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Credit Cycles: Experimental Evidence

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Non-Technical Summary

This paper reports that credit cycles emerged in laboratory economies that were not hit by aggregate shocks and in which information about fundamentals was perfect.

This main result is in our view puzzling because standard theories predict that no cycles should have occurred in such a basic environment. Subjects could borrow funds in the credit market to invest in the risky project. The equilibrium interest rate was obtained by equalizing credit demand and supply. There were no aggregate shocks, that is, the characteristics of the project and of the environment were kept constant. Furthermore, there was perfect information. The possible outcomes of the project and their probability of occurrence were known to subjects. This rules out a number of explanations according to which cycles might have emerged because of a temporary discrepancy between what investors believed fundamentals were and what they actually were.

The fact that we nonetheless observed cycles in this environment thus calls for an alternative explanation. Our initial conjecture was that unlike in standard theories subjects might display some non-rational traits that have implications on their credit demand. Furthermore, we suspected that the degree of irrationality should have evolved over time to possibly explain the cycles. The remainder of the paper investigates whether there is support for these conjectures.

When studying the individual demand for credit, we indeed uncover a number of well-known behavioral biases. A promising bias to explain credit cycles is the break-even motive. This motive leads individuals to take more risk following larger losses. Consistent with this motive, we observe that the demand for credit increased when a subject made a larger loss in the previous period (controlling for wealth). We find that this motive was also present in the aggregate, that is, the equilibrium interest rate was positively correlated with past average losses in the economy.

The reason this bias is promising to explain credit cycles is that it has non-trivial dynamic implications: losses influence the willingness to take risk which itself influences subsequent losses. We study in further detail this dynamic relationship by introducing a break-even motive in a simple model of investment. We indeed find that the model can predict a credit cycle that very much looks like the one we observed: the equilibrium interest rate initially rises and then declines. We introduce the break-even motive by adding a loss aversion term that decreases with past losses. Starting from initial losses, investors become less loss averse and have a higher demand for credit. This increases the equilibrium interest rate. As a result, average losses further increase and investors become even less loss averse. This explosive path continues until the wealth of investors becomes so low that they cannot bid up anymore due to a collateral constraint. At this point, the interest rate starts decreasing.

We also argue that the additional behavioral traits we document could have contributed to higher risk tolerance and thus to interest rates that are much higher than the expected return of the project. First, we find that subjects increased their credit demand following larger gains, consistent with a house money motive. Second and consistent with the gambler's fallacy, subjects were more likely to report that they believe that the good outcome is going to realize when the bad outcome realized in the previous period even though outcomes were drawn independently across periods. Third, subjects who did not obtain credit subsequently increased their demand for credit. This could stem from a competitive motive to be part of the game. Fourth, an alternative and more rational explanation could be that the risk aversion of subjects initially increased over time because subjects became wealthier on average. However, this is inconsistent with the fact that interest rates were higher than the expected return of the project and thus that average wealth actually decreased.

Finally, we study the role of the market environment in generating credit cycles. Markets may play an important role because they create a complementarity between the behaviour of different investors. When some investors increase their credit demand, they increase the equilibrium interest rate that not only they have to pay but also all the other investors who obtained credit. As a result, average losses will be larger compared to an environment in which this complementarity is absent. Larger average losses will in turn reinforce the desire to break even and will increase the aggregate demand for credit and thus the equilibrium interest rate. We ran an additional treatment called the island economy that essentially removed this complementarity. Subjects reported their demand for credit like in the main treatment and only received some if their bid was higher than the idiosyncratic realization of a random variable. Thus, the realized interest rate in one island had no impact on the other islands. We find that the average interest rates across islands did not fluctuate anymore and remained close to the expected return of the project. These results suggest that the market environment played an important role in the emergence of credit cycles.

Furthermore, these results are in contrast to the view that markets can eliminate behavioral biases. First, we find that the behavioral biases uncovered in the market economy are also present in the island economy. Thus, the absence of credit cycles in the island economy suggests that markets instead amplify irrationality, possibly because of the complementarity described above. Second, we do not find support for the main arguments on which this view is based. The first argument assumes that behavioral biases are random deviations from rationality and thus cancel out in the aggregate. By contrast, some of the behavioral biases we document depend on past outcomes and are to some extent predictable. This implies that outcomes and deviations from rationality co-evolve and can thus follow non-trivial dynamics. The second main argument is that the more irrational investors should eventually be driven out of the market as they accumulate losses. Since the same individuals look more or less rational in different periods depending on their prior outcomes, our results suggest instead that irrationality does not have to disappear from the market.

Credit Cycles: Experimental Evidence*

Sascha Baghestanian† and Baptiste Massenot‡

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Abstract

This paper reports that credit cycles emerged in laboratory economies that were not hit by aggregate shocks and in which information about fundamentals was perfect. This main result is in our view puzzling because standard theories predict that no cycles should have occurred in such a basic environment. Subjects could borrow funds in the credit market to invest in the risky project. The equilibrium interest rate equalized credit demand and supply. Among other behavioral biases, we observe that subjects increased their credit demand when they made larger losses in the previous period, consistent with a break-even motive. We find that a simple model of investment enriched with this motive can predict a credit cycle. We also show that the market environment plays a crucial role for the emergence of the cycle, which suggests that markets amplify rather than eliminate irrationality. Overall, our work implies that not only fundamental but also psychological factors can play a role in the emergence of fluctuations in financial markets.

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1 Introduction

This paper reports that credit cycles emerged in laboratory economies that were not hit by aggregate shocks and in which information about fundamentals was perfect.

This main result is in our view puzzling because standard theories predict that no cycles should have occurred in such a basic environment. Subjects could borrow funds in the credit market to invest in the risky project. The equilibrium interest rate was obtained by equalizing credit demand and supply. There were no aggregate shocks, that is, the characteristics of the project and of the environment were kept constant. Furthermore, there was perfect information. The possible outcomes of the project and their probability of occurrence were known to subjects. This rules out a number of explanations according to which cycles might have emerged because of a temporary discrepancy between what investors believed fundamentals were and what they actually were.

The fact that we nonetheless observed cycles in this environment thus calls for an alternative explanation. Our initial conjecture was that unlike in standard theories subjects might display some non-rational traits that have implications on their credit demand. Furthermore, we suspected that the degree of irrationality should have evolved over time to possibly explain the cycles. The remainder of the paper investigates whether there is support for these conjectures.

When studying the individual demand for credit, we indeed uncover a number of well-known behavioral biases. A promising bias to explain credit cycles is the break-even motive. This motive leads individuals to take more risk following larger losses and was first documented by Thaler and Johnson (1990). Consistent with this motive, we observe that the demand for credit increased when a subject made a larger loss in the previous period (controlling for wealth). We find that this motive was also present in the aggregate, that is, the equilibrium interest rate was positively correlated with past average losses in the economy.

The reason this bias is promising to explain credit cycles is that it has non-trivial dynamic implications: losses influence the willingness to take risk which itself influences subsequent losses. We study in further detail this dynamic relationship by introducing a break-even motive in a simple model of investment. We indeed find that the model can predict a credit cycle that very much looks like the one we observed: the equilibrium interest rate initially rises and then declines. We introduce the break-even motive by adding a loss aversion term that decreases with past losses. Starting from initial losses, investors become less loss averse and have a higher demand for credit. This increases the equilibrium interest rate. As a result, average losses further increase and investors become even less loss averse. This explosive path continues until the wealth of investors becomes so low that they cannot bid up anymore due to a collateral constraint. At this point, the interest rate starts decreasing.

We also argue that the additional behavioral traits we document could have contributed to higher risk tolerance and thus to interest rates that are much higher than the expected return of the project. First, we find that subjects increased their credit demand following larger gains, consistent with a house money motive (Thaler and Johnson, 1990). Second and consistent with the gambler's fallacy, subjects were more likely to report that they believe that the good outcome is going to realize when the bad outcome realized in the previous period even though outcomes were drawn independently across periods (Kahneman and Tversky, 1974). Third, subjects who did not obtain credit subsequently increased their demand for credit. This could stem from a competitive motive to be part of the game. Fourth, an alternative and more rational explanation could be that the risk aversion of subjects initially increased over time because subjects became wealthier on average. However, this is inconsistent with the fact that interest rates were higher than the expected return of the project and thus that average wealth actually decreased.

Finally, we study the role of the market environment in generating credit cycles. Markets may play an important role because they create a complementarity between the behavior of different investors. When some investors increase their credit demand, they increase the equilibrium interest rate that not only they have to pay but also all the other investors who obtained credit. As a result, average losses will be larger compared to an environment in which this complementarity is absent. Larger average losses will in turn reinforce the desire to break even and will increase the aggregate demand for credit and thus the equilibrium interest rate. We ran an additional treatment called the island economy that essentially removed this complementarity. Subjects reported their demand for credit like in the main treatment and only received some if their bid was higher than the idiosyncratic realization of a random variable. Thus, the realized interest rate in one island had no impact on the other islands. We find that the average interest rates across islands did not fluctuate anymore and remained close to the expected return of the project. These results suggest that the market environment played an important role in the emergence of credit cycles.

Furthermore, these results are in contrast to the view that markets can eliminate behavioral biases (Fehr and Tyran, 2005). First, we find that the behavioral biases uncovered in the market economy are also present in the island economy. Thus, the absence of credit cycles in the island economy suggests that markets instead amplify irrationality, possibly because of the complementarity described above. Heemeijer et al. (2009) and Fehr and Tyran (2008) show in different contexts that such complementarity can indeed amplify movements in aggregate outcomes. Second, we do not find support for the main arguments on which this view is based. The first argument assumes that behavioral biases are random deviations from rationality and thus cancel out in the aggregate. By contrast, some of the behavioral biases we document depend on past outcomes and are to some extent predictable. This implies that outcomes and deviations from rationality co-evolve and can thus follow non-trivial dynamics. The second main argument is that the more irrational investors should eventually be driven out of the market as they accumulate losses. Since the same individuals look more or less rational in different periods depending on their prior outcomes, our results suggest instead that irrationality does not have to disappear from the market.

Our work is related to the literature studying credit cycles. Fluctuations in credit markets are typically assumed to be the result of either aggregate shocks (productivity, financial friction, information friction...) or multiple equilibria (Bernanke and Gertler, 1989; Holmstrom and Tirole, 1997; Kiyotaki and Moore, 1997; Eggertsson and Krugman, 2012; Brunnermeier and Sannikov, 2014). We show that fluctuations can arise even in the absence of such shocks and emphasize instead the role of psychological factors. This is reminiscent of the general view that excess optimism can lead to financial manias and subsequent panics (Minsky, 1977; Kindleberger and O'Keefe, 2001; Shiller, 2000). More recently, this view has been successfully formalized in models that depart from rational expectations (Fuster et al., 2010; Gennaioli et al., 2012; Barberis et al., 2016; Bordalo et al., 2016; Adam et al., 2015). The use of the experimental methodology in a very simple setup allows us to uncover additional forces that may be at work in the form of changing risk preferences (Guiso et al., 2013; Cohn et al., 2015). Finally, our results are also in line with the idea that credit booms tend to be followed by crises, which has received recent empirical support (Schularick and Taylor, 2012; Jordà et al., 2013; Mian et al., 2015) and has been formalized in a setup with imperfect information (Gorton and Ordoñez, 2016).

Our work is also related to the experimental asset market literature (Smith et al., 1988). A standard observation in those markets is that asset prices increase well beyond the fundamental value of the asset until they peak and crash. Consistent with this result, the interest rates in our setup also display a boom-bust pattern and also largely exceed the fundamental value of the project. Unlike in asset markets, this result cannot be explained by speculation, that is, by the belief to resell at a higher price. In our setup, speculation is not possible because credit cannot be resold. Our work is more in line with Lei et al.

(2001) who show that asset price bubbles persist when capital gains are not possible.

The remainder of the paper is organized as follows. Section 2 presents a baseline model of investment with no cycles. Section 3 introduces the experimental design. Section 4 presents the results. Section 5 shows that a model augmented with a break-even motive can predict a credit cycle and discusses the role of the market environment. Section 6 concludes the paper.

2 Baseline Model

To motivate the experimental design, we present a simple investment model with no aggregate shocks and perfect information. This model does not predict credit cycles.

We consider an environment with a continuum of risk neutral investors of size 1 and indexed by i. Investors make repeated investments into a risky project at every period $t = 1, 2, ...$ The project generates returns $A_1 > 0$ with probability π and $A_2 < 0$ with probability $1 - \pi$ in each period t, and we denote its expected return by $\bar{A} > 0$. The project returns are independently and identically distributed across periods and agents.

To make investments of size I_t^i in period t, investor i has to take out a one-period loan of the same size, paying a competitive market interest rate r_t. Hence, the agent maximizes:

$$\max_{I_t^i}[(A_1 - r_t)\pi + (A_2 - r_t)(1 - \pi)]I_t^i$$

Loans have to be covered by the investor's collateral C_t^i, which cannot be used directly for investment purposes. Hence, investors are credit constrained:

$$(1 + r_t)I_t^i \leq C_t^i.$$

The exogenous supply of credit is S in every period. Under standard market clearing conditions, we obtain that $\int_0^1 I_t^i di = S$ and $r^* = \bar{A}$ if $(1 + \bar{A})S \leq C_t$, where C_t is the aggregate collateral in the economy. Thus, if supply is sufficiently small compared to collateral, the market interest rate equals the expected return of the project. Whenever $(1 + \bar{A})S \geq C_t$, we obtain $r_t^* = C_t/S - 1$. Hence, if supply is sufficiently large relative to collateral, the interest rate is smaller than the expected return of the project.

Collateral evolves over time and is adapted based on past profits R_t^i. More specifically individual collateral evolves according to the following equation:

$$C_{t+1}^i = C_t^i + R_t^i,$$

with C_0^i initially given. The past profit is equal to $R_t^i = (\hat{A}^i - r_t^*)I_t^i$, where $\hat{A}^i \in \{A_1, A_2\}$ is equal to the realized return for individual i.

The aggregate collateral evolves according to the following equation

$$C_{t+1} = (\bar{A} - r_t^*) \min(C_t, S).$$

If $C_0 \geq (1+r^*)S$, the interest rate is equal to $\bar{A}$ and investors make zero profit on average. Aggregate collateral remains constant and equal to C_0. If $C_0 < (1+\bar{A})S$, the interest rate is lower than $\bar{A}$. Investors make a positive profit on average and aggregate collateral increases over time until this inequality is violated. At this point, the interest rate is equal to $\bar{A}$ and aggregate collateral remains constant and equal to $(1+\bar{A})S$.

3 Experimental Design

The experimental environment closely follows the model above.

Demand for credit. The economy consisted of ten subjects who could invest in a one-period risky project at every period t, where $t = 1, 2, ..., 20$. Payoffs were denoted in Taler. For each Taler invested, the project returned either 2 Taler (100% return) with probability 42% or .5 Taler (-50% return) with probability 58%. The reason probabilities were not simply 50% will be further explained below when we present the belief elicitation procedure. The expected return of the project was thus 13%. Return realizations were independent across subjects and periods.

Each subject i was cashless and thus had to borrow money on the credit market against his collateral C_t^i if he wanted to invest in the project. Every period, subjects reported how much they wanted to borrow I_t^i and the maximum interest rate r_t^i they were willing to pay. Subjects made their demand decisions simultaneously and without observing the decisions of other participants. Their total credit repayment had to be lower than their collateral in every period, that is, they could not default:

$$I_t^i(1 + r_t^i) \leq C_t^i.$$

Equilibrium interest rate. The equilibrium interest rate r_t was determined by equalizing the aggregate demand for credit and the exogenous credit supply S via a centralized call market. Subjects with $r_t^i \geq r_t$ obtained credit while subjects with $r_t^i < r_t$ did not. We implemented several credit supply levels among $S = \{100; 200; 300; 400\}$.

Dynamics. Each subject was initially endowed with collateral $C_0 = 100$. At the end of every period, the subjects who obtained credit made a profit $R_t^i = (\tilde{A}_t^i - r_t)I_t^i$, where $\tilde{A}^i$ refers to the realized return of subject i. The subjects who did not obtain credit made $R_t^i = 0$. At the end of every period, these profits were added or subtracted from collateral:

$$C_{t+1}^i = C_t^i + R_t^i.$$

Beliefs. Additionally, subjects could earn money by providing forecasts about project realizations and interest rates. At the beginning of every period, subjects reported whether they believed that the return will be 100% or -50% in the current period and what they believed the equilibrium interest rate will be. Since the low return was more likely, rational subjects should always have reported −50%. (This explains why we did not pick 50% probabilities for each project outcome.) At the end of every session, we picked three project and interest rate forecasts for every subject for payment purposes. Every accurate project forecast and interest rate forecast that was within a ± 3% bandwidth around the actual interest rate resulted in an additional payment of 15 Taler.[1]

Risk aversion, skills and demographics. We gathered further information on risk aversion, skills and demographics for each subject after market trading was concluded, but before participants learned about their earnings from the main task.

We measured risk preferences using the bomb risk elicitation task developed by Crosetto and Filippin (2013). Subjects had to choose how many boxes to collect from a pile of 36 boxes. For each collected box the subjects earned a monetary payment of 10 Taler. One randomly chosen box contained a bomb. The participant did not know in which box the bomb was located and earned nothing if he collected it. Crosetto and Filippin (2013) show that a subject's decision when to stop collecting is a good proxy for subjects' risk preferences.

Finally, we asked some standard control questions such as gender and age. We also elicited self-reported mathematical skills using a Lickert scale ranging from one to ten.

Procedures. All sessions were conducted at the Frankfurt Laboratory of Experimental Economic Research at Goethe University Frankfurt in the winter of 2014. Subjects were recruited via ORSEE (Greiner, 2003). Each subject participated in one session and played two treatments of 20 periods each. In the first set of experiments we ran 7 sessions varying

[1]The incentives to hedge were minimal given the relatively low potential payoffs from the forecasting exercise in comparison to payoffs subjects could have made in the credit market.

supply on a within-subject basis, controlling for order effects. Credit supply was either 100, 200, 300 or 400. In the second set of experiments, we ran 8 sessions keeping supply constant across the 40 periods but varying the price-setting mechanism on a within-subject basis after 20 periods. The first price-setting mechanism is the market economy (ME) described above. The second mechanism is called the island economy (IE) and will be motivated and described in section 5.2. We controlled for order effects and varied credit supply (100 or 200) on a between-subject basis in the latter set of experiments. Table 1 shows a summary of the treatments for each session.

	Price mechanism		Credit supply	
Session	Periods 1-20	Periods 21-40	Periods 1-20	Periods 21-40
1	ME	ME	100	200
2	ME	ME	200	100
3	ME	ME	100	200
4	ME	ME	200	100
5	ME	ME	200	400
6	ME	ME	400	200
7	ME	ME	200	300
8	ME	IE	100	100
9	ME	IE	100	100
10	ME	IE	200	200
11	ME	IE	200	200
12	IE	ME	100	100
13	IE	ME	100	100
14	IE	ME	200	200
15	IE	ME	200	200

Table 1: Experimental Design Parameters and Characteristics. IE refers to island economy, ME refers to market economy. In the first set of experiments we fixed the price-setting mechanism and varied supply across sets of 20 periods (within subject). In the second set of experiments we fixed supply and varied the price-setting mechanism within subjects after 20 periods.

Ten subjects participated in each session for a duration of approximately 90 minutes. The exchange rate was 30 Taler = 1 Euro. Average earnings per subject were 15.6 Euros including a 5 Euro show-up fee.

After the experimenter read the instructions out loud at the beginning of the experiment, subjects answered a number of control questions to test understanding and played one practice round to familiarize themselves with the environment. Instructions for the elicitation of risk preferences were provided on screen.

Programming was done in z-Tree (Fischbacher, 2007). At the end of the experiment, subjects were called forward one by one and paid privately.

4 Results

4.1 Interest Rates

Figure 1 depicts the evolution of the average equilibrium interest rate conditional on credit supply. Under low supply ($S = 100$), we observed credit cycles. Starting from about 20%, the interest rates increased to about 35 % over the first half of the session and then declined back to about 20% over the second half. Furthermore, the interest rate was overall higher than the expected return of the project (13%). These first results are in contrast to what the model predicts. Provided subjects were risk neutral or risk averse, the interest rate should have stayed constant at less than or equal to 13%.

Under high supply ($S \geq 200$), there were no credit cycles. The interest rate started at about the expected return of the project, quickly decreased and then remained roughly constant over the course of a session. It is not surprising that interest rates were lower with higher supply. A standard model with risk-averse investors would also predict roughly constant interest rates that are below the expected return.

4.2 The Role of Past Profits

To explain these credit cycles, our conjecture was that subjects displayed behavioral traits that had implications on their willingness to take risk and thus on their demand for credit. Furthermore, the degree of irrationality should have moved over time to possibly explain the dynamics of the interest rate.

We first study the determinants of individual credit demand. We measure the credit demand of individual i in period t as $Demand_{i,t} = I_t^i(1 + r_t^i)$, that is, their overall willingness to pay for credit. We also decompose the quantity and price components of this measure as a robustness check.

Based on Thaler and Johnson (1990), we suspect that past profits might influence subsequent credit demand. Past profits are an especially promising candidate to explain credit cycles because they can change over time and provided they have an impact on risk aversion they might contribute to creating interesting dynamics. More specifically, we expect credit demand to increase following both larger losses and larger gains. Investors might indeed increase their willingness to take risk following larger gains because they are gambling with the house money. A break-even motive might also induce them to take more risk following larger losses.

Figure 2 shows the relationship between individual demand for credit and past profit.

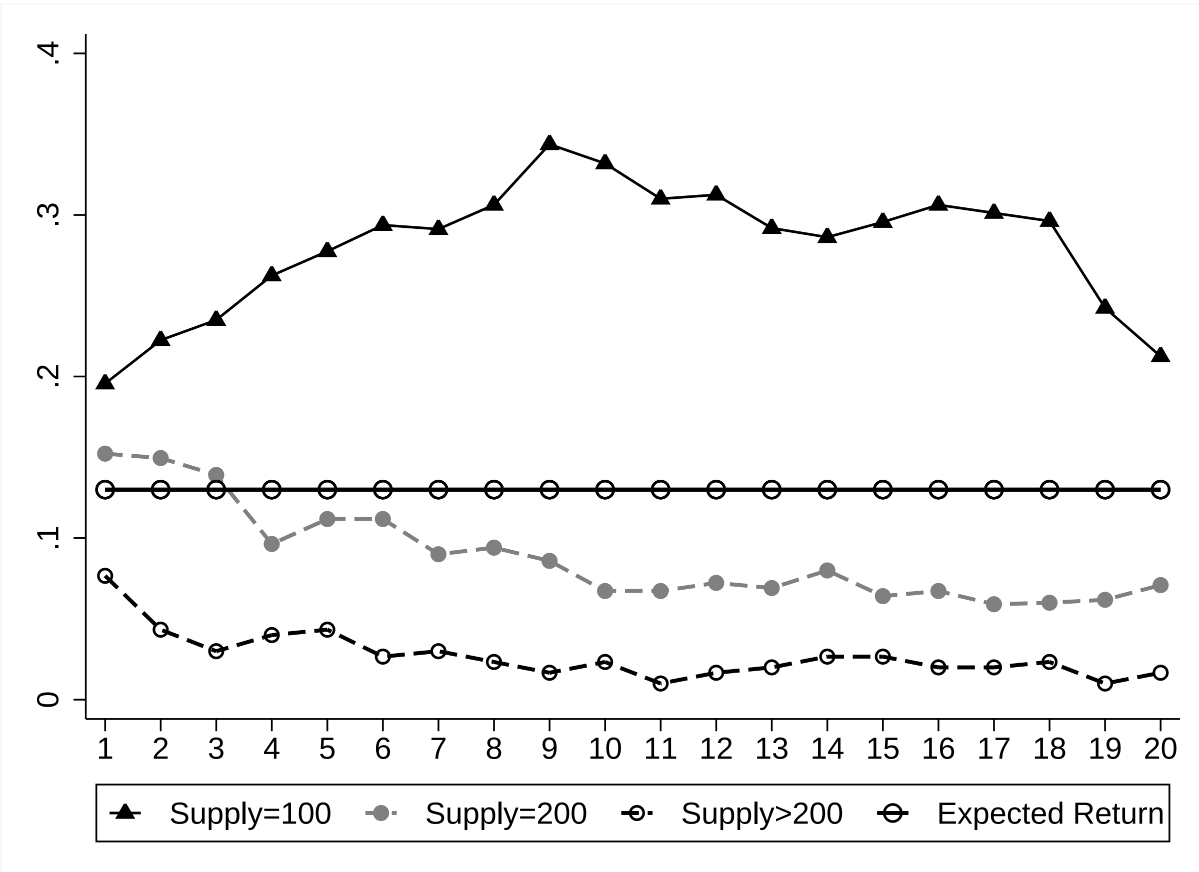

Figure 1: Evolution of equilibrium interest rates

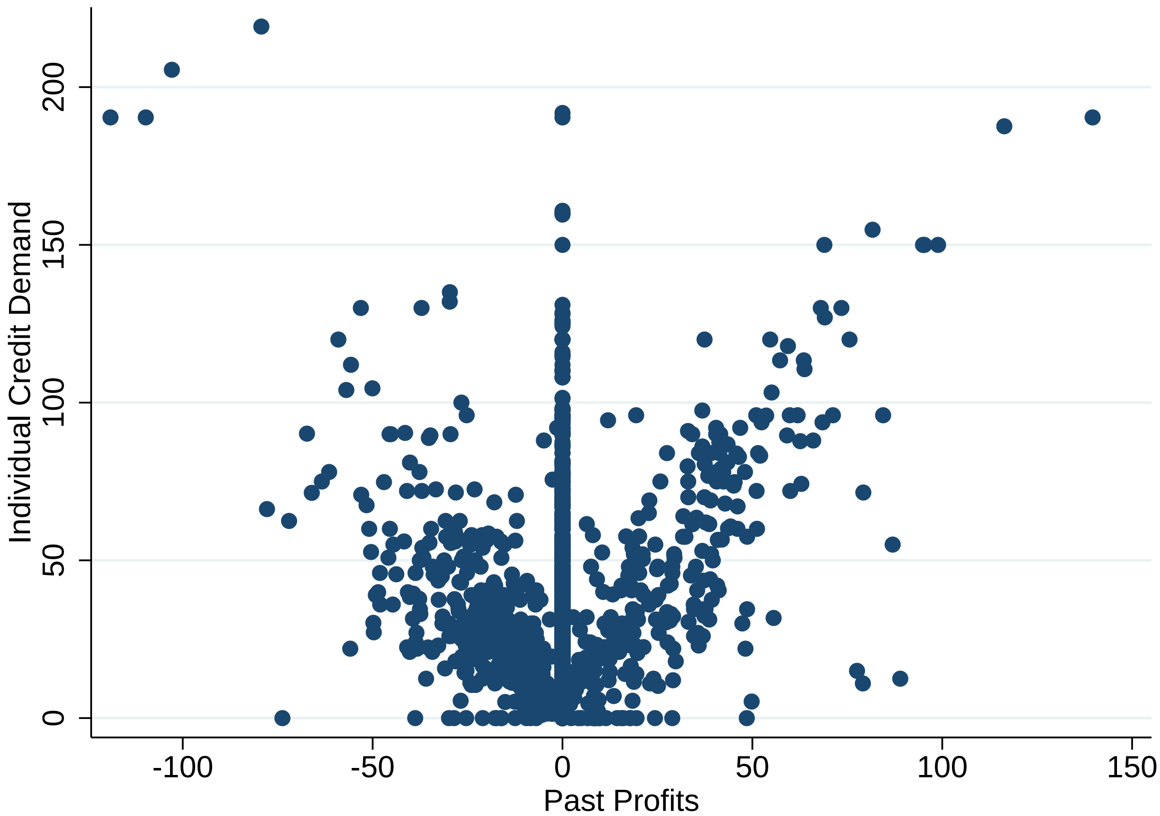

Figure 2: Individual Credit Demand and Past Profits

As expected, the relationship is v-shaped. Both larger prior gains or losses are followed by a higher demand for credit. This is is consistent with both the house money and break-even motives. We also observe a vertical line when subjects made zero profit in the past period. These are the subjects who did not obtain credit in because the interest rate they were willing to pay was not high enough. This suggests that subjects increase their demand for credit when they did not obtain credit in the previous period. This motive could stem from a desire to be part of the game.

To further investigate the significance and robustness of these results, we run regressions of individual credit demand on past losses, past gains, and past zero profit. We also control for collateral, risk aversion, mathematical skills, age, gender, experience, as well as session and supply fixed effects.

The results from these regressions are shown in Table 2. Both larger past losses and gains led to a significantly higher demand for credit. These results confirm the presence of both a break-even and a house-money motive. The results also confirm that subjects who had not participated in the credit market in the previous period and thus made zero profits subsequently increased their demand for credit. As could have been expected, belief in a high return and larger collateral resulted in a higher demand for credit. Experienced subjects had a lower credit demand. Since high interest rates resulted in large losses, subjects might have learned to bid for lower interest rates when they played the game for the second time. The individual characteristics of subjects did not have a significant effect on credit demand. Finally, lower supply also resulted in higher demand for credit (results not reported).

The measure of demand for credit we use in this section consists of both a quantity and price components. We also ran separate regressions for each component (results not reported). The results suggest that the effects documented above work to a larger extent through the quantity demanded, rather than through the interest rate subjects are willing to pay.

We now study whether the effects we document survive in the aggregate, that is, whether they can have an effect on interest rates and thus potentially explain credit cycles. To this end, we run similar regressions as above with the difference that we want to study the effect on the interest rate. The explanatory variables are also averaged over session and period.

The results are shown in Table 4. The interest rates significantly increased following larger average losses. The effect is quantitatively large. An average loss of 50 Taler (50% of the initial collateral) increased the interest rate by at least 15 percentage points. This result confirms the importance of past losses not only at the individual but also at the aggregate level. By contrast, past average gains did not have a significant impact, suggesting that the house-money motive disappeared once taking an aggregate perspective.

We further observe that the interest rate was higher when more subjects believed in a subsequent high return. The effect of beliefs is large in magnitude. If half of the traders hold optimistic beliefs, the interest rate is predicted to increase by five percentage points.

Unsurprisingly, the interest rate increased when credit supply was lower and when average risk aversion was higher. Finally, we find a positive effect of self-perceived math skills. This makes sense if this variable is interpreted as a measure of confidence. Average age also had a positive effect. Gender composition had no significant effect.

4.3 Beliefs

This section presents the results associated with the beliefs about, first, project outcomes and, second, equilibrium interest rates.

	Individual demand for credit			
Past Losses	-0.767***	-0.520***	-0.466***	-0.464***
	(0.217)	(0.0986)	(0.100)	(0.100)
Past Gains	0.567***	0.153**	0.148**	0.146**
	(0.0914)	(0.0739)	(0.0667)	(0.0669)
Zero Past Profit	15.46***	8.160***	7.901***	7.880***
	(2.860)	(1.377)	(1.309)	(1.307)
Inexperience	12.32***	13.98***	12.86***	12.87***
	(2.861)	(2.376)	(2.260)	(2.259)
Collateral		0.174***	0.182***	0.183***
		(0.0306)	(0.0299)	(0.0299)
Optimistic			19.51***	19.54***
			(1.838)	(1.840)
Risk Seeking				0.123
				(0.189)
Skill				-0.947
				(0.682)
Age				-0.323
				(0.246)
Female				1.023
				(2.318)
N	4290	4290	4290	4290

Table 2: **Determinants of individual credit demand.** This Table presents nested random effects models. Standard errors clustered on a individual level are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The left-hand side variable is the individual demand for credit in a period. *Past Losses* are equal to the profits of the previous period if they were negative and zero otherwise. *Past Gains* are equal to the profits of the previous period if they were positive and zero otherwise. *Zero Past Profit* indicates whether the subject made zero profit in the previous period (because he did not obtain credit). *Inexperience* is equal to 1 if subjects play in the first sequence of 20 periods, 0 if they play in the second sequence. *Collateral* refers to the collateral at the beginning of a period. *Optimistic* indicates whether the subject believes the good outcome is going to realize. *Risk Seeking* is equal to the measure of risk tolerance. *Skill* measures the self-perceived math skills (it is discrete and ranges from 1 to 10). *Age* is the age of the subject. *Female* indicates whether the subject is female. Additional controls (not reported) are dummy variables for each credit supply level and session fixed effects.

	Interest rate			
Past Losses	-0.00360**	-0.00358**	-0.00337**	-0.00337**
	(0.018)	(0.020)	(0.037)	(0.037)
Past Gains	-0.00104	-0.000860	-0.000729	-0.000729
	(0.319)	(0.321)	(0.439)	(0.439)
Inexperience	0.112**	0.112**	0.105**	0.105**
	(0.000)	(0.000)	(0.000)	(0.000)
Collateral		-0.000142	-0.000179	-0.000179
		(0.751)	(0.687)	(0.687)
Optimistic			0.109**	0.109**
			(0.001)	(0.001)
Risk Seeking				0.0492**
				(0.000)
Skill				0.0491**
				(0.000)
Age				0.0311**
				(0.000)
Female				0.0875
				(0.549)
N	429	429	429	429

Table 3: **Determinants of Interest Rates**. This Table presents nested random effects models. Standard errors clustered on a within-session level (20 consecutive periods) are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The left-hand side variable is the equilibrium interest rate in a period and session. *Past Losses* are equal to the average profits of the previous period of a session s if they were negative and zero otherwise. *Past Gains* are equal to the average profits of the previous period of a session if they were positive and zero otherwise. *Inexperience* is equal to 1 if subjects play in the first sequence of 20 periods, 0 if they play in the second sequence. *Collateral* refers to the average collateral in a session at the beginning of the period. *Optimistic* is the fraction of subjects in a session who believe the high return is going to realize. *Risk Seeking* is equal to the average measure of risk tolerance elicited in a session. *Skill* measures the average self-perceived math skills of subjects in a session (it ranges from 1 to 10). *Age* is the average age of subjects in a session. *Female* is the fraction of female subjects in a session. The additional controls (not reported) are dummy variables for each credit supply level and session fixed effects.

We asked subjects at the beginning of every period to state whether they believed that the high return or the low return was going to realize this period. Given the distribution of project returns, rational subjects should always have stated that the negative return will realize to maximize their monetary gains. However, we observe that only about 40% of the forecasts were negative.

Next, the results above indicate that credit demand increased when subjects were more optimistic, that is, when they believed in a high return realization. We now study the determinants of these beliefs. We run various regressions to analyze the determinants of beliefs on project returns. We look at the effects of past project realizations. We expect that subjects are more likely to believe in a high return realization when the low return realized in the previous period and vice versa. This would indeed be consistent with the gambler's fallacy (Kahneman and Tversky, 1974). As with credit demand, we also control for the effect of past gains, past losses, zero past profit, inexperience, collateral, the characteristics of subjects, dummy variables for each level of credit supply, and session fixed effects.

Table 4 presents the results. Column 1 shows random effect estimates, column 2 shows estimates using a panel-probit specification and column 3 uses a logit specification. Consistent with the gambler's fallacy, subjects who experienced a low return realization were more likely to believe in a subsequent high return. Since low returns were more frequent by assumption, this could have made subjects more optimistic overall and contribute to explaining the high interest rates. We also find that larger past losses made subjects more optimistic. This suggests that subjects adapted their belief in a way consistent with the break-even motive. Past gains and past zero profit had no significant effect on beliefs. Larger collateral, experience and in some specifications age made subjects more pessimistic. The other characteristics of subjects did not significantly affect beliefs.

We now analyze the data on interest rate beliefs. We use this data to assess the extent to which subjects were able to read the evolution of the interest rate. This is not an obvious exercise since equilibrium interest rates depend in a non straightforward way on the behavior of other subjects. Figure 3 shows the distribution of deviations of forecasts from actual interest rates under low and high supply. Both distributions have their corresponding modes around zero, suggesting that the forecasts were accurate on average. The average forecast deviation was $-.0065$ under low supply and .025 under high supply.

	Optimistic		
	Random Effects	Probit	Logit
Past Outcome	-0.0658**	-0.203***	-0.338***
	(0.0257)	(0.0520)	(0.0871)
Past Losses	-0.00161**	-0.00573**	-0.0108**
	(0.000791)	(0.00241)	(0.00427)
Past Gains	0.000778	0.00241	0.00390
	(0.000825)	(0.00198)	(0.00331)
Past Zero Profit	0.0121	0.0548	0.0901
	(0.0236)	(0.0599)	(0.100)
Inexperience	0.0584*	0.195***	0.323***
	(0.0303)	(0.0582)	(0.0973)
Collateral	-0.000408**	-0.00134***	-0.00227***
	(0.000182)	(0.000395)	(0.000662)
Risk Seeking	-0.00153	-0.00672	-0.0117
	(0.00304)	(0.0120)	(0.0203)
Skill	-0.000949	-0.00173	-0.00240
	(0.0113)	(0.0383)	(0.0649)
Age	0.00669	0.0321**	0.0545**
	(0.00418)	(0.0148)	(0.0252)
Female	0.0252	0.108	0.176
	(0.0467)	(0.153)	(0.259)
N	4290	4290	4290

Table 4: **Determinants of Expected Outcomes**. This table presents nested random effects, probit, and logit models. Standard errors clustered on a individual level are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The left-hand side variable *Optimistic* indicates whether the subject believes that the high return is going to realize. *Past Outcome* is equal to 1 if the return realization of the past period was good, zero otherwise. *Past Losses* are equal to the profits of the previous period if they were negative and zero otherwise. *Past Gains* are equal to the profits of the previous period if they were positive and zero otherwise. *Past Zero Profit* indicates whether the subject made zero profit in the previous period (because he did not obtain credit). *Collateral* refers to the collateral at the beginning of a period. *Inexperience* is equal to 1 if subjects play in the first sequence of 20 periods, 0 if they play in the second sequence. *Risk Seeking* is equal to the measure of risk tolerance. *Skill* measures the self-perceived math skills (it ranges from 1 to 10). *Age* is the age of the individual. *Female* indicates whether the individual is a female. Additional controls (not reported) are dummy variables for each credit supply level and session fixed effects.

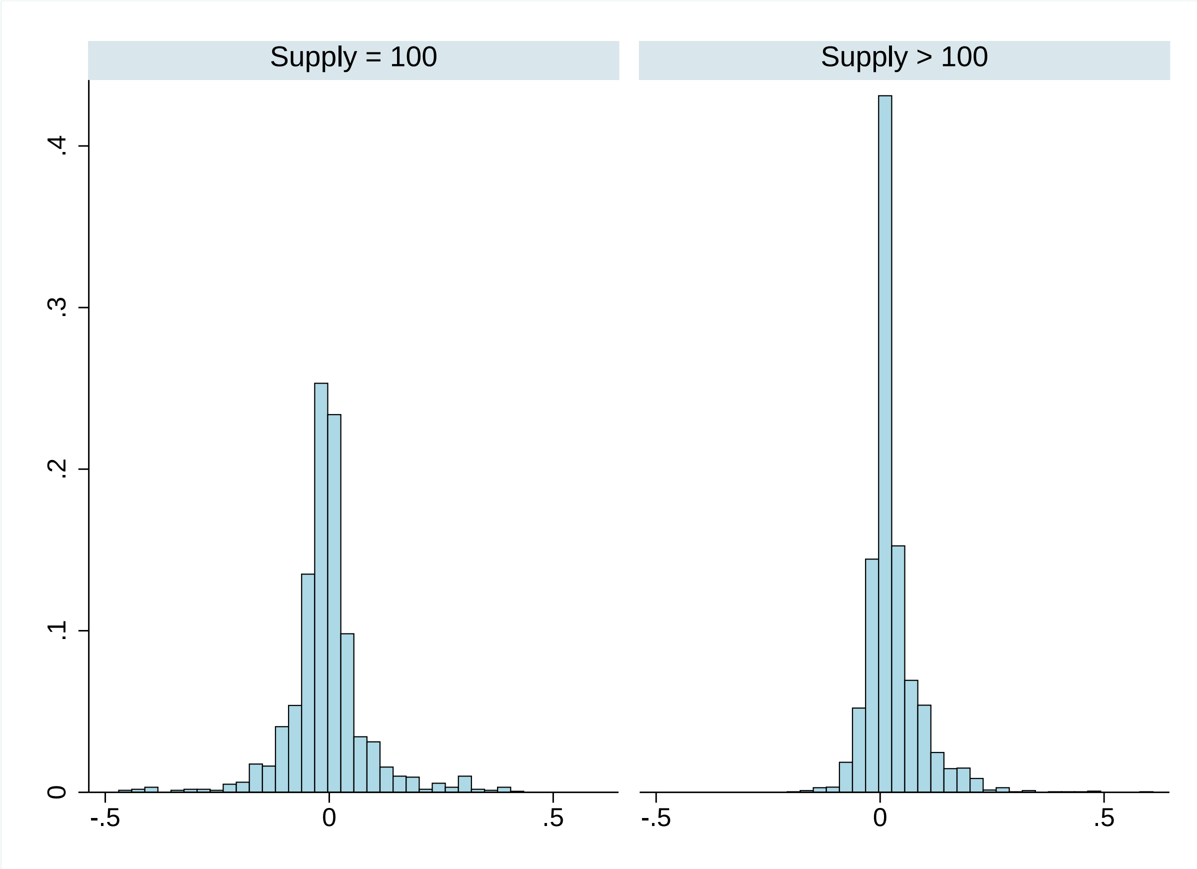

Figure 3: **Interest Rate Forecast Error**. The forecast error is equal to the difference between the interest rate forecast and the realized equilibrium interest rate.

5 Discussion

The most promising behavioral bias explain the credit cycles we observe is the break-even motive because it survives when we look at the aggregate data. Larger average past losses in a session are correlated with larger subsequent interest rates. We show below that once the baseline model is enriched with a break-even motive it can indeed predict a boom-bust cycle in the interest rate. We also found evidence consistent with a house money motive and that could also lead to potentially interesting dynamics, but this effect does not prevail in the aggregate. Finally, subjects increased their credit demand following a negative return realization or when they did not obtain credit in the previous period. These effects could complement the one above by increasing overall risk-taking and explain interest rates that are higher than the expected return.

Another possible channel would be that risk aversion increased when collateral increased which would be consistent with, for example, decreasing relative risk aversion preferences. The implication would be that during the boom part, subjects would accumulate wealth and during the bust their wealth would decrease. This is not consistent with the fact that interest rate were higher than the expected return, and thus that aggregate wealth was decreasing during the boom part. Furthermore, collateral does not predict subsequent interest rates.

Finally, we discuss the role of the market environment on credit cycles to contribute to the debate over whether markets can eliminate irrationality (Fehr and Tyran, 2005). We review the arguments below and run an additional treatment to understand the independent contribution of the market on the credit cycle. Our results suggest that markets amplify rather than eliminate irrationality.

5.1 Augmented Model with a Break-Even Motive

In this section, we show that a simple model of investment in which investors have a break-even motive can generate a credit cycle. The conditions for the cycle to emerge are that credit supply should be low enough, which also consistent with our findings.

The break-even motive asserts that agents become more risk-seeking after facing larger losses. We formalize this idea by assuming that investors attach a weight $\lambda(R_{t-1})$ to their potential losses, where $R_{t-1} = (\bar{A} - r_{t-1})S$ is the average past profit. The function λ is constant and equal to 1 in case of past gains. In case of past losses, it is increasing with the size of these past losses. It is also lower than 1 to reflect the fact that investors take more risk when they previously lost money. Formally, this gives $\lambda' < 0$ and $\lambda < 1$ if $R_{t-1} < 0$ and $\lambda = 1$ if $R_{t-1} \geq 0$.

This weight can be both interpreted as a preference parameter (e.g. varying loss aversion as in Barberis et al. (2001)) or as a weight on the probability. Our experimental evidence is consistent with both interpretations. A loss aversion parameter that is lower than 1 contradicts much of the existing experimental evidence that typically estimates it to be closer to 2. This suggests that the interpretation of this weight as loss aversion parameter might not be the best one or that some characteristics of our environment affected loss aversion. Finally, the model has an important limitation. Ideally, the weight λ should depend on individual rather than average past profit. However, this would require to keep track of the distribution of wealth, which is beyond the scope of the paper. This simplified model keeps a representative agent framework and provides a straightforward illustration of some important forces at work in this environment.

Investors now maximize:

$$\max_{I_t^i}((A_1 - r_t)\pi + \lambda(R_{t-1})(A_2 - r_t)(1-\pi))I_t^i,$$

subject to the same credit constraint as above.

Thus, investors are willing to pay up to:

$$r_t = \tilde{A}(R_{t-1}) = \frac{\pi A_1 + \lambda(R_{t-1})(1-\pi)A_2}{\pi + \lambda(R_{t-1})(1-\pi)} > \bar{A}.$$

If $(1+\tilde{A})S \leq C_t$, aggregate collateral is sufficiently large to accommodate an equilibrium interest rate $r_t^* = \tilde{A}$. If $(1+\tilde{A})S > C_t$, aggregate collateral is too small to absorb the whole credit supply at an interest rate equal to $\tilde{A}$. The equilibrium interest rate becomes equal to $r_t^* = C_t/S - 1$.

Starting from the case $(1 + \tilde{A}(R_{t-1}))S \leq C_t$, the interest rate is equal to $\tilde{A}(R_{t-1})$ and is larger than the expected return of the project. This implies $R_t < 0$. Since from the break-even motive $\lambda' < 0$, investors are willing to pay a higher interest rate than previously and thus $R_t < R_{t-1}$. The interest rate thus increases over time. As losses accumulate, aggregate collateral decreases at the same time. When collateral hits the threshold $(1+\tilde{A})S$, the interest rate $\tilde{A}$ cannot be sustained anymore and has to decrease. At this point, we have $r_t^* = C_t/S - 1$. The interest rate and collateral decrease together. When the interest rate hits $\bar{A}$, the interest rate and aggregate collateral remain constant.

Starting from $(1 + \tilde{A}(R_{t-1}))S > C_t$, the interest rate is lower than $\bar{A}$. Profits are positive and aggregate collateral thus increases. The interest rate also increases until it hits $\bar{A}$. At this point, both collateral and the interest rate remain constant.

Introducing a break-even motive in a simple model of investment can explain the credit cycles. If credit supply is small, interest rates follow a hump-shaped pattern. With interest rates initially above the project's expected return agents accumulate losses, reinforcing their desire to break even. The upward spiral between larger losses, higher interest rates and a greater desire to break even comes to an end once collateral has become sufficiently small. As the collateral constraint starts binding, the interest rate starts decreasing. If credit supply is large, interest rates are low and eventually converge to the expected return from below. This latter prediction is not in line with the observation that with large credit supply interest rates initially decreased and then stayed roughly constant. A possible explanation is that we did not let investors play long enough to accumulate enough collateral for an upward pressure on interest rates to emerge.

5.2 The Role of Markets

Finally, we study the role of the market environment in generating credit cycles. Markets may play an important role because they create a complementarity between the behavior of different investors. When some investors increase their credit demand, they increase the equilibrium interest rate that not only they have to pay but also all the other investors who obtained credit. As a result, average losses will increase compared to an environment in which this complementarity is absent. Larger average losses will in turn reinforce the desire to break even and will increase the aggregate demand for credit and thus the equilibrium interest rate.

We ran an additional treatment called the island economy that essentially removed this complementarity. The only difference with the market economy lied in the mechanism that determined the equilibrium interest rate. As in the main treatment, subjects reported every period how much they wanted to borrow I_t^i and the maximum interest rate r_t^i they were willing to pay. Next, we drew for every subject a uniform random number, u_t^i. Whenever the random number was below r_t^i the subject received the loan and had to pay the interest rate u_t^i. Hence, every subject still reported the maximum interest rate he was willing to pay but unlike in the main treatment the decisions of one subject could not affect the decision of other subjects. Based on the first set of sessions in which we rarely observed interest rates above 50%, we limited the support of u_t^i to be less than or equal to 50%. Subjects were fully informed about the support of u_t^i. Furthermore, the quantity each subject could obtain was bounded above by $S = \{100; 200\}$. We imposed no limits on the individual interest-rate bids and quantities submitted by subjects.

Figure 4 shows the average interest rates paid by subjects in the the island economy. Unlike in the main treatment, interest rates did not fluctuate and remained close to the expected return.[2] The stark difference with the main treatment suggests that the market environment had an impact on credit cycles.

We also study the determinants of credit demand in the island economy to verify whether irrationality was still present at the individual level. We use the same specification as in the main treatment. Table 5 shows the results. We find that the behavioral biases uncovered in the market economy were also present in the island economy. Credit demand increased following larger losses, larger gains, and zero past profit. Optimistic subjects increased their credit demand. The gambler's fallacy was also still at play (results not

[2]Although subjects paid ex-post (on average) an interest rate which corresponds to the expected return, their behavior was not rational. Indeed, given our price-setting mechanism, risk-neutral subjects should always have bid an interest rate of 13%, thereby paying (on average) an interest rate of 6.5% given that the actual interest rate is drawn from a uniform distribution.

reported). The absence of a credit cycle in the island economies thus cannot be explained by the absence of behavioral biases. Subjects were driven by the same motives in both treatments.

Taken together, these results suggest that the market environment played an important role in generating credit cycles, possibly because of the complementarity between the behavior of different investors it created. This result is in line with Heemeijer et al. (2009) and Fehr and Tyran (2008) who show in different contexts that such complementarity can indeed amplify movements in aggregate outcomes. Furthermore, our results suggest that markets do not eliminate irrationality (Fehr and Tyran, 2005). We indeed do not find support for the arguments on which this view is based. First, we do not find that behavioral biases can be seen as some random deviations from rationality and thus cancel out in the aggregate. Instead, some of the behavioral biases we document depend on past outcomes and are to some extent predictable. This implies that outcomes and deviations from rationality co-evolve and can thus follow non-trivial dynamics. Second, irrational investors do not have to be driven out of the market as they accumulate losses. The reason is that the same individuals may look more or less rational in different periods depending on their prior outcomes.

6 Conclusion

We observed credit cycles in laboratory credit markets that were not hit by aggregate shocks and in which information about fundamentals was perfect. Since this result is at odds with the predictions of standard models, we investigated possible explanations that could generate credit cycles. We found that the break-even motive can account for this evidence. Following larger average losses in the economy, the equilibrium interest rate subsequently increased. We then showed that a simple model of investment enriched with this break-even motive could generate a credit cycle. Finally, we showed that the market environment played an important role in the emergence of the credit cycle because it generates a complementarity in the behavior of different investors.

Our work has implications on the origins of fluctuations in financial markets. Most models focus on aggregate changes in fundamentals, like for example financial or information frictions. By contrast, our work suggests that psychological forces might generate fluctuations of their own. While much work has suggested that booms may be the result of overly optimistic investors, we suggest that changing risk preferences may play an additional role, which is in line with the findings of Guiso et al. (2013) and Cohn et al. (2015).

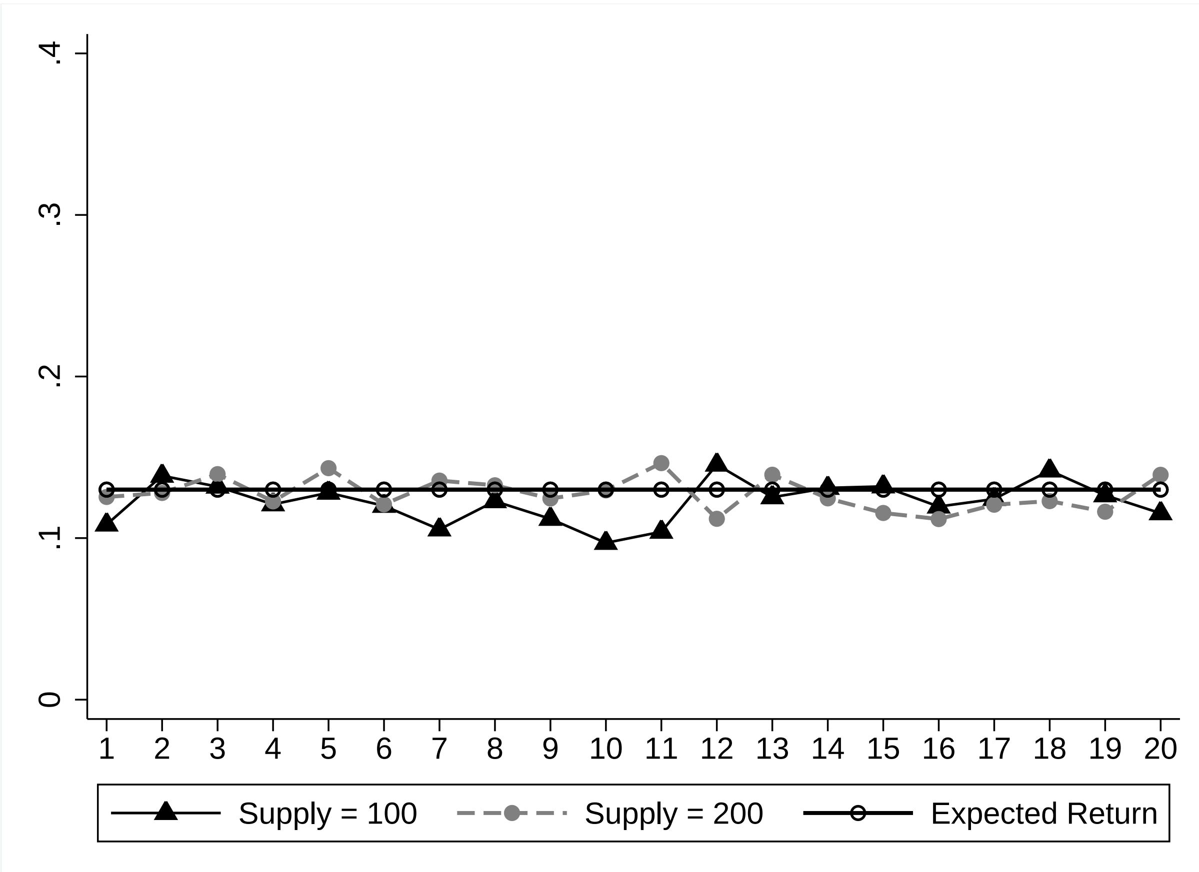

Figure 4: Evolution of average interest rates in the island economy

	Individual demand for credit			
Past Losses	-0.644***	-0.381***	-0.350***	-0.337***
	(0.128)	(0.111)	(0.112)	(0.112)
Past Gains	0.682***	0.256**	0.260**	0.250**
	(0.0972)	(0.109)	(0.109)	(0.109)
Zero Past Profit	16.96***	8.515***	8.953***	8.729***
	(2.777)	(2.154)	(2.094)	(2.111)
Inexperience	-5.878	1.652	3.535	-13.05
	(8.068)	(7.158)	(7.187)	(10.99)
Collateral		0.215***	0.211***	0.211***
		(0.0354)	(0.0345)	(0.0353)
Optimistic			14.62***	14.80***
			(2.002)	(2.008)
Risk Seeking				0.715***
				(0.260)
Skill				0.257
				(0.900)
Age				-0.110
				(0.163)
Female				2.189
				(3.232)
N	1560	1560	1560	1560

Table 5: **Determinants of individual credit demand (island economy).** This Table presents nested random effects models. Standard errors clustered on a individual level are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The left-hand side variable is the individual demand for credit in a period. The right-hand side variables are: *Past Losses* are equal to the profits of the previous period if they were negative and zero otherwise. *Past Gains* are equal to the profits of the previous period if they were positive and zero otherwise. *Zero Past Profit* indicates whether the subject made zero profit in the previous period (because he did not obtain credit).*Inexperience* is equal to 1 if subjects play in the first sequence of 20 periods, 0 if they play in the second sequence. *Collateral* refers to the collateral at the beginning of a period. *Optimistic* indicates whether the subject believes the good outcome is going to realize. *Risk Seeking* is equal to the measure of risk tolerance. *Skill* measures the self-perceived math skills (it is discrete and ranges from 1 to 10). *Age* is the age of the subject. *Female* indicates whether the subject is female. Additional controls (not reported) are dummy variables for each credit supply level and session fixed effects.

Finally, our results suggest that booms are systematically followed by busts. This could have implications on policy since busts might be avoided by exerting corrective action during the boom phase.

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