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Competitive Blind Spots and The Cyclicalities of Investment: Experimental Evidence

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Abstract

We report laboratory experiments investigating the cyclicalities of profit-enhancing investment in a competitive environment. In our setting, optimal investment is counter-cyclical when investment costs fall following market downturns. However, we do not observe counter-cyclical investment. Instead, we see much less strategic behavior than our rational investment model anticipates. Our participants exhibit what Porter (1980) terms a competitive blind spot, and heuristic investment models where individuals invest a fixed percentage of their liquidity, or a fixed percentage of anticipated market demand, better fit our data 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

business cycles, duopoly experiments, experimental economics, heuristics; investment

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).

Our research is motivated by the fact that aggregate research and development (R&D) investment is, in fact, procyclical.^[2] This well-documented result (Barlevy, 2007) belies the Schumpeterian story and suggests that managers may invest suboptimally during recessions. Possible explanations for this result include the presence of binding liquidity constraints (Aghion *et al.*, 2012), of high R&D adjustment costs (Brown and Petersen, 2011), and of the lack of full appropriability of much R&D (Barlevy, 2007). But 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] With an experiment, we can precisely examine the cyclicity of investment.

A more general motivation for our research is the paucity of experiments examining competition in the presence of frequent, exogenous cost changes. There is some extant experimental research on exogenous supply shifts in Double Auction environments (see Williams, 1979; Williams and Smith, 1984), and on competition with endogenous cost changes in posted-offer settings (see Isaac and Reynolds, 1992; Darai *et al.*, 2010; Sacco and Schmutzler, 2011; Smyth, 2016; Aghion *et al.*, 2018).^[4] But to the best of our knowledge, only one paper (Davis *et al.*, 1993) has directly considered the effects of exogenous cost changes on competition in a nonauction environment.^[5]

Our experimental environment abstracts essential features of firms' investment decisions. In our motivating duopoly model, recessions make investing in future profits cheaper so that optimal investment is counter-cyclical. In our experimental design, investment cost changes are not subtle, and they are timed to permit clean identification of counter-cyclical investment—if it occurs. We make investment *half* as costly following a recessionary period as after an expansionary period in our *Cost Change* treatment.

Surprisingly, average participant investment does not spike with cost reductions in *Cost Change*. Our participants' response to the cost change is 15% 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 observe little counter-cyclical investment in our stylized experiment with such 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 much better than the optimal investment path does.

Because liquidity appears to play a crucial role in how participants make investments in our *Cost Change* treatment, we report a *Liquidity* treatment with asymmetric liquidity constraints. If participants use liquidity-based heuristics when investing, we should observe large differences in investment across liquidity types. We do in fact find that participants who are randomly endowed with either low- or high- liquidity make decisions that are consistent with a liquidity-based investment heuristic.

In sum, incentivized individuals in our competitive investment environment act less strategically than our rational investment model predicts. Our data thus buttress the Carnegie School's (Simon, 1955; Cyert, March, 1992) seminal behavioral contributions to industrial organization and the theory of the firm. Of course, discrepancies between theory and data are par for the experimental economic course. What is novel here is our competitive investment setting—one with stark incentives for counter-cyclical investment, yet one with little counter-cyclical investment actually observed.

More broadly, our paper contributes to several other literatures. Our experimental markets are extended and contextualized proportional-prize contests, so the paper adds to the growing experimental contest literature.^[6] We mostly frame our paper in microeconomic terms, but it is also related to the burgeoning experimental macroeconomics literature. In particular, it corresponds to previous macroeconomic experiments examining expectations, forecasting, and feedback (Assenza *et al.*, 2014) as well as decision-making in dynamic environments (Duffy, 2015). Finally, to the extent that our results are externally valid, they contribute to the literature on the cyclicity of investment.^[7]

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 in our experiments. We next report our experimental results in Section 4, beginning with our baseline *No Cost Change* treatment and our *Cost Change* treatment. Then we discuss possible reasons why our data are not consistent with our optimal investment model and report results from our *Liquidity* treatment. Finally, Section 5 concludes.

MOTIVATING MODEL

In this section, 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 profit-enhancing investment: (a) Investment *today* affects profit *tomorrow*, (b) Market demand and investment costs are related, and (c) Investment liquidity is constrained.

Our model assumes two firms engaged in profit-enhancing investment competition.^[8] Time is finite and composed of periods indexed by t , where T is the model's final period. Firms earn revenue $R_t = s_t M_t$, where s_t denotes the firm's market share in Period t , and M_t is the value of the market in that period. The firm's market share is determined according to:

$$s_t(x_{t-1}x'_{t-1}) = \frac{x_{t-1}}{x_{t-1} + x'_{t-1}}$$

(1)

where x_{t-1} is the firm's investment in Period $t - 1$, and x'_{t-1} is their rival's investment in the same period. Thus, each firm's market share is their investment last period divided by the total market investment last period.[9]

Note from the functions given above that revenue is increasing in market share and thus also increasing in investment. However, firms bear costs associated with their investments. The firm's investment cost in Period t is $C_t = \alpha_t(\Delta M_{t-1})x_t$, where $\Delta M_{t-1} = M_{t-1} - M_{t-2}$. To capture counter-cyclical investment costs, we assume that:

$$\alpha_t \Delta M_{t-1} = \begin{cases} \alpha_H & \text{if } \Delta M_{t-1} \geq 0 \\ \alpha_L & \text{if } \Delta M_{t-1} < 0 \end{cases}$$

(2)

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

Figure 1 illustrates the timing of the cost change. Cost changes take effect one period after a recession.[10] At the beginning of each period, the firms observe the value of the economy, M_t , and their investment cost coefficient, $\alpha_t(\Delta M_{t-1})$. Both firms then simultaneously make investments x_t , where $x_t \leq \phi R_t$. The coefficient ϕ affects the firm's liquidity. In other words, firms must choose investments that are less than or equal to their current liquidity-adjusted revenues. Finally, the next period begins, M_{t+1} is observed, and R_{t+1} is realized.

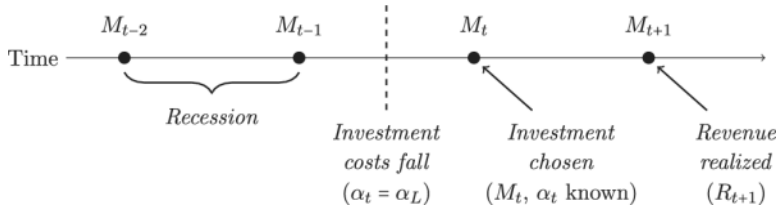


Figure 1 Timeline for investment cost change

We construct a symmetric, optimal investment path over all periods in the model by backwards induction. In Period T , the firm simply receives revenue $R_T = s_T M_T$ and the game ends, so the final investment decisions occur in Period $T - 1$. The firm's profit maximization problem is identical in all periods between Period 2 and Period $T - 1$. The two-period problem is:

$$\max_{\{x_t\}} R_t - \alpha_t(\Delta M_{t-1})x_t + s_{t+1}(x_t x'_t) \mathbf{E}_t[M_{t+1}] + \lambda(\phi R_t - x_t)$$

(3)

where we assume no discounting and where $\lambda \geq 0$ is a Kuhn-Tucker multiplier.

Because $s_{t+1}(x_t, x'_t)$ is increasing at a decreasing rate in x_t , while the cost of investing increases at a constant rate, optimal investment will not exhaust the firm's liquidity (i.e., $\lambda = 0$) for a

sufficiently large liquidity level. We construct an optimal investment path where liquidity is not exhausted in any period. Differentiating (3) with respect to x_t and setting $\lambda = 0$ yields:

$$-\alpha_t(\Delta M_{t-1}) + \frac{x'_t}{(x_t + x'_t)^2} \mathbf{E}_t[M_{t+1}] = 0$$

This becomes:

$$BR_t(x'_t) = \sqrt{x'_t \left[\frac{\mathbf{E}_t[M_{t+1}]}{\alpha_t(\Delta M_{t-1})} \right] x'_t}$$

(4)

Imposing symmetry ($x_t + x'_t$), $BR_t(x'_t)$ and $BR'_t(x_t)$ imply that:

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

(5)

Equation (4) is illustrated in Figure 2. There are two distinct regions in the plot that can be thought of in terms of a firm's expectations about its rival's investment. When a firm anticipates their rival investing above the optimal investment (x^*), they should respond in the opposite direction. However, when a firm anticipates their rival investing below x^* , they should respond in the same direction. So investments are neither purely strategic complements nor purely strategic substitutes in this environment.

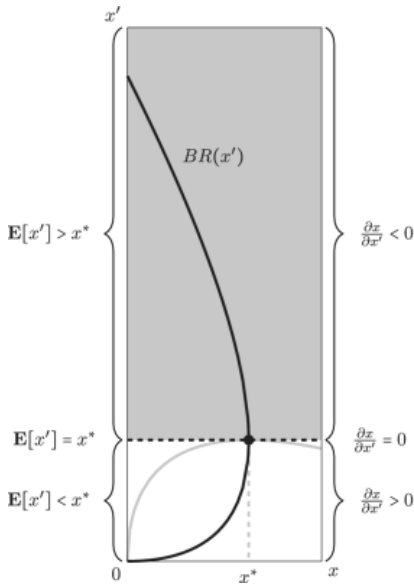


Figure 2 Example best response curve

Note two opposing effects in Equation (5): *Ceteris paribus*, investment increases in the market demand forecast ($\mathbf{E}_t[M_{t+1}]$) and decreases in the cost parameter (α_t). The value of the market is assumed to be autoregressive of order 1, $AR(1)$. Its value in Period t is $M_t = \mu + \rho M_{t-1} + \epsilon_t$,

where μ and ρ are constants and $\epsilon_t \sim N(0, \sigma^2)$. Note that because the noise term is mean zero, $E_t[M_{t+1}] = \mu + \rho M_t$. On our optimal investment path, investing x_t^* in Period t allows the firm to invest optimally in Period $t + 1$ (in expectation).[11]

At this point, we can precisely define "cyclical investment" and "counter-cyclical investment" in our specific experimental setting.[12] When $\alpha = 1$, optimal investment increases when market demand is expected to increase, and it decreases when market demand is expected to decrease ("cyclical"). On the other hand, optimal investment increases sharply in the first period for which $\alpha < 1$ ("counter-cyclical"). Depending on the length of the recession, optimal investment may remain higher than it otherwise would be with $\alpha = 1$ for several periods. As we discuss in Section 3, in one of our experimental treatments (*No Cost Change*), optimal investment is always cyclical; in our other two treatments, counter-cyclical investments are optimal immediately following market downturns.

Our model can be viewed as a kind of proportional-prize contest (Long and Voutsden, 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 to incorporate several "stylized facts" about investment.

Since investments take time to generate revenue, investment in the current period (t) affects a player's share of the prize in the *next* 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, since firm liquidity may vary over the course of the business cycle, the maximum feasible effort varies period-to-period.

EXPERIMENTAL DESIGN AND PROCEDURES

This section describes our experimental design and explains how we conducted our experiments. To translate our motivating model into an experiment, we set the cost parameter so that $\alpha_H = 1.0$ and $\alpha_L = 0.5$, and we use the same, pre-drawn market path in each of our experimental sessions. This path is randomly realized with $M_1 = 128$ and $M_{t+1} = 10 + 0.9M_t + \epsilon_t$, where $\epsilon_t \sim N(0, 100)$.

Periods 1–30 of the market path are shown in Figure 3 (the lighter, thicker line), along with the optimal investment path (the darker, thinner line). In Period 1, optimal investment is $x_1^* \approx 31$ and each participant can invest $x_1 \leq 64$. 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.[13] For the 30 periods shown in the figure, the market has 19 expansionary and 11 recessionary periods (the low cost periods are shown in gray in Figure 3).

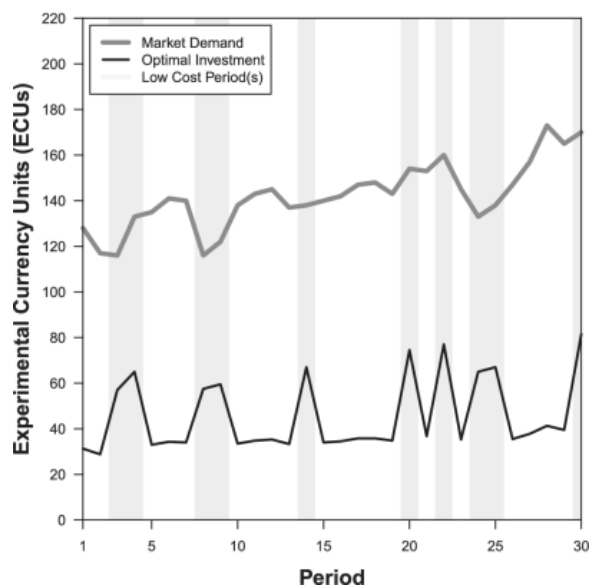


Figure 3 Market demand and optimal investment by period

Our experiments were conducted with 166 participants at a mid-sized liberal arts university. They were run in zTree (Fischbacher, 2007) with our participants recruited via proprietary recruitment software. Each session included approximately 15 min of instructions, which are produced in full in Appendix C. 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 Change*, *Cost Change*, and *Liquidity*. Table 1 provides information about each treatment. Our treatments were programmed to run for a maximum of 50 periods, but our participants were told only that the experiment would last for "many periods." [14] We ran each session for as long as possible, conditional on finishing the session within 2 hr. As Table 1 shows, sessions featured between 21 and 39 investment decisions ("Periods"). After participants made what, unbeknownst to them was their final investment decision, they were informed that the session was over. Their payment included their revenue from market demand in the next period (i.e., Period T in the model in Section 2).

1 TABLE Experiment summary

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

In all three treatments, each participant made investment decisions every period. Our program randomly assigned participants to duopolies prior to the experiment and they remained in the same duopoly 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" option.

When participants were ready to make their actual investment, they entered their chosen investment and predictions about the other participant's investment ("paired participant's investment") and about market demand.[15] 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 market revenue ("return"), their investment, their rival's investment ("paired participant's investment"), past cost parameters, investment costs, period profits, and their cumulative profit.

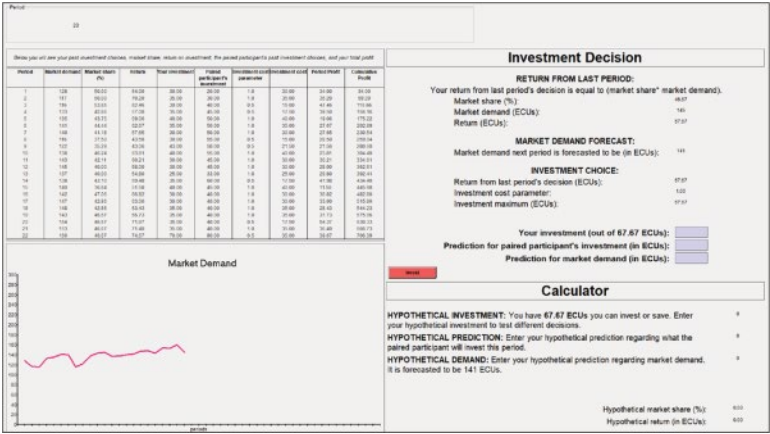


Figure 4 Experiment screenshot [Color figure can be viewed at wileyonlinelibrary.com]

We exogenously varied the cost parameter, α_t , and the liquidity parameter, ϕ , across our three treatments. *No Cost Change* 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 Change* is our baseline treatment. *Cost Change* participants had symmetric liquidity, and as described in Section 2, investment costs changed following market "recessions" with a one-period lag.

Our third treatment, *Liquidity*, is identical to our other treatments except that one of the two duopolists in each market had $\phi = 0.75$, so that $x_t' \leq 0.75R_t'$. The asymmetric liquidity constraints were private information (participants were only told their own liquidity constraint and were told nothing about their rival's liquidity). As the experiment progressed, the $\phi = 1.00$ duopolist could infer that their rival was more liquidity constrained (and vice versa) from the history of investment decisions and outcomes on their screen. Participants saw total market demand, their own return, and the

investment of their paired participant for each past period on their screen (see Figure 4). From this information, they could calculate their paired participant's return and so could potentially "back out" their paired participant's liquidity constraint.

The model in Section 2 motivates several investment hypotheses.

1 Hypothesis *No Cost Change* investment will be positively correlated with next period's expected market value.

This hypothesis follows directly from Equation (5) in Section 2. In *No Cost Change*, the cost parameter, α_t , is always unity, so optimal investment is solely a function of next period's expected market value ($E_t[M_{t+1}]$). When the market forecast increases, investment should increase, and vice versa.

2 Hypothesis *Cost Change* investment will be negatively correlated with the cost parameter.

Hypothesis 2 also follows immediately from Equation (5). In *Cost Change*, the cost parameter varies between $\alpha_H = 1.0$ and $\alpha_L = 0.5$. Holding constant the expected market value, optimal investment doubles across periods when the cost parameter changes from α_H to α_L . After the market value declines, the cost parameter changes, and investment should spike as shown in Figure 3.

3 Hypothesis *Liquidity* investment will be positively correlated with the liquidity parameter. For participants with high liquidity, investment will be negatively correlated with the cost parameter.

This hypothesis states that $\phi = 1.00$ participants will invest more than $\phi = 0.75$ participants. We intentionally designed *Liquidity* to be as similar as possible to *Cost Change*. The *only* difference between the two treatments was that "100%" was replaced by "75%" in the text of the $\phi = 0.75$ participants' instructions (see Appendix C). Previous contest experiments show an "endowment effect" or a "spending heuristic" where chosen effort scales with the endowment of effort (Sheremeta, 2011; Brookins *et al.*, 2015). So we anticipate a "liquidity effect" where observed investment increases in the feasible amount of investment.

Furthermore, participants with $\phi = 1.00$ are hypothesized to vary their investment according to the cost parameter in line with Equation (5). To the extent that $\phi = 0.75$ participants are liquidity constrained, we hypothesize that their investment is less sensitive to changes in the cost parameter and more sensitive to changes in the market value.

RESULTS

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

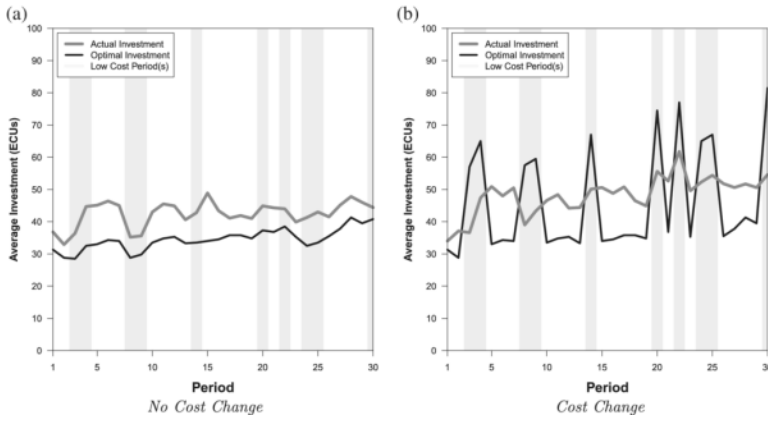


Figure 5 Average investment by period, by treatment

Figure 5a shows that, on average, actual *No Cost Change* investment tracked the optimal investment path fairly well but was consistently above it. On the basis of Figure 5, the optimal investment path plausibly organizes the *No Cost Change* data, but there is clear evidence of over-investment. The same cannot be said for the *Cost Change* data. Figure 5b reveals that, on average, actual *Cost Change* investment was above the optimal investment path when $\alpha_t = 1.0$ and below the optimal path when $\alpha_t = 0.5$.

We now examine *No Cost Change* and *Cost Change* investment more rigorously with regression analysis. Our estimating specification is[16]:

$$\Delta \ln(Invest_{m,t}) = \beta_0 + \beta_1 \Delta \ln(Forecast_t) + \beta_2 \Delta \ln(Cost_t) + \beta_3 \Delta Feasible_{m,t} + \epsilon_{m,t}$$

(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 participant in market m is so liquidity-constrained that they cannot invest the optimal investment in Period t (x_t^*), and equals 0 otherwise, and $\epsilon_{m,t}$ is an error term.[17]

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 or session 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 the Driscoll-Kraay standard errors. For the *No Cost Change* 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 $\hat{\beta}_1^* = 1.00$ and $\hat{\beta}_2^* = -1.00$ for *Cost Change*.

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

2 TABLE Regression results

$\Delta \ln(\text{Invest}_{m,t})$	No Cost Change		Cost Change		
Constant	-0.00	0.00	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\Delta \ln(\text{Forecast}_t)$	1.00***	0.89***	1.15***	1.28***	1.28***
	(0.24)	(0.25)	(0.27)	(0.27)	(0.27)
$\Delta \ln(\text{Cost}_t)$				-0.08***	-0.15***
				(0.03)	(0.05)
$\Delta \text{Feasible}_{m,t}$		0.33***			0.07*
		(0.10)			(0.04)
R^2	0.02	0.10	0.03	0.04	0.05
Observations	755	755	888	888	888

Note: Pooled OLS coefficient estimates with Driscoll-Kraay standard errors in parenthesis.

* Statistical significance <.10.

** Statistical significance <.05.

*** Statistical significance <.01.

For *Cost Change*, we estimate that lowering investment costs increases investment. However, our estimate of the effect of lowering investment costs by half is only 15% of that predicted by our motivating model (-0.15/-1.00). In Appendix A, we estimate specification (6) using only data from the minimum number of periods in both treatments across sessions (30 for *No Cost Change* and 21 for *Cost Change*). Using this sample, the estimated effect of lowering investment costs by half in *Cost Change* is 13% of that predicted by our motivating model.[18]

From the preceding analysis, we conclude:

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

2 Result In *Cost Change*, 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 2. We interpret Result 1 as a manifestation of the "overbidding" phenomenon that is frequently observed in experimental contests (Sheremeta, 2013; Dechenaux *et al.*, 2015). In *Cost Change*, participants over-invest when $\alpha = 1.0$ as in *No Cost Change*, but under-invest when $\alpha = 0.5$. Why do the data not support Hypothesis 2?

Suboptimal investment in Cost Change

We now consider possible explanations for our *No Cost Change* and *Cost Change* results: Participants were confused, 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.

Confusion

Perhaps participants did not understand that investment costs change, did not understand how costs change, or that costs change for both participants. Our complete instructions are presented in Appendix C. 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 changes, and as we detail below, our data are not well-fit by assuming that participants ignored the cost changes.[19]

More generally, when $\alpha = 0.5$, a participant's best response curve "shifts out." Given this, a participant must believe that their rival will either *drastically* increase or reduce their investment before said participant will *not* want to increase their own investment when their own cost parameter falls to $\alpha = 0.5$. Such extreme beliefs are inconsistent with the participants' reported expectations about their rival's investment (see Figure 7).[20]

Cooperation

Did participants cooperate with their supposed rival? There are a small number of *No Cost Change* and *Cost Change* markets where participants clearly "cooperated." However, there is considerable heterogeneity across markets; there were markets where investment fell over time, but also markets where investment escalated over time. See Figures A2–A8 in Appendix A for the time series of average investment in all of our experimental markets. On average, as Figure 5 clearly shows, participants were supracompetitive in *No Cost Change* and in *Cost Change* when $\alpha = 1.0$.

There is a simple, straightforward reason to doubt cooperation as an explanation for our results. If participants employed *any* sort of cooperative strategy, we should see actual, average investments *below* the optimal, noncooperative investment paths in Figure 5. But we find the exact opposite. In particular, the observed *No Cost Change* data in Figure 5a simply do not suggest cooperation.[21]

Nonrational expectations

In Equation (5), optimal investment is a function of the forecast of next period's market demand and the cost parameter. In 8 of the first 10 periods (and in 16 of the first 20 periods) actual market demand exceeded the rational forecast, $E_t[M_{t+1}] = 10 + 0.9M_t$. This potentially influenced our participants to employ a nonrational, alternative forecast.[22] 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 ($E_t[M_{t+1}] = M_{t+1}$), (2) Participants forecast according to the unincentivized demand forecasts they submit when entering their investment levels, and (3) Participants forecast using adaptive learning. Assumptions (1) and (2) are self-explanatory, but assumption (3) requires elaboration.

Following the adaptive learning literature in macroeconomics (see Evans and Honkapohja, 2001), we suppose that our participants' perceived law of motion for market demand was:

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

(7)

with a and b unknown to the participant and where 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 $\{M_i\}_{i=1}^t$. [23] 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 the figure that assuming nonrational forecasting, but maintaining Equation (5), does not generate investment paths that fit the data well, because the counterfactual forecasts imply optimal investments that are essentially identical to the optimal investment implied by rational forecasting.

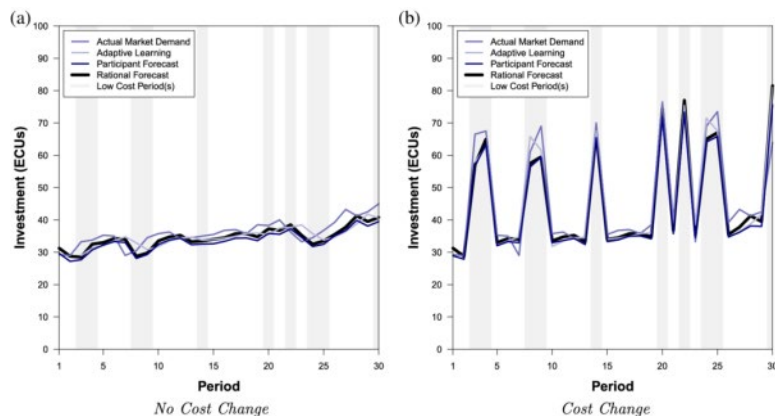


Figure 6 Optimal investment by period, by forecast assumption [Color figure can be viewed at wileyonlinelibrary.com]

Heuristics

In Figure 7, participants' expectations about their rivals' investment (the dashed lines) are fairly consistent with their rivals' actual investment in *No Cost Change* and *Cost Change*. [24] The figure suggests that our participants made their investment decisions by some other calculus than maximizing Equation (3), because actual and expected investment are so similar and neither 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?

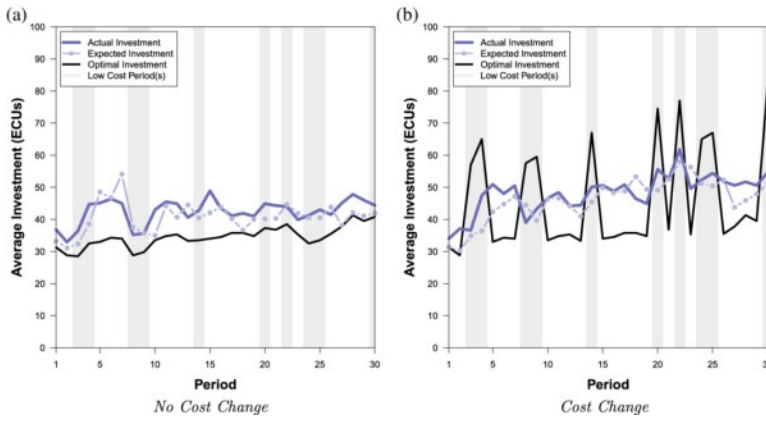


Figure 7 Expectations by period, by treatment [Color figure can be viewed at wileyonlinelibrary.com]

The theory of selective attention provides a possible explanation (Hanna *et al.*, 2014; Schwartzstein, 2014).[25] If attention is costly, important economic variables may be neglected in favor of others that are less informative, but which are more easily noticed. Agents may optimize along more the 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. Figure 4 shows that all of the above information is prominently displayed on participants' decision screens. If participants are selectively attentive 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.[26] We consider the following rules-of-thumb:

"Ignore Cost" Assume the cost parameter always equals 1: $x_t = E_t[M_{t+1}]/4$

"Imitation" Match my rival's lagged investment: $x_t = x'_{t-1}$

"Forecast%" Invest a fixed percentage of the market forecast: $x_t = \lambda E_t[M_{t+1}]$

"Liquidity%" Invest a fixed percentage of liquidity: $x_t = \gamma \phi R_t$

(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 predictive power as heuristics.[27] For comparison purposes, we also consider the optimal investment path (Optimal).

The strategies Optimal and Imitation consider the participant'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 participant's own situation or the exogenous market situation. These latter three heuristics are consistent with

selective attention: the participant 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 and γ from (8) are estimated separately for each participant using ordinary least squares regressions. $Invest_{i,t}$ 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 liquidity in t . Finally, the estimating sample includes Periods 1–30, except for the two *Cost Change* sessions which include 21 and 26 total periods.

Figure 8 shows kernel densities by treatment and participant type for $\hat{\lambda}_i$ (Figure 8a) and $\hat{\gamma}_i$ (Figure 8b). The average values of $\hat{\lambda}_i$ and $\hat{\gamma}_i$ over all participants (denoted $\bar{\lambda}$ and $\bar{\gamma}$) are reported in Table 3. We use Kolmogorov–Smirnov tests to assess whether differences exist in the distributions of $\hat{\lambda}_i$ and $\hat{\gamma}_i$ across *No Cost Change* and *Cost Change*. 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 Change* and *Cost Change* for the distributions of λ estimates ($p = .185$), but there is a difference for the distributions of γ estimates ($p = .086$).

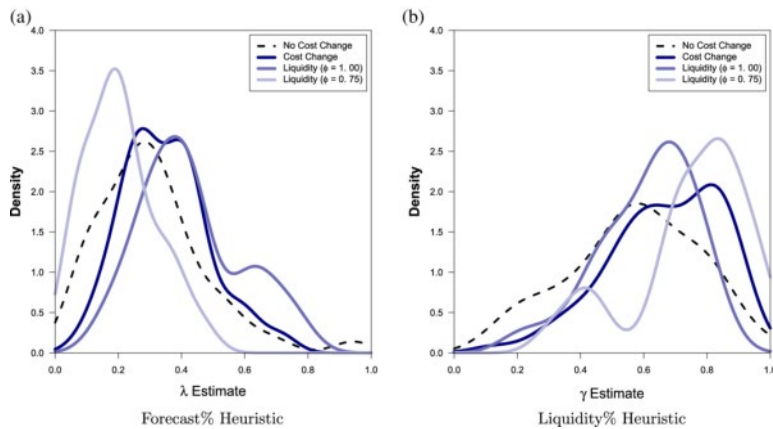


Figure 8 Kernel densities [Color figure can be viewed at wileyonlinelibrary.com]

3 TABLE Heuristic comparison

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

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

^a Relative to optimal investment in *Cost Change*.

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 participants whose lowest RMSE was that strategy is also presented. So, for example, Liquidity% generates the lowest RMSE for 72% (52/72) of *Cost* participants. For each treatment and participant 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 Change* participants invested 57% of their liquidity and that *Cost Change* participants invested 67% of their liquidity each period.

Our analysis leads us to conclude:

3 Result The heuristics *invest a fixed percentage of the market forecast* and *invest a fixed percentage of liquidity* better fit our *No Cost Change* and *Cost Change* 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 participant invested 57% (67%) of their liquidity in *No Cost Change* (*Cost Change*). Because liquidity appears to play a crucial role in our participants' investment decisions, we now report a treatment with asymmetric liquidity constraints.

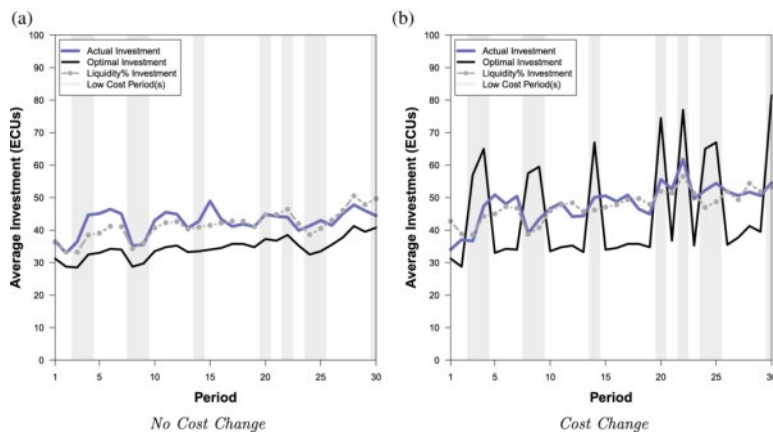


Figure 9 Heuristic investment by period, by treatment [Color figure can be viewed at wileyonlinelibrary.com]

The effect of liquidity on investment

In this section, we consider the effects of exogenous liquidity asymmetry on investment in our experimental environment. In *Liquidity*, one duopolist could invest $1.00R_t$ each period, whereas their rival could only invest $0.75R_t$ each period. The asymmetric liquidity constraints did not preclude participants from investing according to the optimal investment for *Cost Change*, if participants had always previously invested the optimal amount.

While *Liquidity* participants were not informed about the asymmetric constraints on investment in the instructions, market history was reported on their screen. Before data collection, we hypothesized that observed investment would be related to the liquidity constraint (Hypothesis 3). In light of our conclusion that many *No Cost Change* and *Cost Change* participants use the rule-of-

thumb *invest a fixed percentage of liquidity*, we certainly expect a difference in investment across $\phi = 1.00$ participants and $\phi = 0.75$ participants.

Figure 10 shows both average investment over time and average expected investment over time. The solid time series are for actual investment and the dashed investment paths are those predicted by the Liquidity% heuristic (see Table 3). Clearly, $\phi = 1.00$ participants invested more on average than did $\phi = 0.75$ participants. In per period terms, they invested 59.0 ECUs compared to 28.4 ECUs for $\phi = 0.75$ participants.[28] For comparison, *Cost Change* participants invested 47.5 ECUs on average.[29]

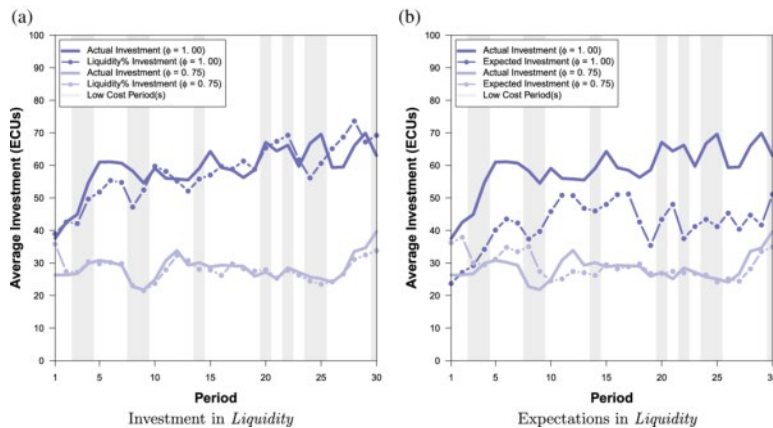


Figure 10 Investment and expectations by period, Liquidity treatment [Color figure can be viewed at wileyonlinelibrary.com]

As we do for our other treatments, we present time series for average expectations in *Liquidity*. Figure 10b shows that $\phi = 1.00$ participants' expectations about their rivals' investment were, on average, good because the dashed line showing $\phi = 0.75$ expected investment tracks $\phi = 0.75$ actual investment very closely (especially after Period 15). However, $\phi = 0.75$ participants consistently underestimated their rivals' investments. On average, they predicted that $\phi = 1.00$ participants 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 $\phi = 1.00$ rival was influenced by their own return.[30]

Table 4 presents estimates of specification (6) (and two additional, simpler specifications) with *Liquidity* data pooled over $\phi = 1.00$ and $\phi = 0.75$ participants. Across the three specifications in Table 4, the response to forecast demand is much lower in magnitude than in *No Cost Change* or *Cost Change*. When we control for the feasibility of the optimal investment level, the estimated coefficient on $\Delta \ln(Cost_t)$ of -0.13 is very close to the -0.15 estimate for *Cost Change*.[31]

4 TABLE Regression results

$\Delta \ln(Invest_{m,t})$	Liquidity		
Constant	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
$\Delta \ln(Forecast_t)$	0.44**	0.50***	0.45**
	(0.19)	(0.18)	(0.17)
$\Delta \ln(Cost_t)$		-0.04	-0.13***

		(0.03)	(0.04)
$\Delta Feasible_{m,t}$			0.13***
			(0.04)
R^2	0.01	0.01	0.03
Observations	804	804	804

Note: Pooled OLS coefficient estimates with Driscoll-Kraay standard errors in parenthesis.

*Statistical significance <.10.

** Statistical significance <.05.

*** Statistical significance <.01.

Table 3 contains *Liquidity* comparisons of the same heuristics previously reported for *No Cost Change* and *Cost Change*. As in those treatments, the *Liquidity%* rule-of-thumb has the lowest average RMSE. Forecast% and *Liquidity%* explain the data roughly as well for $\phi = 1.00$ participants; Forecast% has the lowest RMSE for 10 $\phi = 1.00$ participants, whereas *Liquidity%* has the lowest RMSE for 13 participants. On the other hand, *Liquidity%* has the lowest RMSE for 22 $\phi = 0.75$ participants (92% of all such participants). Because $\phi = 0.75$ participants were liquidity-constrained, this result is hardly surprising.

A Kolmogorov–Smirnov test indicates a significant difference between the distribution of $\hat{\lambda}_i$ for *Liquidity* $\phi = 1.00$ participants and the analogous distribution for *Liquidity* $\phi = 0.75$ participants ($p = .000$; $n_{L1.00} = 24$, $n_{L0.75} = 24$). It also suggests a significant difference in the distribution of $\hat{\gamma}_i$ across participant types ($p = .013$). However, the distribution of $\hat{\lambda}_i$ for $\phi = 1.00$ participants is not significantly different from the distribution of $\hat{\lambda}_i$ for *Cost Change* markets ($p = .106$; $n_C = 36$, $n_{L1.00} = 24$). Nor is the distribution of $\hat{\gamma}_i$ significantly different across *Liquidity* $\phi = 1.00$ participants and *Cost Change* markets ($p = .269$).

This last test result is very interesting. Our *Cost Change* participants and our *Liquidity* participants who were randomly selected for the $\phi = 1.00$ role were from the same participant population and they saw the *exact* same instructions (see Appendix C). 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 Change* participants competed with equally-liquid rivals, whereas $\phi = 1.00$ *Liquidity* participants 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:

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

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

We now summarize our results and conclude.

DISCUSSION AND CONCLUSION

Standard economic theory and business sentiment both tout the virtues of counter-cyclical investment. Yet in an important and well-studied case (research and development investment), observed investment is procyclical. In this paper, we report novel laboratory experiments examining profit-enhancing investment competition over a business cycle, and more generally, exploring how frequent cost changes affect market competition. Our experimental approach lets us investigate these questions in a controlled fashion.

In our *Cost Change* treatment, optimal investment is counter-cyclical immediately following a recessionary period, yet observed investment is decidedly not. On average, our data are better fit by assuming that participants invest a fixed percentage of the market demand forecast or a fixed percentage of their liquidity, than by supposing that they invest according to a game-theoretic investment path. Our participants appear to use investment heuristics, and either do not incorporate the strategic implications of cost changes into their decision-making at all, or do so only modestly.

To further explore the use of heuristics in investment competition, we report a *Liquidity* treatment which is identical to our *Cost Change* treatment in every respect, save for asymmetric liquidity constraints. Our *Liquidity* participants make investment decisions that are consistent with a liquidity-based investment heuristic. Participants who are randomly-endowed with relatively high liquidity invest more than their rivals who are randomly-endowed with relatively low liquidity.

Many industrial organization experiments explore demand shocks and market competition (see Potters and Suetens, 2013), but we are aware of only one other nonauction experiment (Davis *et al.*, 1993) that directly examines the effects of frequent cost changes on market competition. Our paper contributes to the behavioral industrial organization literature (see Ellison, 2006; Armstrong and Huck, 2014; Grubb and Tremblay, 2015) by providing empirical examples of how bounded rationality can affect competition. Our results suggest that profit-enhancing investments may not be chosen in a purely "rational" manner with clear regard for rival investment. In the strategy literature, Porter (1980) terms this a competitive blind spot.

Our environment can be viewed as a sequence of contextualized proportional-prize contests. Because contests and Cournot games are related (see Menezes and Quiggin, 2010), we suspect that our results may generalize to classic Cournot, Bertrand, and Bertrand-Edgeworth markets with frequent cost changes. But this is an open empirical question that we believe deserves future experimental economic attention.

Our data are consistent with results from the experimental contest literature. In all *No Cost Change* periods and in *Cost Change* periods where $\alpha = 1.00$, average observed investment exceeds optimal investment. This is further evidence of "overbidding" in experimental contests—even when the repeated contest is given an explicit investment competition frame, has a stochastic prize, nonconstant effort costs, and a maximum effort constraint that is history-dependent.[32] Additionally, our conclusion that participants employ a liquidity heuristic is in line with previous contest experiments showing a spending heuristic—observed effort increases in the endowment of effort (Sheremeta, 2011; Brookins *et al.*, 2015).

Finally, to the extent that our results are externally valid, they suggest that procyclical investments are a function of competitive blind spots—of agents focusing inward more than outward to determine investments. 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.[33] We offer this conclusion tentatively, because individual agents may use suboptimal investment heuristics, but market competition may select more strategic, more "rational" (though not necessarily optimal) agents for survival (Alchian, 1950).

This is the first experimental research to consider the cyclicity of profit-enhancing investment. Our approach is broad, but our paper suggests a number of intriguing, focused extensions. In particular, with a larger market of four or six participants, will participants that invest strategically take market share away from participants who 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 cyclicity of investment, and of frequent cost changes in competitive environments, are promising avenues for future experimental research.

ACKNOWLEDGMENTS

We thank the Economic Science Institute for funding. For helpful comments, we thank Philip Brookins, Stephen Cole, Joy Buchanan, seminar participants at Ohio University, conference participants at the Economic Science Association and the Southern Economic Association annual meetings, and Shakun Mago and two anonymous referees. We also thank Megan Luetje for help conducting the experiments. Naturally, any errors are our own.

APPENDIX A

In this appendix, we present robustness checks for the regressions results from Tables 2 and 4. We use the same specifications but restrict the estimating samples so that they only include data from the period minima for each treatment, across sessions: 30 periods for *No Cost Change*, 21 periods for *Cost Change*, and 30 periods for *Liquidity*. We also present comparisons between actual market demand and the participants' predictions about market demand, and the time series of average investment for all 83 markets.

TABLE A1 Regression results

$\Delta \ln(Invest_{m,t})$	No Cost Change		Cost Change		
Constant	−0.01	−0.00	0.01	0.01	0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
$\Delta \ln(Forecast_t)$	1.00***	0.91***	1.25***	1.37***	1.37***
	(0.25)	(0.27)	(0.30)	(0.32)	(0.33)
$\Delta \ln(Cost_t)$				−0.06*	−0.13*
				(0.03)	(0.07)
$\Delta Feasible_{m,t}$		0.21**			0.07
		(0.07)			(0.06)
Estimating sample	1–30	1–30	1–21	1–21	1–21
(periods)					

R^2	0.03	0.06	0.04	0.04	0.05
Observations	667	667	720	720	720

Note: Pooled OLS coefficient estimates with Driscoll-Kraay standard errors in parenthesis.

*Statistical significance <.10.

**Statistical significance <.05.

***Statistical significance <.01.

TABLE A2 Regression results

$\Delta \ln(Invest_{m,t})$		Liquidity	
Constant	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
$\Delta \ln(Forecast_t)$	0.43*	0.46**	0.39**
	(0.21)	(0.19)	(0.19)
$\Delta \ln(Cost_t)$		-0.02	-0.11**
		(0.03)	(0.05)
$\Delta Feasible_{m,t}$			0.13***
			(0.04)
Estimating sample	1–30	1–30	1–30
(periods)			
R^2	0.01	0.01	0.03
Observations	696	696	696

Note: Pooled OLS coefficient estimates with Driscoll-Kraay standard errors in parenthesis.

*Statistical significance <.10.

**Statistical significance <.05.

***Statistical significance <.01.

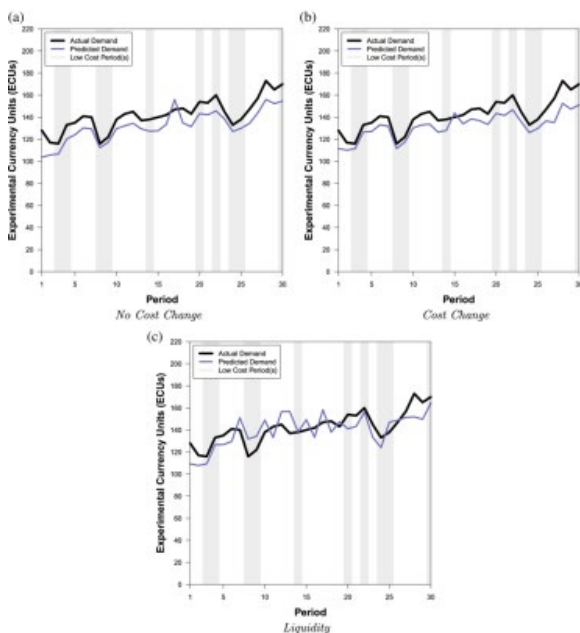


Figure A1 Market demand predictions, by period [Color figure can be viewed at wileyonlinelibrary.com]

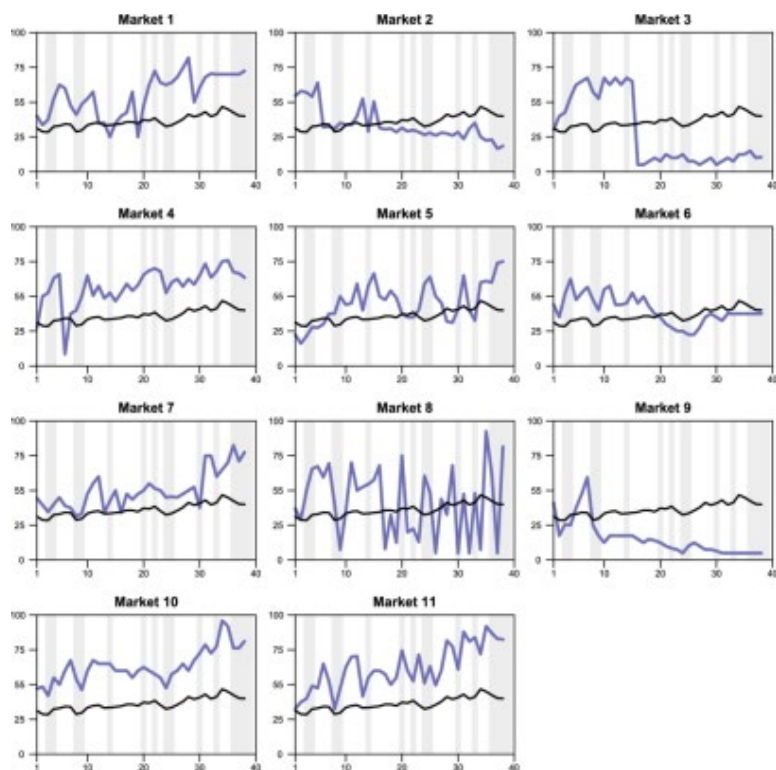


Figure A2 No Cost Change Markets (Session 1) In each subfigure, the vertical axis shows Investment in ECUs and the horizontal axis shows the Period. Average investment is the thicker, lighter line and optimal investment is the thinner, darker line [Color figure can be viewed at wileyonlinelibrary.com]

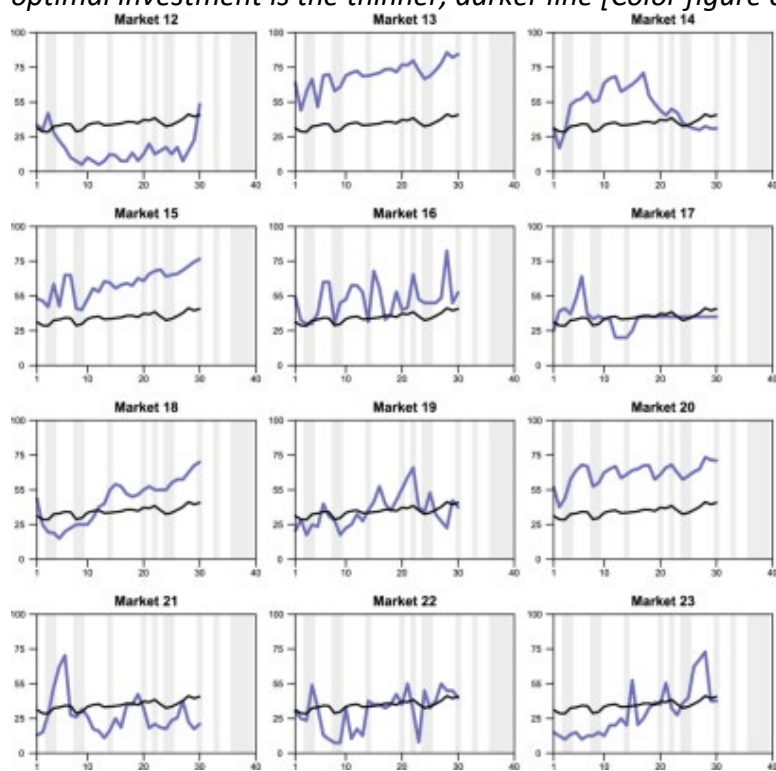


Figure A3 No Cost Change Markets (Session 2) In each subfigure, the vertical axis shows Investment in ECUs and the horizontal axis shows the Period. Average investment is the thicker, lighter line and optimal investment is the thinner, darker line [Color figure can be viewed at wileyonlinelibrary.com]

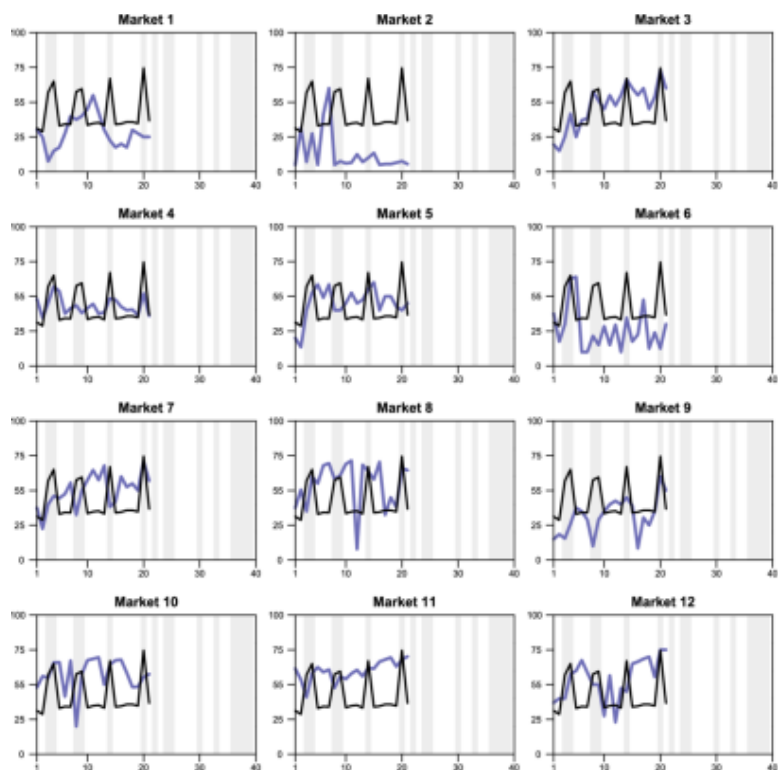


Figure A4 Cost Change Markets (Session 1) In each subfigure, the vertical axis shows Investment in ECUs and the horizontal axis shows the Period. Average investment is the thicker, lighter line and optimal investment is the thinner, darker line [Color figure can be viewed at wileyonlinelibrary.com]

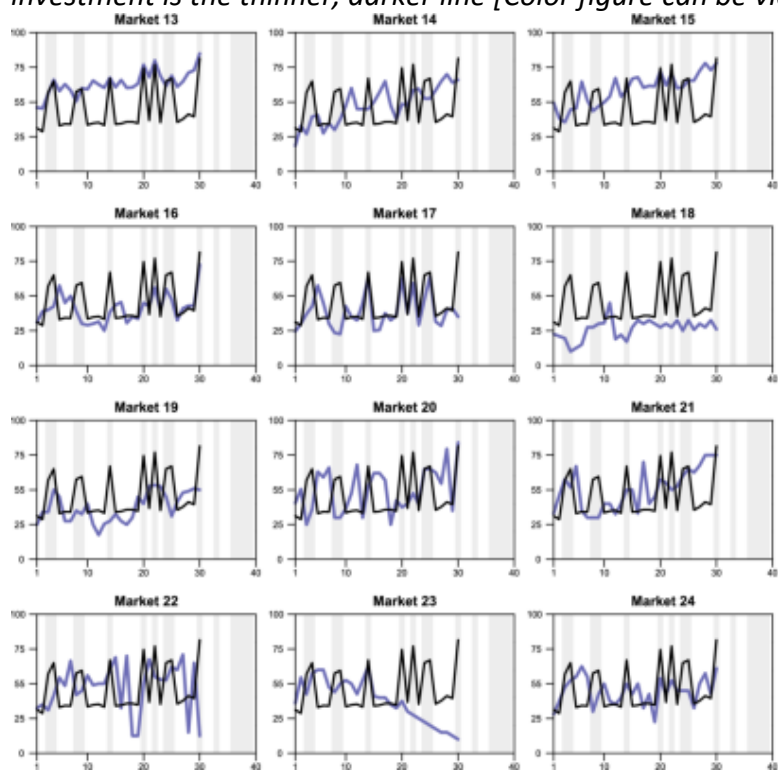


Figure A5 Cost Change Markets (Session 2) In each subfigure, the vertical axis shows Investment in ECUs and the horizontal axis shows the Period. Average investment is the thicker, lighter line and optimal investment is the thinner, darker line [Color figure can be viewed at wileyonlinelibrary.com]

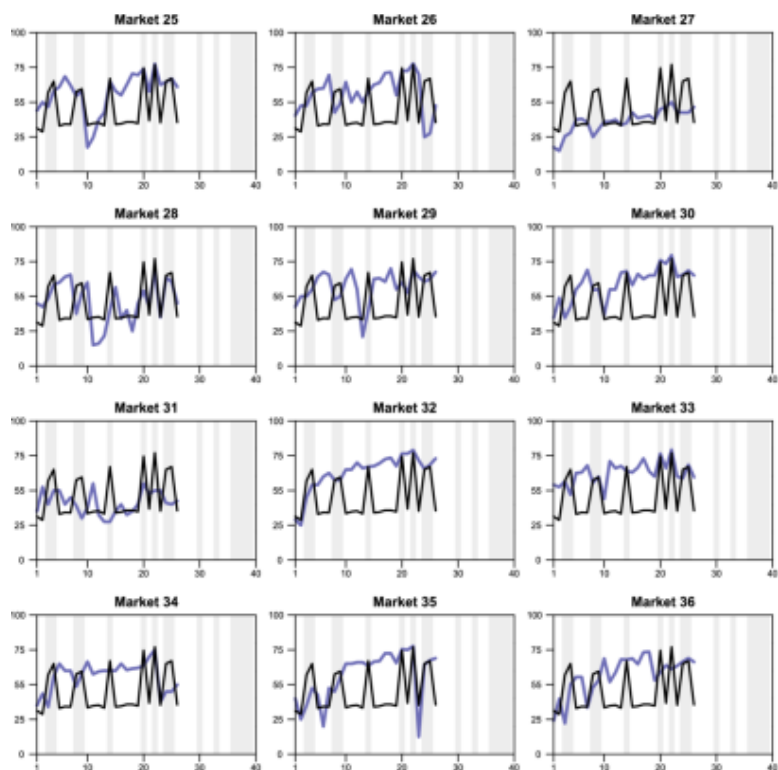


Figure A6 Cost Change Markets (Session 3) In each subfigure, the vertical axis shows Investment in ECUs and the horizontal axis shows the Period. Average investment is the thicker, lighter line and optimal investment is the thinner, darker line [Color figure can be viewed at wileyonlinelibrary.com]

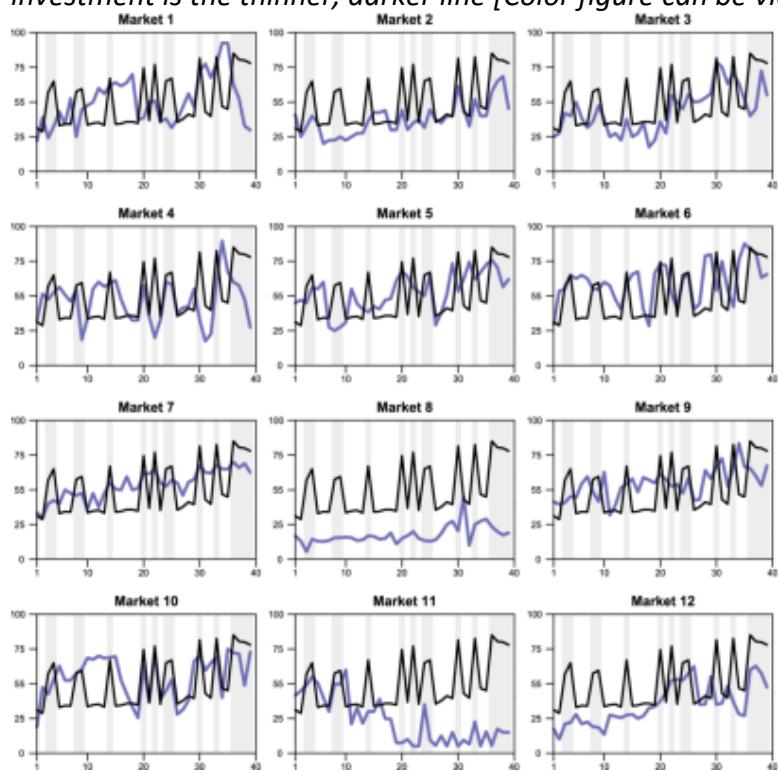


Figure A7 Liquidity Markets (Session 1) In each subfigure, the vertical axis shows Investment in ECUs and the horizontal axis shows the Period. Average investment is the thicker, lighter line and optimal investment is the thinner, darker line [Color figure can be viewed at wileyonlinelibrary.com]

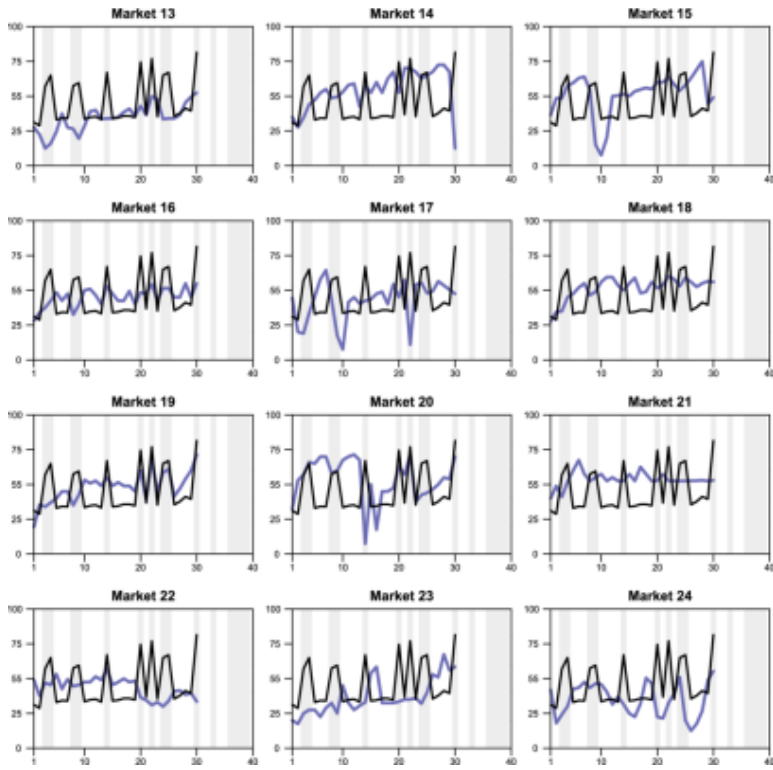


Figure A8 Liquidity Markets (Session 2) In each subfigure, the vertical axis shows Investment in ECUs and the horizontal axis shows the Period. Average investment is the thicker, lighter line and optimal investment is the thinner, darker line [Color figure can be viewed at wileyonlinelibrary.com]

APPENDIX B

In this appendix, we examine optimal and nonoptimal investment strategies assuming that the model in Section 2 is either finitely-repeated or indefinitely-repeated.

Optimal investment when the model is finitely-repeated

When the model in Section 2 is finitely-repeated, we can derive a parameter restriction on market demand (M_t) that must hold so that investing x_t^* in Period t makes it possible (in expectation) to invest x_{t+1}^* in Period $t + 1$. We also report the liquidity endowment necessary for x_1^* to be feasible in Period 1.

As explained in Section 2, symmetric optimal investment in any period between Period 2 and Period $T - 1$ is:

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

(B1)

This optimum is feasible when $x_t^* \leq \phi R_t$ for both firms.

In any Period t between Period 2 and Period $T - 2$, the firm must be able to invest according to Equation (B1). In Period $t + 1$, the firm must also be able to invest according to Equation (B1). So

we must check that, in expectation, investing optimally in Period t will allow the firm to invest optimally in Period $t + 1$. Both of the following inequalities must hold:

$$\begin{aligned} x_t^* &\leq \phi s_t(x_{t-1}^*, x_{t-1}^{*'}) M_t \\ x_{t+1}^* &\leq \phi s_{t+1}(x_t^*, x_t^{*'}) \mathbf{E}_t[M_{t+1}] \end{aligned}$$

When x_t is chosen, $\phi s_t(x_{t-1}^*, x_{t-1}^{*'}) M_t$ is known. If both firms invest x_t^* in Period t , they will split the market in Period $t + 1$. In other words, $s_{t+1}(x_t^*, x_t^{*'}) = 1/2$, or:

$$x_{t+1}^* \leq \left(\frac{\phi}{2}\right) \mathbf{E}_t[M_{t+1}]$$

We can also substitute in for x_{t+1}^* using Equation (B1), so that:

$$\frac{\mathbf{E}_{t+1}[M_{t+2}]}{4\alpha_{t+1}(\Delta M_t)} \leq \left(\frac{\phi}{2}\right) \mathbf{E}_t[M_{t+1}]$$

This becomes:

$$\frac{\mathbf{E}_{t+1}[M_{t+2}]}{\mathbf{E}_t[M_{t+1}]} \leq 2\phi\alpha_{t+1}(\Delta M_t)$$

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

$$\frac{\mu + \rho(\mu + \rho M_t)}{\mu + \rho M_t} \leq 2\phi\alpha_{t+1}(\Delta M_t)$$

Rearranging the above, we get:

$$M_t \geq \frac{\mu + \mu\rho - 2\mu\phi\alpha_{t+1}(\Delta M_t)}{2\rho\phi\alpha_{t+1}(\Delta M_t) - \rho^2}$$

If this condition on the value of the market is satisfied, a firm can (in expectation) invest the optimal amount in any two periods t and $t + 1$ between Period 2 and Period $T - 2$. Given our experimental parameterization, this condition holds in all such periods. In Period 1, both firms can invest optimally because $x_1^* = 31.25$ and both firms are endowed with 64.00 to invest.

Investment strategies when the model is finitely-repeated

In this section, we assume that the model in Section 2 is finitely-repeated. We contrast optimal (mutual best-response) investment and profit with the investments and profits from several alternative strategies. The strategies we consider are:

"Optimal/Optimal Investment": $x_t = x_t' = \frac{\mathbf{E}_t[M_{t+1}]}{4\alpha_t(\Delta M_{t-1})}$

"Cooperative/Cooperative Investment": $x_t = x_t' = \left(\frac{1}{2}\right) \frac{\mathbf{E}_t[M_{t+1}]}{4\alpha_t(\Delta M_{t-1})}$

"Heuristic/Heuristic Investment": $x_t = x_t' = \left(\frac{3}{10}\right) \mathbf{E}_t[M_{t+1}]$

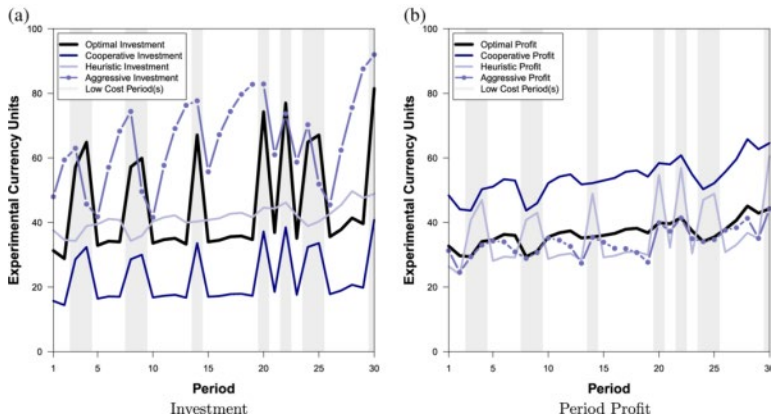
(B2)

"Aggressive/Best-Response Investment": $x_t = \left(\frac{3}{4}\right) R_t$

$$x'_t = \sqrt{x_t \left[\frac{\mathbf{E}_t[M_{t+1}]}{\alpha_t(\Delta M_{t-1})} \right]} - x_t$$

In other words, Cooperative/Cooperative Investment means that both firms invest half of the noncooperative, optimal investment. Heuristic/Heuristic Investment entails both firms investing 30% of expected market demand. Finally, Aggressive/Best-Response Investment assumes that one firm (the "aggressor") invests 75% of their liquidity, while their rival best-responds to this investment. While these four strategies are hardly exhaustive, they illustrate a variety of potential investment profiles.

Each of the four strategies in Equation (B2) is a function of $\mathbf{E}_t[M_{t+1}]$, so we must evaluate this expectation. As in our experiment, we set $M_1 = 128$ and $\mathbf{E}_t[M_{t+1}] = 10 + 0.9M_t$. In this section, we set M_t to be the actual demand path from the experiment. Investments for each of the four strategies are shown in Figure B9a and the resulting period profits are plotted in Figure B9b. For Aggressive Investment, the aggressor's investment and profit are graphed.



B9 Investment and profit by period, by strategy [Color figure can be viewed at wileyonlinelibrary.com]

Note from Figure B9 that Cooperative Investment is always lower than Optimal Investment, which means that cooperative profits are larger than optimal profits. Recall that Heuristic Investment does not depend on the cost parameter, α . For the particular rule-of-thumb we plot (invest 30% of expected market demand), Heuristic Investment [profit] exceeds Optimal Investment [is smaller than optimal profit] in all but the low cost periods, where the reverse is true. Finally, Aggressive Investment is almost always larger than Optimal Investment, so that aggressive profit is almost always smaller than optimal profit.

This section illustrates a few of the many possible strategies in our experiment. In a finitely-repeated setting, only Optimal/Optimal Investment is a mutual best-response. Other strategies with low investment levels, such as Cooperative/Cooperative Investment, result in larger profit than does optimal investment. But on the other hand, Heuristic/Heuristic Investment or an aggressive investment strategy can result in smaller than optimal profit.

Investment strategies when the model is indefinitely-repeated

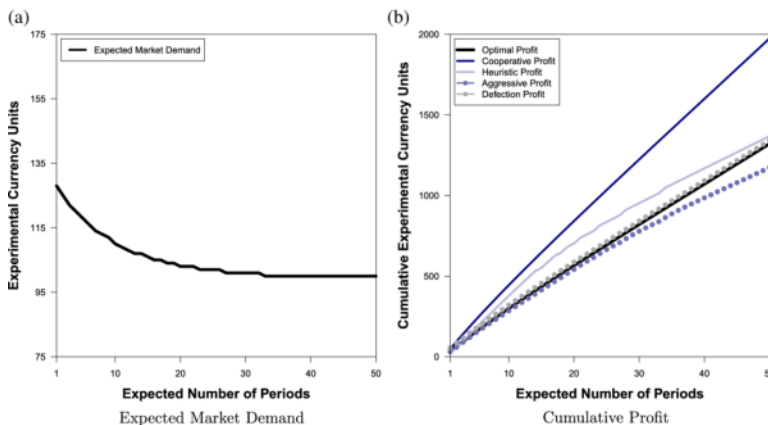
In this section, we assume that the model in Section 2 is indefinitely-repeated. Because participants do not know the total number of experimental periods, it is conceivable that they view their investment decisions as part of an indefinitely-repeated game.

Consider an indefinite-horizon version of our motivating model from Section 2. Instead of the investment game lasting T periods, assume that after each period, there is always a δ chance of another period being played. The expected number of periods in this model is $\tilde{T}(\delta) = \frac{1}{1-\delta}$. Letting $\pi_t(x_t, x'_t)$ denote profit in period t , for a particular continuation probability, δ , cumulative profit is:

$$\text{Cumulative Profit} \equiv \sum_{t=1}^{\tilde{T}(\delta)} \pi_t(x_t, x'_t)$$

(B3)

We examine the same strategies that we did when considering the finitely-repeated model (i.e., the strategies in Equation (B2) in Appendix B). However, we now use the *ex ante* expected path of market demand for $\mathbf{E}_t[M_{t+1}]$. This is a sequence, $\{128, 125, 123, 120, \dots\}$, that converges to 100.[34] Figure B10a shows the path of expected market demand. We note that any one randomly drawn demand path—such as the one we employ in our experiment—need not converge so quickly. The cumulative profit for Optimal/Optimal Investment, Cooperative/Cooperative Investment, Heuristic/Heuristic Investment, and Aggressive/Best-Response Investment (the aggressor's profit is shown) is graphed on the expected experiment length in Figure B10b. In the indefinitely-repeated model, Cooperative/Cooperative Investment is a mutual best-response if both firms adopt the following (grim) trigger strategy: *Invest the cooperative amount in Period 1 and in every period thereafter unless your rival invests more than the cooperative amount, in which case invest the optimal investment amount in every period thereafter*. "Defecting" from cooperation involves investing 29 ECUs in Period 1, and the optimal investment in every period thereafter. The cumulative profit from defecting corresponds to the dashed, Defection Profit line in Figure B10b. Note that this particular cooperative investment is preferred to defection when the expected number of periods exceeds one period.



B10 Indefinitely-repeated model results [Color figure can be viewed at wileyonlinelibrary.com]

This section illustrates that "cooperative" investments can be supported as mutual best-responses when the model in Section 2 is indefinitely-repeated. There are, of course, many alternative "cooperative," "heuristic," and "aggressive" strategies not considered here that are best-responses in the indefinitely-repeated model.[35]

APPENDIX C

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

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. Sixty *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 us 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:

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

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:

$$C = 1.0 \times X$$

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 us denote market demand this period by $M1$, and market demand last period by $M0$. Here is 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, that is, 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 1000 random numbers, the average of these 1000 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.

Footnotes

1. Examples 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. For example, AT&T's [6] annual report notes: "In times of heavy demand for new plant or new methods...it is often necessary to defer work on problems of this kind [fundamental research] and devote energies of the staff to matters of more immediate concern. In periods of reduced activity it is possible to attack vigorously those major problems whose solution will be of great future benefit" (AT&T, [6]).
2. Zajac and Bazerman ([47]) 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?)."
3. The former suggests less investment, the latter more. Identification is even trickier with inter-industry variation in how liquidity hampers R&D investment (Ouyang, [33]).
4. Exogenous shifts in demand have received more attention. For a survey of this work, see Potters and Suetens ([35]).
5. This paper examines both double auction and posted offer markets with demand, supply, and demand-and-supply shifts. Its posted offer "cycling supply" and "trend demand" markets are the most related to the present paper. There is convergence to the competitive equilibrium in the former but not in the latter.
6. Our experiment contains the terms "investment" and "market demand" but not "firm." To review the extent to which our experiment is contextualized, please see Figure 4 and the instructions in Appendix C.
7. The external validity of our data must be judged in light of the reality that decision-making in many firms is complex. But one of the seminal papers in the investment-cyclicality literature (Aghion et al., [1]) models individual entrepreneurs—not firms. We gain insight into the cyclicality of investment from such a model, and we also gain some insight from the interactions of incentivized human participants in a stylized setting.
8. We use a duopoly setting so that we can examine strategic interaction. One can imagine an alternative monopoly setting where a firm chooses an investment level, and their revenue is stochastic but increasing in their investment. In this alternative setting, hypotheses such as "a monopolist will increase their investment when their investment costs decrease" can be analyzed, but strategic interaction cannot. We are not aware of any such experiments.
9. Obviously, the effect of investment in markets may be long-lived. We impose a one-period effect here as the most tractable way of modeling how investment today affects profit tomorrow.
10. This assumption captures the fact that the macroeconomy typically has a delayed effect on investment costs.
11. Market demand must exceed a certain threshold to ensure that this is possible. We derive the appropriate parameter restriction and report the liquidity endowment necessary for x_1^* to be

feasible in Period 1 in Appendix B. Appendix B also examines nonmutual-best-response investment strategies in the finitely-repeated model and considers optimal investment in an indefinitely-repeated version of the model.

12. In general, a variable is said to be cyclical [counter-cyclical] when "deviations from trend [in the variable] are positively [negatively] correlated with deviations from trend in real GDP" (Williamson, [46]).
13. The exchange rate between ECUs and U.S. dollars was 60 ECUs to \$1.00 in all treatments.
14. We wanted the experiment length to be common knowledge and constant across sessions, but we deemed this infeasible after observing the heterogeneity in participant decision time in a pilot session (due to calculator use). If participants view the experiment as an indefinite game, cooperation is possible in theory (see Appendix B), but the data quite clearly reject the notion that participants invest "cooperatively." This suggests that valid concerns about the disconnect between theory and experimental design are not, in fact, a major issue for our results. There are three Cost Change sessions because Session I of Cost Change was relatively short compared to the other sessions. 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.
15. To avoid "deficit spending," participants had to invest at least 5 ECUs each period.
16. Standard tests suggest that multicollinearity is not an issue for specification (6) with our data.
17. We use Feasible instead of a participant's budget because our unit of observation is a market-period, not an individual participant-period.
18. The effect of lowering investment costs by half is 22% of that predicted by our motivating model when we drop the first 10 periods from our estimating sample.
19. Maybe participants did not understand that their rival's costs changed when their own costs changed. If a participant understands that their own costs change, but believes that their rival always has $\alpha = 1.0$, their investment best-response is very similar to the optimal investment path in Figure 3 (the spikes when $\alpha = 0.5$ are only slightly less pronounced) and thus is very different from the actual investment path. We note here that slight departures from the optimal investment path do not explain the observed data either. If one participant in a market is slightly off the optimal path, the other participant should invest very near the optimal path, because the best response curve is flat in the neighborhood of optimal investment.
20. 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 lowering investment costs by half only changes from -0.15 to -0.22 when we drop Periods 1–10 from our estimating sample in Section 4's regression analysis. Moreover, it is not clear whether greater experience leads to more competition (and results closer to the optimal investment path) or to more cooperation in our experimental environment.
21. It is also conceivable that participants were "competitive" during market expansions and "cooperative" during market recessions. We would expect to see counter-cyclical cooperation strategies in No Cost Change if such strategies were employed at all, because coordination would have been easier with α always at unity. But again, average investment in No Cost Change was consistently above optimal investment in both expansions and recessions (see Figure 5a). So there is no support for a counter-cyclical collusion result in the (rough) spirit of Rotemberg and Saloner ([36]). It is possible that the cost change itself triggered cooperative investment (Cost Change participants were "competitive" with $\alpha = 1.0$ but "cooperative"

with $\alpha = 0.5$). However, we find this conjecture far less parsimonious than the heuristic conjecture outlined in Section 4.1.4.

22. Figure A1 in Appendix A shows that in all three treatments, participants' predictions about market demand were not, on average, radically different from actual demand.
23. We estimate \hat{a} and \hat{b} for Periods 3–30. There is not enough data to estimate prior to Period 3.
24. The 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.
25. Of course this theory is preceded by Simon ([41]), Cyert and March ([13]), and Leibenstein ([29]) among others. Related theories of "rational inattention" are also plausible here.
26. Examples of heuristic use by 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 Hall and Hitch, [24]; Hanson, [26]). 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, [32]).
27. Recall that the forecast is $\mathbf{E}_t[M_{t+1}] = 10 + 0.9M_t$.
28. The per period investment figures are averaged over Periods 1–30 since both sessions had at least 30 periods.
29. For Periods 1–30, No *Cost Change* participants earned 28.6 ECUs per period on average. The equivalent figures are 30.1 for *Cost Change*, 44.8 for *Liquidity* $\phi = 1.00$, and 24.6 for *Liquidity* $\phi = 0.75$.
30. Participants with $\phi = 1.00$ actually had an average return of 97.2 ECUs per period.
31. The estimated coefficient on $\Delta \ln(\text{Cost}_t)$ is -0.16 when we drop the first 10 periods from our estimating sample. Optimal investment was feasible for $\phi = 1.00$ [$\phi = 0.75$] participants 91% [37%] of the time. These percentages are driven by the low cost periods where optimal investment was possible 78% [7%] of the time for $\phi = 1.00$ [$\phi = 0.75$] participants.
32. There is robust evidence of overbidding in experimental contests generally (Sheremeta, [40]; Dechenaux et al., [16]). More specifically, Fallucchi et al. ([20]) find overbidding in proportional-prize contests with rival feedback (as we have) and Chowdhury et al. ([12]) report overbidding in proportional-prize contests where the cost of effort is linear in effort (as here).
33. There is recent experimental evidence that CEOs act less strategically (more cooperatively) than otherwise-identical, non-CEOs (Holm et al., [27]).
34. When $\rho < 1$, the autoregressive process $X_t = \mu + \rho X_{t-1} + \varepsilon_t$ is stationary and converges to $\frac{\mu}{1-\rho}$. Given our parameterization ($\mu = 10$ and $\rho = 0.9$) market demand converges to 100.
35. We consider a "Cooperative/Cooperative Investment" strategy of $x_t^*/2$. Many other cooperative strategies involving investments less than x_t^* —including zero investment—are mutual best-responses in the indefinitely-repeated model. However, none of these alternatives appear relevant because the data are always above x^* (on average) when $\alpha = 1.0$.

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