change, or that costs change for both firms? Our complete instructions are presented in Appendix II. They cover the cost change at length and include stark reminders such as: “When market demand falls, investment costs fall.” Moreover, as Figure 4 shows, participants saw their investment cost parameter (α_t) on their computer screen. We have no evidence that participants were not aware of, or did not understand the investment cost change, and as we detail below, our data are not well-fit by assuming that participants ignored the cost changes.

Maybe participants did not understand that their rival’s costs changed when their own costs changed. Our instructions do not make this explicit, but it is implied. Moreover, if a firm believes that their rival always has $\alpha = 1.0$, their investment best-response is very similar to the optimal investment path in Figure 7b (the spikes when $\alpha = 0.5$ are slightly less pronounced)—and thus is very different from the actual investment path.¹¹

Another possible explanation for why our participants invested suboptimally is that our participants initially had no experience in our complex environment. As with most experiments, we cannot exclude this possibility. However, our estimate of the effect of

¹¹We note that slight departures from the optimal investment path do not explain the observed data either. If one firm in a market is slightly off the optimal path, the other firm should investment very near the optimal path, because the best response curve is very flat in the neighborhood of optimal investment.

lowering investment costs by half only changes from -0.11 to -0.16 when we drop periods 1-10 from our estimating sample in Section 4’s regression analysis. Moreover, *a priori* it is uncertain whether greater experience leads to more competition (and results closer to the optimal investment path) or to more cooperation in our experimental environment.

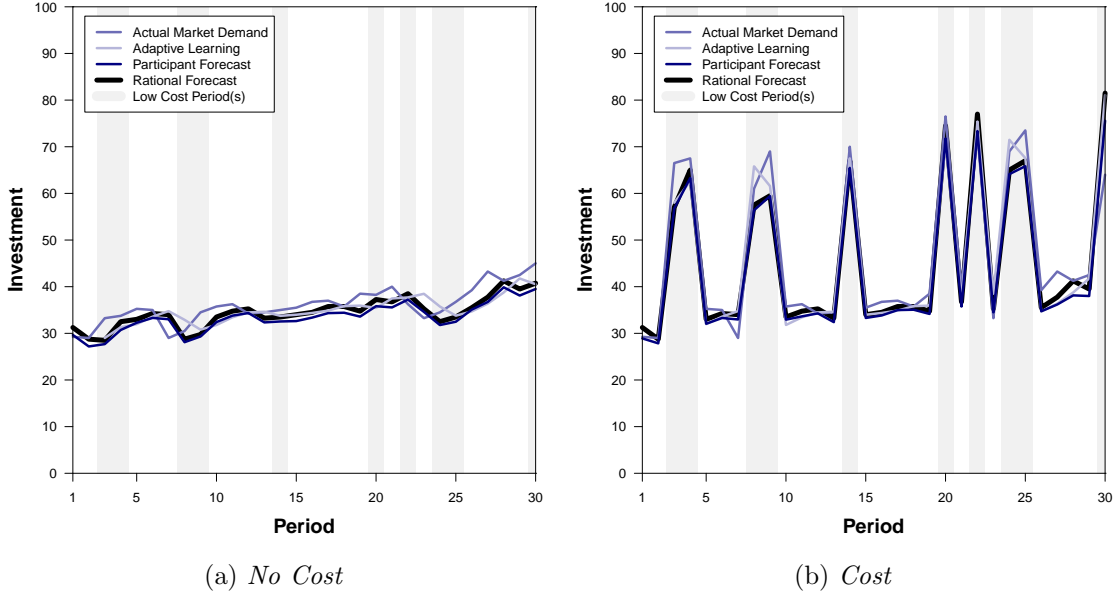
Did participants cooperate with their supposed rival? There are individual *No Cost* and *Cost* markets where firms clearly cooperated. However, there is considerable heterogeneity across firms and across markets; there were markets where investment fell over time, but also markets where investment escalated over time. On average, as Figure 5 shows, participants were supracompetitive, not cooperative in *No Cost*, and in *Cost* when $\alpha = 1.0$.¹²

In equation (5), optimal investment is a function of the forecast of next period’s market demand and the cost parameter. In 2 of the first 10 periods (and in 3 of the first 20 periods) actual market demand exceeded the rational forecast, $\mathbf{E}_t[M_{t+1}] = 10 + 0.9M_t$. Perhaps this influenced our participants to employ an alternative forecast rather than the rational forecast? To examine this possibility, we calculate optimal investment under three counterfactual forecasting assumptions: (1) Participants are able to perfectly forecast next period’s actual market demand ($\mathbf{E}_t[M_{t+1}] = M_{t+1}$), (2) Participants forecast using adaptive learning, and (3) Participants forecast according to the unincentivized demand forecasts they submit when entering their investment levels. Assumptions (1) and (3) are self-explanatory, but assumption (2) requires elaboration.

Following the adaptive learning literature in macroeconomics (see, for example, Evans and Honkahoja, 2001), we suppose that our participants’ perceived law of motion for

¹²It is conceivable that *Cost* participants were “competitive” during market expansions, and “cooperative” during market recessions. But, again, average investment in *No Cost* is consistently above optimal investment in both expansions and recessions (see Figure 5a). We would expect counter-cyclical cooperation strategies to be employed in *No Cost* if such strategies are employed at all. So, on average, there is no support for a counter-cyclical collusion result in the (rough) spirit of Rotemberg and Saloner (1986).

Figure 6: Optimal Investment by Period, by Forecast Assumption



market demand was:

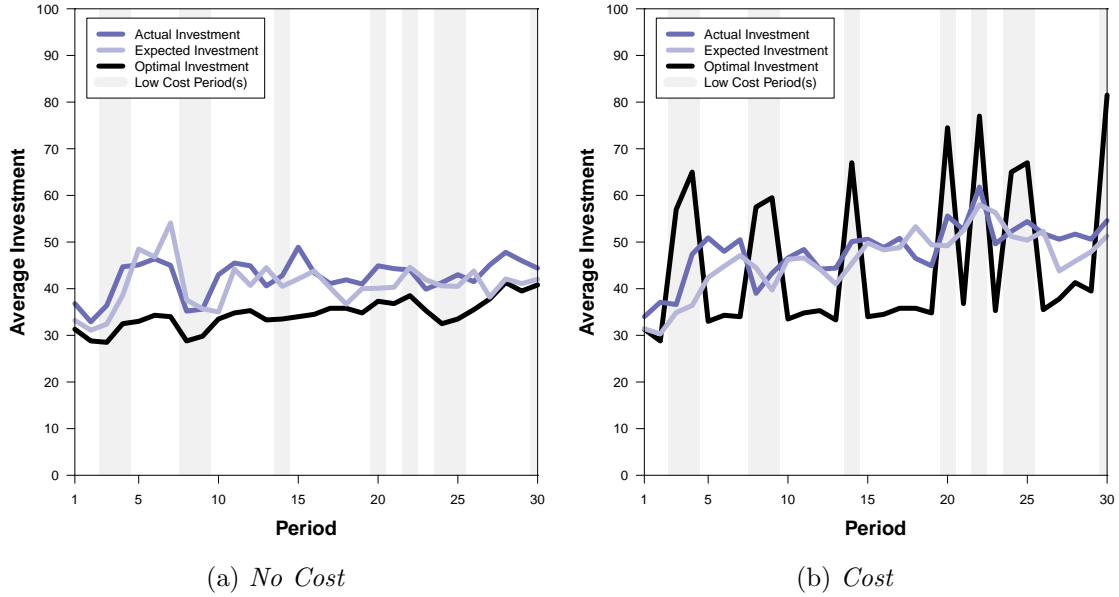
$$M_t = a + bM_{t-1} + \eta_t \tag{7}$$

with a and b unknown to the participant and η_t is an error term. Of course, participants *were* told that $a = 10$ and $b = 0.9$, but perhaps—for whatever reason—they formed their own beliefs about the value of these two parameters. We assume that in each period t , participants estimated \hat{a} and \hat{b} by least squares, using all available past market data up to period t , or $\{M_i\}_{i=1}^t$.¹³ Their assumed forecast of demand in period $t + 1$ is then $\mathbf{E}_t[M_{t+1}] = \hat{a} + \hat{b}M_t$.

Figure 6 shows optimal investment under our three counterfactual forecasting assumptions and assuming the rational forecast. The average of each counterfactual forecast was substituted into equation (5) to obtain the optimal investment time series. It is clear from

¹³We estimate \hat{a} and \hat{b} for periods 3-30. There is not enough data to estimate prior to period 3.

Figure 7: Expectations by Period, by Treatment



the figure that assuming non-rational forecasting, but maintaining equation (5), does not generate investment paths that fit the data well.

In Figure 7, participants' expectations about their rivals' investment are fairly consistent with their rivals' actual investment in *No Cost* and *Cost*.¹⁴ The figure suggests that our participants made their investment decisions by some other calculus than maximizing equation (3), because neither actual nor expected investment match the optimal investment path in either treatment. If our participants were boundedly-rational and did not invest optimally—according to our game theoretic model's notion of optimality, how might they have made their investment decisions?

The theory of selective attention provides a possible explanation (Schwartzstein 2014;

¹⁴The time series of the average best response to expected rival investment is very similar to the time series of optimal investment, so participants were not best-responding to the expected investment of their rival.

Hanna, et al. 2014).¹⁵ If attention is costly, important economic variables may be neglected in favor others that are less informative, but which are more easily noticed. Agents may optimize along more noticeable dimensions, while failing to optimize along the most important dimensions.

In our experiment, participants may be attentive to exogenous variables such as past market demand or the forecast of future market demand. Or they may be attentive to their current liquidity or their rivals' past investment, but not to their future liquidity or their rivals' future investment. If so, they have a competitive *blind spot* and “will either not see the significance of events (such as a strategic move) at all, will perceive them incorrectly, or will perceive them only very slowly” (Porter, 1980).

Selectively attentive participants will not determine investment according to equation (5), but may instead apply heuristics (“rules-of-thumb”) to the variables within their focus. A number of possible investment heuristics seem reasonable in our setting.¹⁶ We consider the following rules-of-thumb:

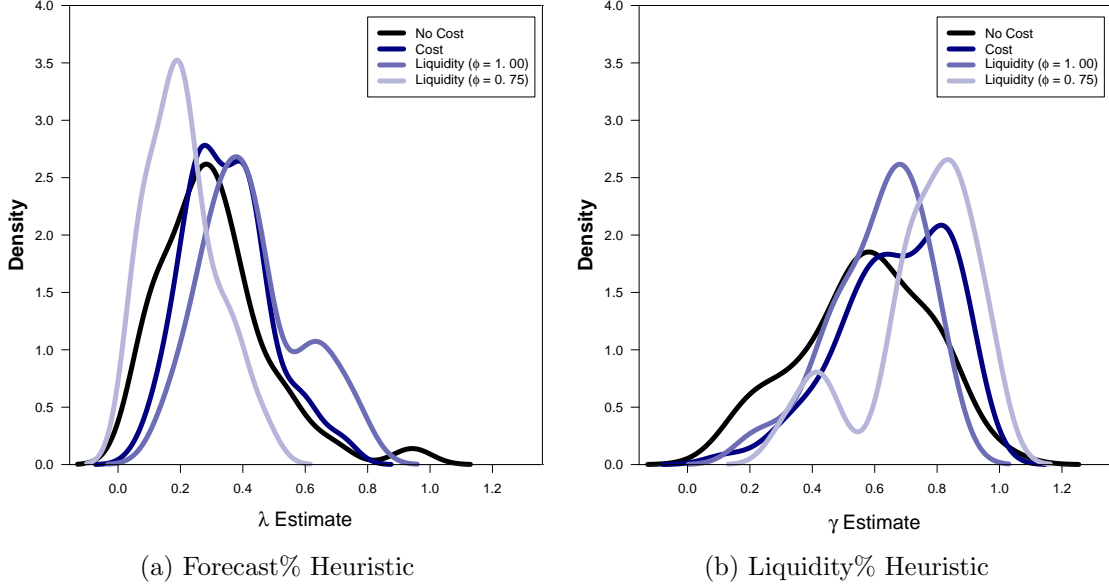
$$\begin{aligned}
 \text{“Ignore Cost”} & \quad \text{Assume the cost parameter always equals 1:} & x_t^i &= \mathbf{E}_t[M_{t+1}]/4 \\
 \text{“Imitation”} & \quad \text{Match my rival’s lagged investment:} & x_t^i &= x_{t-1}^{-i} \\
 \text{“Forecast\%”} & \quad \text{Invest a fixed percentage of the market forecast:} & x_t^i &= \lambda_i \mathbf{E}_t[M_{t+1}] \\
 \text{“Liquidity\%”} & \quad \text{Invest a fixed percentage of liquidity:} & x_t^i &= \gamma_i s_t^i M_t
 \end{aligned} \tag{8}$$

While *invest a fixed percentage of current market demand* is another reasonable heuristic, current market demand and the market forecast are collinear so they have nearly identical

¹⁵Of course this theory is preceded by Simon (1955), Cyert and March (1963; 1992), and Leibenstein (1969) among others. Related theories of “rational inattention” are also plausible here.

¹⁶Examples of heuristic use by real firms abound. Notably, cost-plus pricing heuristics are employed by many firms where an item is priced by applying a fixed mark up to the item’s average cost (see, e.g., Hall and Hitch, 1939; Hanson, 1992). Also, “Several studies have documented that many firms have as a decision rule that R&D expenditures should be a roughly constant fraction of sales” (Nelson and Winter, 1982).

Figure 8: Kernel Densities



predictive power as heuristics.¹⁷ For comparison purposes, we also consider the optimal investment path (“Optimal”).

The strategies Optimal and Imitation consider the firm’s rival, though Imitation is backwards-looking—it considers what the rival *did*, not what they will or what they might *do*. On the other hand, Ignore Cost, Forecast%, and Liquidity% ignore the rival and only concern the firm’s own situation, or the exogenous market situation. In each case, the heuristic is consistent with selective attention: the firm focuses on rivals’ past investment, or on the market forecast, or on their own liquidity.

To assess the Forecast% and Liquidity% heuristics, the coefficients λ_i and γ_i from (8) are estimated separately for each firm using ordinary least squares. $Invest_{i,t}$ is the dependent variable in each regression, there is no constant term, and the sole regressor in each specification is either $Forecast_t$ or is Firm i ’s maximum liquidity in t . Finally, the

¹⁷Recall that the forecast is $\mathbf{E}_t[M_{t+1}] = 10 + 0.9M_t$.

estimating sample is periods 1-30, except for the two *Cost* sessions with 21 and 26 periods.

Figure 8 shows kernel densities by treatment and firm type for $\widehat{\lambda}_i$ (Figure 8a) and $\widehat{\gamma}_i$ (Figure 8b). The average values of $\widehat{\lambda}_i$ and $\widehat{\gamma}_i$ over all firms (denoted $\bar{\lambda}$ and $\bar{\gamma}$) are in Table 3. We use Kolmogorov-Smirnov tests to assess whether differences exist in the distributions of $\widehat{\lambda}_i$ and $\widehat{\gamma}_i$ across *No Cost* and *Cost*. To satisfy an independence assumption of the test, we average estimates at the market level ($n_{NC} = 23, n_C = 36$). According to the tests, there is no difference across *No Cost* and *Cost* for the distributions of λ estimates ($p = 0.185$), but there is a difference for the distributions of γ estimates ($p = 0.086$).

Table 3 shows the average root-mean-square-error (RMSE) for each investment strategy relative to actual investment. For each strategy, a count of the number of firms whose lowest RMSE was that strategy is also presented. So, for example, Liquidity% generates the lowest RMSE for 72% (52/72) of *Cost* firms. For each treatment and firm type, Liquidity% fits the actual investment data better than the alternative strategies, though Forecast% also outperforms the optimal investment path. The former heuristic suggests that, on average, *No Cost* firms invested 57% of their liquidity and that *Cost* firms invested 67% of their liquidity each period.

Our analysis leads us to conclude:

Result 3 The heuristics *invest a fixed percentage of the market forecast* and *invest a fixed percentage of liquidity* better fit our *No Cost* and *Cost* data than does optimal investment.

How well does the Liquidity% heuristic match the data visually? Figure 9 compares actual investment, optimal investment, and investment assuming that each firm invested 57% (67%) of their liquidity in *No Cost* (*Cost*). Because liquidity appears to play a crucial role in our participants' investment decisions, we now report a treatment with asymmetric liquidity constraints.

Table 3: Heuristic Comparison

Treatment		Optimal	Ignore Cost	Imitation	Forecast%	Liquidity%
<i>No Cost</i>	Mean RMSE	27.90		41.81	18.10	14.73
	<i>n</i> out of 46	0		5	14	27
					$\bar{\lambda} = 0.31$	$\bar{\gamma} = 0.57$
<i>Cost</i>	Mean RMSE	28.97	27.08	38.72	18.38	14.03
	<i>n</i> out of 72	1	0	4	15	52
					$\bar{\lambda} = 0.35$	$\bar{\gamma} = 0.67$
<i>Liquidity</i> ($\phi = 1.00$)	Mean RMSE	33.98 ^a	34.81 ^a	46.62	20.49	18.45
	<i>n</i> out of 24	0	0	1	10	13
					$\bar{\lambda} = 0.43$	$\bar{\gamma} = 0.61$
<i>Liquidity</i> ($\phi = 0.75$)	Mean RMSE	30.52 ^a	21.02 ^a	47.99	13.36	7.11
	<i>n</i> out of 24	0	0	0	2	22
					$\bar{\lambda} = 0.21$	$\bar{\gamma} = 0.75$

^aRelative to optimal investment in *Cost*

Notes: Mean RMSE is averaged over all participants by treatment and firm type. “*n* out of *X*” is how times the strategy had the lowest RMSE among the four candidate strategies. Comparisons should be made across columns, but not across rows.

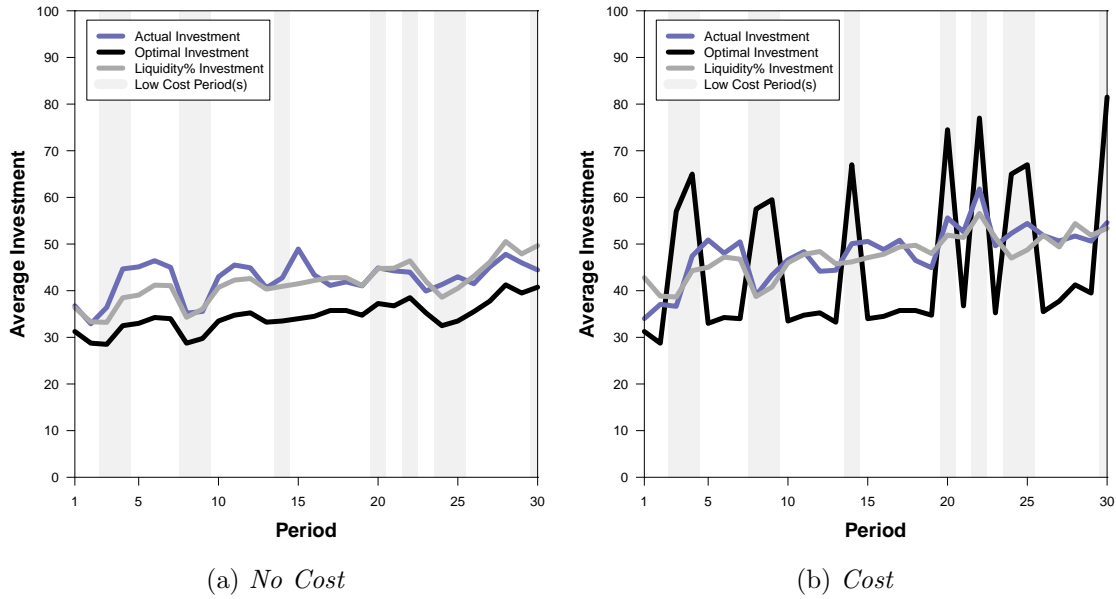
4.2 How does liquidity affect investment?

We now consider the effects of exogenous liquidity asymmetry on investment in our experimental environment. Recall that in *Liquidity*, one duopolist could invest R_t^i each period, whereas their rival could only invest $0.75R_t^{-i}$ each period. The asymmetric liquidity constraints did not preclude firms from investing according to the optimal investment for *Cost*, if participants had always previously invested the optimal amount.

While *Liquidity* participants were not informed about the asymmetric constraints on investment in the instructions, they may have inferred a difference in liquidity over time from the market history reported on their screen. Before data collection, we hypothesized that this would occur, so that actual investment would be inversely related to the liquidity constraint (Hypothesis 2). After data collection, in light of our contention in Section 4.1 that participants use the rule-of-thumb *invest a fixed percentage of liquidity*, we certainly expect a difference in investment across $\phi = 1.00$ firms and $\phi = 0.75$ firms.

Figure 10 shows both average investment over time and average expected investment

Figure 9: Heuristic Investment over Time



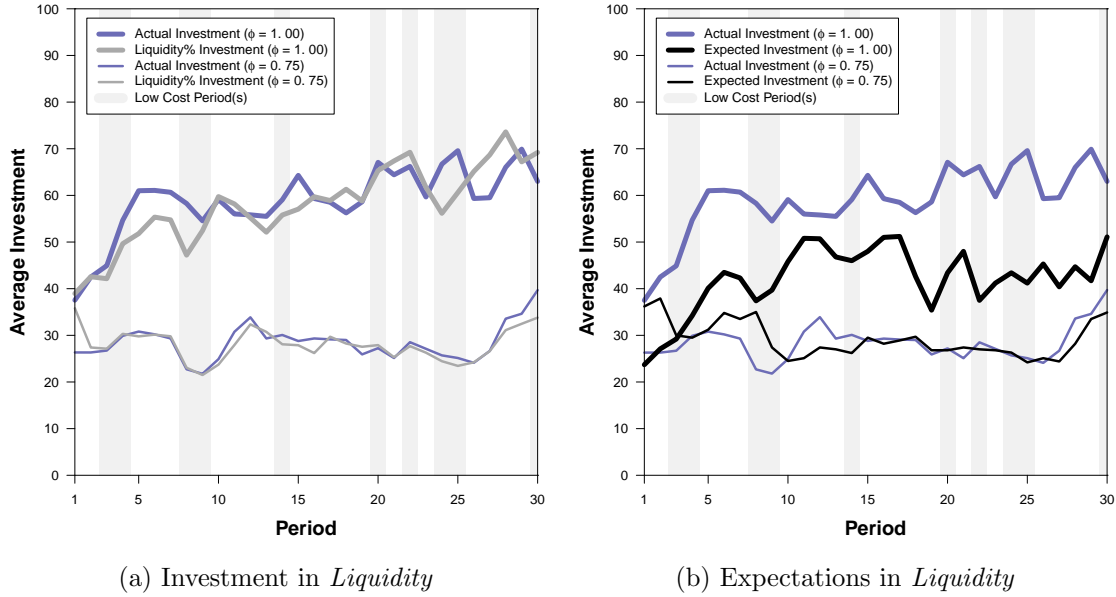
over time. The blue time series are for actual investment and the gray investment paths are those predicted by the Liquidity% heuristic (see Table 3). Clearly, $\phi = 1.00$ firms invested more on average than did $\phi = 0.75$ firms. In per period terms, they invested 59.0 ECUs compared to 28.4 ECUs for $\phi = 0.75$ firms.¹⁸ For comparison, *Cost* firms invested 47.5 ECUs on average.¹⁹

As we do for our other treatments, we present time series for average expectations in *Liquidity*. Figure 10b shows that $\phi = 1.00$ firms' expectations about their rivals' investment were, on average, good. However, $\phi = 0.75$ firms consistently underestimated their rivals' investments. On average, they predicted that $\phi = 1.00$ firms would invest 44.6 ECUs. This figure was above their own average maximum liquidity (37.0 ECUs), but was slightly less than their own average return of 49.3 ECUs. We suspect that their prediction about their

¹⁸The per period investment figures are averaged over periods 1-30.

¹⁹For periods 1-30, *No Cost* firms earned 28.6 ECUs per period on average. The equivalent figures are 30.1 for *Cost*, 44.8 for *Liquidity* $\phi = 0.01$, and 24.6 for *Liquidity* $\phi = 0.75$.

Figure 10: Investment and Expectations over Time



$\phi = 1.00$ rival was influenced by their own return.²⁰

Table 4 presents estimates of specification (6) (and two additional, simpler specifications) with *Liquidity* data pooled over $\phi = 1.00$ and $\phi = 0.75$ firms. Across the three specifications in Table 4, the response to forecast demand is much lower in magnitude than in *No Cost* or *Cost*. When we control for the feasibility of the optimal investment level, the estimated coefficient on $\Delta \ln(Cost_t)$ of -0.07 is close to, but slightly smaller in magnitude than the -0.11 estimate for *Cost*.²¹

Table 3 contains *Liquidity* comparisons of the same heuristics previously considered for *No Cost* and *Cost*. As in those treatments, the *Liquidity%* rule-of-thumb has the lowest average RMSE. *Forecast%* and *Liquidity%* explain the data roughly as well for $\phi = 1.00$ firms; *Forecast%* has the lowest RMSE for 10 $\phi = 1.00$ firms, whereas *Liquidity%* has the

²⁰In fact, firms with $\phi = 1.00$ had an average return of 97.2 ECUs per period.

²¹The estimated coefficient on $\Delta \ln(Cost_t)$ is -0.09 when we drop the first 10 periods from our estimating sample.

Table 4: Regression Results

$\Delta \ln(Invest_{m,t})$	Liquidity		
$\Delta \ln(Forecast_t)$	0.44** (0.19)	0.50*** (0.18)	0.56*** (0.20)
$\Delta \ln(Cost_t)$		-0.04 (0.03)	-0.07** (0.03)
$Feasible_{m,t}$			0.10*** (0.03)
R^2	0.01	0.01	0.02
Observations	804	804	804

Notes: Pooled OLS coefficient estimates with Driscoll-Kraay standard errors in parenthesis. Statistical significance: *** < 0.01, ** < 0.05, * < 0.10.

lowest RMSE for 13 firms. On the other hand, Liquidity% has the lowest RMSE for 22 $\phi = 0.75$ firms (92% of all such firms). Because $\phi = 0.75$ firms were liquidity-constrained, this result is hardly surprising.

A Kolmogorov-Smirnov test indicates a significant difference between the distribution of $\widehat{\lambda}_i$ for *Liquidity* $\phi = 1.00$ firms and the analogous distribution for *Liquidity* $\phi = 0.75$ firms ($p = 0.000$; $n_{L1.00} = 24, n_{L0.75} = 24$). It also suggests a significant difference in the distribution of $\widehat{\gamma}_i$ across firm types ($p = 0.013$). However, the distribution of $\widehat{\lambda}_i$ for $\phi = 1.00$ firms is not significantly different from the distribution $\widehat{\lambda}_i$ for *Cost* markets ($p = 0.106$; $n_C = 36, n_{L1.00} = 24$). Nor is the distribution of $\widehat{\gamma}_i$ significantly different across *Liquidity* $\phi = 1.00$ firms and *Cost* markets ($p = 0.269$).

This last test result is very interesting. Our *Cost* participants and our *Liquidity* participants who were randomly selected for the $\phi = 1.00$ firm role were from the same participant population and they saw the *exact* same instructions (see Appendix II). However, they faced very different competitive conditions. If both sets of participants made their investments a function of the competitiveness of their markets, we might expect a significant difference in estimated heuristics across the two treatments because *Cost* firms competed with

equally-liquid rivals whereas $\phi = 1.00$ *Liquidity* firms had a decided liquidity advantage. Our finding of no difference suggests that participants in both treatments had a Porterian *blind spot* to their competition, because Forecast% and Liquidity% are not functions of competition—at least not directly.

We can report that:

Result 4 In *Liquidity*, average investment was inversely related to liquidity.

Result 5 *Liquidity* $\phi = 1.00$ firms and *Cost* firms invested similar percentages of their liquidity, whereas $\phi = 0.75$ firms invested significantly more of their liquidity.

We now summarize our results and conclude.

5 Discussion and Conclusion

We report data from novel laboratory experiments on the cyclicalities of investment. In our *Cost* treatment, optimal investment is counter-cyclical, yet actual investment was pro-cyclical. On average, our data are better fit by assuming that participants used investment rules-of-thumb than by supposing that they invested according to the optimal, game theoretic investment path. Their investment heuristics involved either investing a fixed percentage of the market demand forecast or of their liquidity.

Our environment can be viewed as an extended and contextualized proportional-prize contest. In all *No Cost* periods, and in *Cost* periods where $\alpha = 1.00$, the actual, average investment exceeded optimal investment. This result is further evidence of “overbidding” in experimental contest settings—even when the repeated contest is given an explicit investment-competition frame, has a stochastic prize, non-constant effort costs, and a maximum effort constraint that is history-dependent. Our conclusion that participants employ

a liquidity heuristic is also in line with previous contest experiments showing endowment effects (Price and Sheremeta, 2001; Brookins, et al., 2015).

Behavioral industrial organization has lately turned to the demand side of markets (Ellison, 2016; Grubb and Tremblay, 2016 and citations therein), but there is a continuing focus on the supply side of markets (e.g., Cyert and March, 1963). Our paper joins the latter camp as an empirical example of how bounded rationality affects market competition. It suggests that investments are not chosen in a purely “rational” manner with clear regard for rival investment. In the strategy literature, Porter (1980) terms this a competitive *blind spot*.

This research sheds some light on how frequent cost changes affect market competition. Many market experiments explore the effects of changes in demand on competition, but we are not aware of any closely related experiments examining the effects of frequent cost changes on competition. Our firms either do not incorporate cost changes into their decision-making at all, or do so only modestly. Contests and Cournot games are related (see, e.g., Menezes and Quiggin, 2010), and future research can examine whether our conclusions extend empirically to classic Cournot, Bertrand, or Bertrand-Edgeworth markets with frequent cost changes.

Finally, to the extent that our results are externally valid, they *might* suggest that pro-cyclical investment may be a function of competitive *blind spots*—of firms focusing inward more than outward to determine investment. Even granting that Fortune 500 firms may “think” game theoretically, many markets contain managers who may employ heuristics (Busenitz and Barney, 1997) and who may be subject to *blind spots*. We offer this conclusion tentatively, however, because individual firms may use suboptimal investment heuristics, but market competition may select more strategic, more “rational” (though not necessarily optimal) firms for survival (Alchian, 1950).

This is the first experimental research to consider the cyclicalness of investment, so we take a broad view, but our paper suggests a number of intriguing, focused extensions. In particular, with a larger market of four or six firms, will firms that invest strategically take market share away from firms that invest heuristically? And if our participants are selectively attentive, is their focus affected by competitive pressure? In the long-run, does attention turn to more strategically-relevant variables? With open questions like these, we believe that the cyclicalness of investment is a promising avenue for fruitful future experimental research.

6 References

- Aghion, Philippe, Philippe Askenazy, Nicolas Berman, Gilbert Cette, and Laurent Eymard. "Credit constraints and the cyclicalities of R&D investment: Evidence from France." *Journal of the European Economic Association* 10, no. 5 (2012): 1001-1024.
- Alchian, Armen. "Uncertainty, evolution, and economic theory." *Journal of Political Economy* 58, no. 3 (1950): 211-221.
- Barlevy, Gadi. "On the cyclicalities of research and development." *The American Economic Review* 97, no. 4 (2007): 1131-1164.
- Brookins, Philip, John Lightle, and Dmitry Ryvkin. "An experimental study of sorting in group contests." *Labour Economics* 35 (2015): 16-25.
- Brown, James, and Bruce Petersen. "Cash holdings and R&D smoothing." *Journal of Corporate Finance* 17, no. 3 (2011): 694-709.
- Busenitz, Lowell, and Jay Barney. "Differences between entrepreneurs and managers in large organizations: Biases and heuristics in strategic decision-making." *Journal of Business Venturing* 12, no. 1 (1997): 9-30.
- Cason, Timothy, William Masters, and Roman Sheremeta. "Entry into winner-take-all and proportional-prize contests: An experimental study." *Journal of Public Economics* 94, no. 9 (2010): 604-611.
- Cyert, Richard, and James March. *A behavioral theory of the firm: Second edition*. Malden, MA: Blackwell (1963; 1992).
- Duffy, John. "Macroeconomics: A survey of laboratory research." In *The handbook of experimental economics, volume 2* (2016).
- Ellison, Glenn. "Bounded rationality in industrial organization." *Econometric Society Monographs* 42 (2006): 142.
- Evans, George, and Seppo Honkapohja. *Learning and expectations in macroeconomics*. Princeton University Press (2001).
- Fischbacher, Urs. "z-Tree: Zurich toolbox for ready-made economic experiments." *Experimental Economics* 10, no. 2 (2007): 171-178.
- Ghemawat, Pankaj. "The risk of not investing in a recession." *MIT Sloan Management Review* 34, no. 2 (1993): 51.

- Grubb, Michael, and Victor Tremblay. "Introduction: Behavioral industrial organization." *Review of Industrial Organization* 47, no. 3 (2015): 243-245.
- Hall, Robert, and Charles Hitch. "Price theory and business behaviour." *Oxford Economic Papers* no. 2 (1939): 12-45.
- Hanna, Rema, Sendhil Mullainathan, and Joshua Schwartzstein. "Learning through noticing: Theory and evidence from a field experiment." *The Quarterly Journal of Economics* 129, no. 3 (August 2014): 1311-1353.
- Hanson, Ward. "The dynamics of cost-plus pricing." *Managerial and Decision Economics* 13, no. 2 (1992): 149-161.
- Leibenstein, Harvey. "Organizational or frictional equilibria, X-efficiency, and the rate of innovation." *The Quarterly Journal of Economics* 83, no. 4 (1969): 600-623.
- Menezes, Flavio, and John Quiggin. "Markets for influence." *International Journal of Industrial Organization* 28, no. 3 (2010): 307-310.
- Nelson, Richard and Sidney Winter. *An evolutionary theory of economic change*. Harvard University Press (1982).
- Ouyang, Min. "On the cyclicity of R&D." *Review of Economics and Statistics* 93, no. 2 (2011): 542-553.
- Porter, Michael. *Competitive strategy: Techniques for analyzing industries and competitors*. New York, NY: The Free Press (1980).
- Rotemberg, Julio, and Garth Saloner. "A supergame-theoretic model of price wars during booms." *The American Economic Review* 76, no. 3 (1986): 390-407.
- Schwartzstein, Joshua. "Selective attention and learning." *Journal of the European Economic Association*, 12, no. 6, (December 2014): 1423-1452.
- Simon, Herbert. "A behavioral model of rational choice." *The Quarterly Journal of Economics* 69, no. 1 (1955): 99-118.
- Long, Ngo Van, and Neil Vousden. "Risk-averse rent seeking with shared rents." *The Economic Journal* 97, no. 388 (1987): 971-985.
- Price, Curtis, and Roman Sheremeta. "Endowment effects in contests." *Economics Letters* 111, no. 3 (2011): 217-219.
- Vossoughi, Sohrab. "The silver lining to scarcity: It drives innovation." *Harvard Business Review Digital Article* (March 01, 2012).

7 Appendix I

This appendix explains how the optimal investment path is determined. Differentiating Equation (3) with respect to x_t^i and rearranging yields the following best-response function:

$$x_t^i = \sqrt{x_t^{-i} \left[\frac{\mathbf{E}_t^i[M_{t+1}]}{\alpha_t^i(\Delta M_{t-1})} \right]} - x_t^{-i} \quad (1)$$

Symmetric optimal investment in a period is then:

$$x_t^* = \frac{\mathbf{E}_t^i[M_{t+1}]}{4\alpha_t^i(\Delta M_{t-1})} \quad (2)$$

This optimum exists so long as x_t^* is feasible, which it is provided that $x_t^* \leq \phi^i R_t^i, \forall i$.

We construct the optimal investment path over many periods by backwards induction. In Period T , the firm simply receives revenue $R_T = s_T M_T$ and the game ends. The first actual decision is in Period $T-1$. Here, the firm must invest according to (2). In Period $T-2$, the firm must also invest according to (2). We must check that, in expectation, investing optimally in Period $T-2$ will allow the firm to invest optimally in Period $T-1$. The relevant inequality is:

$$x_{T-1}^* \leq \phi^i s_{T-1}^i \mathbf{E}_{T-2}^i[M_{T-1}] \quad (3)$$

Plugging (2) into the left hand side of (3):

$$\frac{\mathbf{E}_{T-1}^i[M_T]}{4\alpha_{T-1}^i(\Delta M_{T-2})} \leq \phi^i s_{T-1}^i \mathbf{E}_{T-2}^i[M_{T-1}] \quad (4)$$

Rearranging and plugging in $s_{T-1}^i = 1/2$ yields:

$$\frac{\mathbf{E}_{T-1}^i[M_T]}{\mathbf{E}_{T-2}^i[M_{T-1}]} \leq 2\phi^i \alpha_{T-1}^i(\Delta M_{T-2}) \quad (5)$$

Because $\mathbf{E}_t^i[M_{t+1}] = \mu + \rho M_t$, this becomes:

$$\frac{\mu + \rho(\mu + \rho M_{T-2})}{\mu + \rho M_{T-2}} \leq 2\phi^i \alpha_{T-1}^i(\Delta M_{T-2}) \quad (6)$$

Rearranging, we get:

$$M_{T-2} \geq \frac{\mu + \rho\mu - 2\phi^i \mu \alpha_{T-1}^i(M_{T-2})}{2\phi^i \rho \alpha_{T-1}^i(M_{T-2}) - \rho^2} \quad (7)$$

If this condition on the value of the market is satisfied, the agent can, in expectation, invest the optimal amount in Period $T-1$. Inequality (3) must also hold for all periods from 1 to $T-2$. Given our parametrization, it holds for all periods. Finally, in Period 1, Firm i can invest optimally because $x_1^* = 31.25$ and both firms have 64.00 available to invest.

8 Appendix II

This appendix contains the complete experimental instructions for all three treatments. The *No Cost* instructions are presented as the default. Changes to the instructions for the *Cost* participants and for the $\phi = 1.00$ *Liquidity* participants are identified by { **angle brackets** }. The $\phi = 0.75$ *Liquidity* participants receive the lone instruction change identified by ‹‹ **double angle brackets** ››.

Introduction

Welcome. You have volunteered to participate in an experiment where your choices will influence how much real money you earn. Your earnings, including your \$7.00 show-up fee, will be paid to you privately, in cash, at the end of the experiment.

Please remain quiet and do not communicate with other participants or attempt to observe their decisions. You will be asked to leave the lab if you violate these rules. Please read the following instructions carefully. Then click the ‘Finish Instructions’ button when you are ready to move on.

The Basics

In today’s experiment, you will be randomly and anonymously paired with another participant. You will interact with this same participant throughout the entire experiment, but your identity will remain anonymous. This experiment is composed of **periods**. In each period, you will have funds available to either keep or invest. Your funds will be denominated in Experimental Currency Units, or *ECUs* for short. 60 *ECUs* will be worth \$1.00 at the end of the experiment.

Investing

Each period, you will decide how much to invest. You will be able to invest as little or as much as you like, so long as your investment is less than a maximum amount which will depend on your return from the previous period’s investment. Your return on investment will be determined by these three factors:

1. The **market demand**
2. Your investment decision
3. Your paired participant’s investment decision

Together, your investment decision and your paired participant’s investment decision will determine your **market share**.

Market Shares

If you invest X ECUs and your paired participant invests Y ECUs in a given period, your market share, which we will call S , in the next period, will be calculated according to the following formula:

$$S = X / (X + Y)$$

In other words, your market share will be your investment divided by the sum of both your investment and your paired participant’s investment. You and your paired participant will make your

respective investment decisions at the same time without knowing each other's choices.

It is important to remember that your investment decision in a particular period, say Period 3, determines your market share in the next period, or Period 4 in this example. You will only learn how much your paired participant invested in Period 3, in Period 4. Your paired participant will only learn how much you invested in Period 3, in Period 4.

Note: If both you and your paired participant chose to invest the same amount (i.e. $X=Y$), your market share next period will be $S = 0.50$ or 50%.

Period Profit

Your profit in a particular period will be determined by your market share (which, again, will depend on your investment decision in the previous period), by market demand, and by an investment cost.

Let's refer to your market share as S , to market demand as M , and to your investment cost as C . Your period profit will be calculated according to the following formula:

$$\text{Period Profit} = S \times M - C$$

In other words, your period profit will be your share of the market demand minus the amount you spend on investing.

Your Investment Maximum and Minimum

The amount of funds you will have available to invest in any given period will be limited by your return on last period's investment according to the following formula:

$$\begin{aligned} \text{Investment Maximum} &= 100\% \times S \times M \\ \langle\langle \text{Investment Maximum} &= 75\% \times S \times M \rangle\rangle \end{aligned}$$

The computer interface will remind you of your current investment maximum. Your investment minimum will always be:

$$\text{Investment Minimum} = 5$$

Investment Costs

The **investment cost parameter** will determine your total investment costs; its value will be 1.0. Suppose you invest X ECUs in a particular period. Your investment costs will be:

$$C = 1.0 * X$$

where 1.0 is the investment cost parameter.

*(Investment costs will be determined by how much you choose to invest and by whether market demand increased or decreased last period. The **investment cost parameter** will determine your total investment costs; its value will be either 1.0 or 0.5. Suppose you invest X ECUs in a particular*

period. If market demand *increased* or *stayed the same* last period, your investment costs will be:

$$C = 1.0 * X$$

where 1.0 is the investment cost parameter. On the other hand, if market demand *decreased* last period, your investment costs will be:

$$C = 0.5 * X$$

where 0.5 is the investment cost parameter. In other words, if market demand decreased *last period*, your investment *this period* will be half as expensive as if market demand had instead increased or stayed the same last period. Put another way: **When market demand falls, investment costs fall.** The computer interface will remind you of your current investment cost parameter in each period.)

Cumulative Profit

Take a second look at the above formula for period profit. If your investment cost is less than your investment maximum, you will earn a positive period profit. Anytime your period profit is positive, your **cumulative profit** will increase. The computer interface will remind you of your cumulative profit throughout the experiment. You will be paid your cumulative profit at the end of the experiment.

Market Demand

As mentioned above, market demand (M) will increase, stay the same, or decrease from period-to-period. Market demand will increase, stay the same, or decrease randomly.

Let's denote market demand this period by $M1$, and market demand last period by $M0$. Here's how market demand will be determined:

$$M1 = 10 + 0.9 * M0 + R$$

In other words, this period's market demand will be the number 10, plus 90% of last period's market demand, plus R .

R is short for "random," and it denotes a random number picked by the computer. The actual value of R will vary each period, i.e., it will be randomly drawn each period. Although it will vary, there is a 99% chance that R will be some number from -26 to +26; on average, it will be 0. Another way to think about this is that if the computer picked, say, a 1,000 random numbers, the average of these 1,000 random numbers would be 0.

The computer interface will give you a **market demand forecast** each period. Because R is 0 on average, this forecast will be:

$$\text{Market demand forecast of next period's } M = 10 + 0.9 * (M \text{ this period})$$

Note: Actual market demand can, and very likely will, differ from the forecasted value because while R is 0 on average, it is random!

Additional Information

Again, you will not learn how much your paired participant has invested in a period until the next period. However, each period, the computer interface will ask you for a prediction about your paired participant's investment before you submit your own investment. *Importantly, this prediction will not be shared with your paired, or any other, participant!*

The computer interface will also ask you for a prediction about next period's market demand.

The Calculator

The computer interface will contain a calculator. You can use this calculator to "test out" different investment amounts. The calculator will use the predictions you enter about your paired participant's investment and about market demand to provide you with an estimate of what your return might be next period given various hypothetical investments. *Note: Using the calculator is entirely optional.*

Remember: Your actual market share and thus your period profit will depend on your paired participant's decision as well as your own.

Final Words

In each period click on the 'Make investment decision' button when you are ready to make your investment decision. The calculator will no longer be available in that period. Three input boxes will appear and you will indicate your own investment decision, your prediction about your paired participant's investment, and your prediction about next period's market demand. Be sure to click the 'Invest' button to finalize your decisions, followed by a button that will show you the results and which will advance you to the next period.

If you have any questions, please remain seated and silent but raise your hand so that a proctor can come answer your question privately. When you have finished reading the instructions, please click on the 'Finish instructions' button to begin the experiment. You can review your hardcopy of these instructions at any point during the experiment.

Quick Summary

- This experiment is composed of many periods
- In each period, you will make an investment decision
- You will have an investment maximum and an investment minimum
- Your investment decision and your paired participant's investment decision will determine your market share for the next period

*(Investment costs partly depend on a parameter that can change depending on what market demand did last period; **when market demand falls, investment costs fall**)*

- Market demand changes randomly each period (see above for the formula)

- Your period profit will *increase* with your **market share** and with **market demand**
{ Your period profit will *increase* with your **market share** and with **market demand** and will *decrease* with your **investment costs** }
- Your cash earnings at the end of the experiment will include all of your period profits