House of Finance
SAFE
Working Paper Series

Sascha Baghestanian - Baptiste Massenot

# Predictably Irrational: Gambling for Resurrection in Experimental Asset Markets?

SAFE Working Paper No. 104

## Non-Technical Summary

Can the recent extreme events in financial markets be explained by individual irrational behavior? Economists do not have a definite answer to this question. On the one hand, some economists argue that behavioral biases play an important role in financial booms and busts (Shiller, 2000). On the other hand, other economists argue that competitive markets offset these biases. Irrational investors should, indeed, either be driven out of the market as their wealth evaporates or be outweighed by the more rational participants (Fehr and Tyran, 2005).

In order to study whether markets are successful in offsetting individual behavioral biases, we compare the outcomes of experimental financial markets in a standard market economy to a more artificial "island" economy. In the market economy, subjects compete against each other for credit which they can use to invest in a risky project. The equilibrium interest rate ensures that all available credit is allocated. In the island economy, the environment is identical except for market interactions. Instead, subjects report their demand for credit and only receive some if their bid is higher than the realization of a random variable. The allocation mechanism is thus independent from the other participants on the island while it is based on the decisions of the other participants in the market. The comparison of aggregate outcomes between these two environments tells us about the causal impact of an essential feature of competitive markets.

We find substantial differences between market and island outcomes. Market prices display a bubble pattern. They first increase above the fundamental value of the project and then typically crash towards the end of the session. By contrast, average prices across islands closely track the (constant) fundamental value of the project. These results do not support the claim that competitive markets correct individual biases, rather the contrary.

We also find that gambling for resurrection is an important factor to explain these patterns. Empirically, average losses are positively correlated with subsequent prices to a significant extent. Motivated by this evidence, we show that a simple model of investment in which investors suffer from a desire to gamble for resurrection leads to implications consistent with the price patterns we observe. When subjects suffer initial losses on average, a desire to make up for these losses induces them to take even more risk which further increases prices. As a result, further losses accumulate and so does the desire to resurrect. As their wealth evaporates, subjects become more and more constrained and have to decrease their demand at some point. Prices start decreasing as a result.

Gambling for resurrection also nuances the claim that irrational investors will be driven out of the market as they accumulate losses. This claim implicitly assumes that individuals are either always rational or always irrational. However, while investors may have different fixed preferences, the behavioral biases we uncover depend on prior outcomes that are independently distributed across

subjects. This implies that biases are to some extent random and that the same individuals might be more or less rational in different periods. Thus, it may take some time before irrational behavior completely disappears from the market, if ever.

# Predictably Irrational: Gambling for Resurrection in Experimental Asset Markets?*

Sascha Baghestanian† and Baptiste Massenot‡

15th May 2015

**Abstract**

Do markets correct individual behavioral biases? In an experimental asset market, we compare the outcomes of a standard market economy to those of a an island economy that removed market interactions. We observe asset price bubbles in the market economy while prices are stable in the island economy. We also find that subjects took more risk following larger losses, resulting in larger prices and consistent with a gambling for resurrection motive. This motive can translate into bubbles in the market economy because higher prices increase average losses and thus reinforce the desire to resurrect. By contrast, the absence of such a strategic complementarity in island economies can explain the more stable outcome. These results suggest that markets do not correct behavioral biases, rather the contrary.

*We would like to thank Gabriele Camera, Michael Kosfeld, Sergey V. Popov, Ferdinand von Siemens and Anthony Ziegelmeyer for very useful suggestions as well as seminar participants at Queen's university Belfast, the SAFE retreat in Bad Homburg, the macro reading group at Goethe University, the yearly meeting of the micro department of Goethe University in the Kleinwalsertal, the LABSI behavioral and experimental finance workshop in Siena, the experiments in monetary policy workshop in Lyon, the behavioral aspects in macroeconomics and finance conference in Milan, and the HeiKaMax workshop in Mannheim. We gratefully acknowledge research support from the Research Center SAFE, funded by the State of Hessen initiative for research LOEWE.

†Goethe University and SAFE Research Center, baghestanian@econ.uni-frankfurt.de

‡Goethe University and SAFE Research Center, massenot@safe.uni-frankfurt.de

# 1 Introduction

Can the recent extreme events in financial markets be explained by individual irrational behavior? The economics profession does not have a definite answer. On the one hand, some economists argue that behavioral biases play an important role in financial booms and busts [Shiller, 2000]. On the other hand, other economists argue that competitive markets would offset these biases. Irrational investors should indeed either be driven out of the market as their wealth evaporates or be outweighed by the more rational participants [Fehr and Tyran, 2005].

To study whether markets themeselves are successful in offsetting individual behavioral biases, we compare the outcomes of experimental financial markets in a standard market economy to a more artificial "island" economy. In the market economy, subjects compete with each other to obtain credit which they can use to invest in a risky project. The equilibrium interest rate ensures that all the available credit is allocated. In the island economy, the environment is identical with the exception that it removes the market interactions. Subjects report their demand for credit and only receive credit if their bid is higher than the realization of a random variable. The allocation mechanism is thus independent of the other participants in the island while it is based on the decisions of the other participants in the market. Comparing aggregate outcomes between these two environments tells us about the causal impact of an essential feature of competitive markets.

We find that market and island outcomes differ. Market prices display a bubble pattern. They first increase above the fundamental value of the project and then typically crash towards the end of the session. By contrast, average prices across islands closely track the (constant) fundamental value of the project. These results do not support the claim that competitive markets correct individual biases, rather the contrary.

Looking at the individual demands for credit reveals a number of well-known behavioral biases that are present in both the island and the market economies. We find evidence of gambling for resurrection that makes investors take more risk after experiencing larger losses. A house money effect leads investors to take more risk after experiencing larger gains. These two biases were first documented in Thaler and Johnson [1990].[1] We also find that investors suffer from the gambler's fallacy [Kahneman and Tversky, 1974]. They are more likely to forecast a good outcome after experiencing a bad outcome, in spite of outcomes being always independently drawn from the same distribution.

We now come back to our initial question of whether individual irrationality survives or vanishes in competitive markets. Empirically, we find that only gambling for resurrection survives in the aggregate. Average losses are significantly positively correlated with subsequent prices. Motivated by this evidence, we then show that a simple model of investment in which investors suffer from a desire to gamble for resurrection has implications consistent with the price patterns we observe. If subjects make initial losses on average, a desire to make up for these losses

[1] Thaler and Johnson [1990] used the terminology "break-even effect" instead of gambling for resurrection.

induces them to take even more risk, which further increases prices. Losses further accumulate as a result and so does the desire to resurrect. As their wealth evaporates, subjects become more and more constrained and have to decrease their demand at some point. Prices start decreasing as a result.

What specific characteristic of markets can lead to asset price bubbles? Fehr and Tyran [2005] conjectured that even a small amount of irrationality can lead to large deviations from the rational outcome if there is "strategic complementarity" in the behavior of individuals, that is, if an increase of the action of one individual generates an incentive for another individual to also increase his action. Gambling for resurrection in our setup provides a nice example of strategic complementarity. As subjects increase their demand for credit, the interest rate increases and so do average losses and the resurrection motive increases. In the islands, by contrast, these mechanics are absent since the interest rate in one island has no impact on the other islands. The market thus amplifies irrationality. Our work extends earlier references that also emphasized the importance of strategic complementarity for aggregate outcomes [Fehr and Tyran, 2008, Heemeijer et al., 2009].

Gambling for resurrection also nuances the claim that irrational investors will be driven out of the market as they accumulate losses. This claim implicitly assumes that individuals are either rational or irrational forever. While investors may have different fixed preferences, the behavioral biases we uncover depend on prior outcomes that are independently distributed across subjects. This implies that biases are to some extent random and that the same individuals might be more or less rational in different periods. Thus, it may take some time before irrationality completely disappears from the market, if ever.

Our work is related to the experimental asset market literature [Smith et al., 1988]. A standard observation in those markets is that prices indeed increase well beyond the fundamental value of the asset over the first half of the experiment until they peak and crash. While there is some evidence suggesting that such bubbles result from the belief to resell at an inflated price to a "greater fool", there is also a growing consensus that irrational behavior plays an additional role. For instance, Lei et al. [2001] show that even if capital gains are not possible, the standard bubble-crash pattern persists. Our work extends this line of research by pointing out specific behavioral biases that can generate bubbles and by emphasizing the crucial role of the market. Compared to this literature, our setup is more basic to minimize the chance that irrationality may drive market prices. We believe that such a basic environment strengthens the claim that bubbles are generated by behavioral biases. Speculative capital gains are not possible in our setup because assets only last for one period. Return realizations are idiosyncratic rather than aggregate. Aggregate shocks might generate simultaneous and similar behavioral responses which might act as a destabilizing force. By contrast, idiosyncratic shocks increase the chance that behavioral biases will cancel out in the aggregate and thus that aggregate prices will not reflect individual irrational behavior. Our credit market frame might be less loaded with boom-bust pattern associations. The supply of the asset is exogenous. Endogenous supply might indeed amplify price movements if few subjects want to sell when prices are low thus contributing to the boom and many subjects want to sell when prices are high thus precipitating the crash. Exogenous supply rules out these amplifying forces and should make prices more stable. Finally, one-period assets naturally have a constant fundamental value, thus mitigating another potential source of confusion [Kirchler et al., 2012].

A remaining open question is how our results extend to more standard asset market experiments in which assets are longer-lived. Losses become a more complex object in such environments and may not only emerge from relatively low dividend realizations but also from foregone capital gains and actual capital losses. These differences make it more complicated to identify a resurrection motive in a setting with long-lived assets because losses are more difficult to measure. However, losses might still be salient in investors' minds and influence their decisions.

Gambling for resurrection has been shown to have implications in various settings. It may lead banks to invest in unprofitable projects [Rochet, 2009], firms to bid excessively in procurement auctions [Calveras et al., 2004], and leaders to fail to end a war [Downs and Rocke, 1994]. Anecdotally, the founder of FedEx reportedly once saved the company by taking its last \$5,000 and turning it into \$32,000 by gambling in Las Vegas. To the best of our knowledge, we are the first to show that gambling for resurrection can also contribute to the emergence of asset price bubbles.

The remainder of the paper is organized as follows. Section 2 presents the experimental design. Section 3 shows the results. Section 4 provides a simple theoretical framework consistent with the results. Section 5 concludes the paper.

## 2 Experimental Design

**Demand for credit.** Subjects 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 become clear 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. Subjects were credit constrained and could not default. Their total credit repayment had to be lower than their collateral in every period, that is,

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

**Market economy (ME).** Aggregating the individual demands for credit gave the aggregate demand for credit. In ME, 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 $S = \{100; 200; 300; 400\}$.

**Island economy (IE).** To understand the independent contribution of the market environment, we ran a separate IE treatment. A Becker-DeGroot-Marschak mechanism cleared the market. As in ME, subjects reported their individual credit demand every period. 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 ME the decisions of subjects did not affect one another. Based on the pilot 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.

**Dynamics.** Subjects played the game for sequences of 20 periods. Each subject was initially endowed with collateral $C_0$. At the end of every period subjects had to repay their loans together with the corresponding interest rate payment. Profits were either $R_t^i = (\tilde{A}_t^i - r_t)I_t^i$ for subjects who obtained credit, where $\tilde{A}^i$ refers to the realized return of subject $i$, or equal to $R_t^i = 0$ for subjects who did not obtain credit. 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 $-50\%$. 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 $\pm$ 3% bandwidth around the actual interest rate resulted in an additional payment of 15 Taler.[2]

[2] The incentives to hedge loan demands against forecasts and vice versa were minimal given the relatively low potential payoffs from the forecasting exercise in comparison to payoffs subjects could have made in the credit market.

**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 market stage.

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. Another reason to choose this task is that it is easy to explain to subjects.

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.

**Relationship with the asset market experiment literature.** Although we use a credit market frame to reduce associations with boom-bust patterns, the setting is otherwise equivalent to a more standard asset market experiment [Smith et al., 1988] in which assets are short-lived. Project returns can be thought of as dividends and a unit of credit as an asset. Each Taler invested in such an asset can either yield a dividend of 1 Taler (100% return) or generate a loss of -0.5 Taler (-50% return). Unlike typical asset market experiments, assets last for only one period. This rules out the possibility of future capital gains and thus rational speculation. Lei et al. [2001] achieve a similar purpose by preventing subjects from reselling their assets. Our framework further differs along the following dimensions. First, return realizations are independent across subjects rather than correlated. If behavioral biases associated with aggregate dividend shocks drive prices, this increases the chance that behavioral biases will cancel out in the aggregate. Second, credit supply is exogenous. Subjects have no selling decisions to make only buying decisions. This not only rules speculation out but also eliminates some of the amplifying forces that endogenous supply may bring. Few people want to sell when prices are low which helps prices to take off. When prices peak, by contrast, many people want to sell which precipitates the crash. These forces are absent in a setting with exogenous supply. Finally, one-period assets naturally make the fundamental value constant which has been shown to reduce confusion [Kirchler et al., 2012]. These differences to the standard design were motivated by our desire to minimize the chance that irrationality would play a role. In our view, this strengthens the claim that behavioral biases can affect mis-pricing.

**Procedures.** All sessions were conducted at the Frankfurt Laboratory of Experimental Economics at the 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 under the ME treatment varying 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 market clearing mechanism (ME/IE) on a within subject basis after 20 periods. We controlled for order effects and varied supply on a between subject basis in the latter set of experiments. Credit supply was either 100 or 200. The experimental design parameters and a summary of the treatments for each session are illustrated in Table 1.

[Table 1 about here.]

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 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.

# 3 Results

## 3.1 Interest Rates

Figure 1a depicts the ME interest rates conditional on credit supply. Under low supply ($S = 100$), prices are higher than expected returns, tend to build up over the course of the session, and dip towards the end. Interest rates thus exhibit a bubble pattern. Under high supply ($S \geq 200$), prices are generally below expected returns and tend to decrease over time. Figure 1b shows the average prices paid by subjects in the IE treatment. Unlike in ME, interest rates tend to remain close to the expected return.[3]

[Figure 1 about here.]

The market environment thus seems to have a significant impact on interest rates. This has a natural interpretation if some subjects are more optimistic than others. For the moment, we think of optimism as a high willingness to pay but we further investigate its determinants below. When credit supply is small, only the most optimistic subjects obtain credit and this translates into a high equilibrium interest rate. This is in contrast to the high supply treatment. Since credit is abundant, even pessimistic subjects who are willing to pay little receive

[3] Although subjects paid ex-post (on average) an interest rate which corresponds to the expected return, their behavior was not rational. Indeed, given that our price-setting mechanism, subjects should always 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.

credit. Furthermore, even optimists might bid less than their willingness to pay because credit is abundant anyway. The interest rates are intermediate in IE compared to ME because they represent the average willingness to pay of both optimistic and pessimistic subjects. Indeed, subjects do not compete with each other for credit in IE. An alternative interpretation that we further investigate below is that the market environment itself changes the degree of optimism or pessimism of participants.

We complement the qualitative analysis with standard statistical tests. These tests largely confirm the initial findings. For each of the 20 periods, we compute two standard bubble measures commonly used in the literature (Kirchler et al. [2010]). We use the relative deviation $RD = \frac{1}{20}\sum_{t=1}^{20}\frac{r_t - FV}{FV}$ to measure over- and undervaluation and the relative absolute deviation $RAD = \frac{1}{20}\sum_{t=1}^{20}\frac{|r_t - FV|}{FV}$ to measure mis-pricing. Averages and confidence intervals of these measures are depicted in Figures 2 and 3. We observe significant over-valuation in ME under low supply ($p \approx 0$) and significant under-valuation under high supply ($p \approx 0$). RD measures are also significantly different between low and high supply (Kruskal-Wallis (KW)-$p = .001$). The difference in RD across ME and IE is significant under low supply (KW-$p = .007$) and under high supply (KW-$p = .068$), at least at a 10% level. In terms of mis-pricing, we observe significant differences across different supplies within ME ($KW - p = .054$) but not within IE (KW-$p \approx 1$). Comparing RAD across ME and IE we observe significant differences in mis-pricing under low- but not under high supply (KW-$p = .042$ and KW-$p = .36$, respectively).

[Figure 2 about here.]

[Figure 3 about here.]

### 3.2 Determinants of Interest Rates

We now analyze the determinants of market interest rates. The main variable of interest is past profit $\overline{Profits}_{s,t-1}$ averaged across subjects for each session $s$ and period $t$. From Thaler and Johnson [1990], we expect this relationship to be non linear. Following larger losses, subjects want to resurrect and become more risk-seeking. Following larger gains, subjects want to gamble with the house money and also become more risk-seeking. Thus, the relationship between interest rates and past profit is expected to be v-shaped. As a result, we regress interest rates on past average gains $\overline{Profits}^{+}_{s,t-1}$ with a coefficient expected to be positive and past average losses $\overline{Profits}^{-}_{s,t-1}$ with a coefficient expected to be negative.

We also control for average beliefs about project realization $\overline{ProjectBelief}_{s,t}$. Under biased beliefs and the assumption that subjects do not fully understand stochastic processes, we expect that this variable has a positive effect on prices. Optimism should increase demand, thereby increasing prices. We further control for average collateral, risk aversion, age, math skills, as well as gender composition. We also control for experience by introducing a dummy which takes a value of one for the first 20 periods of the experiment. Previous evidence suggests that experience reduces bubbles [Dufwenberg et al., 2005, Haruvy et al., 2007] and hence we expect that the coefficient of this variable is positive. Finally, we include session and supply indicator variables.

The results are shown in Table 2. Columns 1-4 show that prices significantly increase following larger average losses ($p < 5\%$). The effect is quantitatively large. An average loss of 50 Taler (50% of the initial collateral) increases the interest rate by at least 15 percentage points. Past average gains have no significant impact on future prices. These results are consistent with the gambling for resurrection effect but do not support the house money effect at the aggregate level. Column 5 assumes a linear relationship between interest rate and past average profits, that is, it does not separate between positive and negative past profits. The coefficient is negative and significant ($p = .016$).

We further observe that if subjects are on average more optimistic, that is, more of them believe in a subsequent high return, the interest rate increases ($p < 1\%$). This is consistent with the idea that more optimistic investors have a higher demand for credit. The resulting higher aggregate demand increases the market price. The effect of beliefs is large in magnitude. If half of the traders hold optimistic beliefs, prices increase by five percentage points. We further investigate the determinants of beliefs below. Since rational subjects should always report the most likely outcome, that is, the low return, this result also suggests that subjects have difficulties with understanding stochastic processes [Smith et al., 2000, Lei and Vesely, 2009].

We also find that supply has a negative effect on interest rates ($p < 1\%$), consistent with the figures and the non-parametric tests presented above. Average risk-seeking affects interest rates positively ($p < 1\%$). Unsurprisingly, if people are on average more risk seeking, their demand for credit increases and so do prices. Self perceived math skills affect prices positively ($p < 1\%$). This variable could be interpreted as a measure of average confidence, generating a positive pressure on interest rates. Average age also increases prices ($p < 1\%$). Gender composition has no significant effect.

Lastly, we check whether our results also hold on a subset of observations in which credit supply was either 100 or 200. We perform this step since these are also the relevant supplies in IE and we do not want the effects to be driven by prices under a supply of 300 and 400. Column 6 shows that the results are unaffected qualitatively.

Since interest rates in IE are random, a regression similar to the one presented for ME to quantify the determinants of average interest rates would be meaningless. Instead, we focus on the determinants of individual demand in both ME and IE in the next section.

[Table 2 about here.]

### 3.3 Determinants of Demand

We now analyze the individual demand for credit and its determinants. Initially we measure the overall value of the 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.

Figures 5a and 5b show the relationship between individual demand for credit and past profit in ME and IE, respectively. The relationship is v-shaped in both environments: Both larger prior gains or losses are followed by a higher demand for credit. This is is consistent with both the house-money and the gambling for resurrection effects. These two effects are fairly symmetric in IE, indicating that past positive and negative profits have a similar effect on demand. By contrast, credit demand seems to respond more strongly to past losses than to past gains in ME. This could explain why only the gambling for resurrection effect is significant at the aggregate level. Subjects with zero past profit did not obtain credit and subsequently increased their credit demand.

[Figure 4 about here.]

We now further investigate the determinants of credit demand. We run panel regressions of individual demand on the same explanatory variables as with the interest rate but at the individual level: past losses, past gains, beliefs, wealth, risk aversion, mathematical skills, age, gender, experience, as well as session and supply fixed effects. We also include a dummy for zero past profits.

The results from these regressions are shown in Table 3. Columns 1-3 show the results for ME. Both larger past losses and gains lead to a significantly higher demand for credit ($p < 1\%$ and $p < 5\%$, respectively). These results confirm the graphical analysis and suggests the presence of both a gambling for resurrection and a house-money effect. Furthermore, the coefficient on past losses is larger in absolute terms than the coefficient on the house-money effect. An F-test on the equality of the absolute value of both coefficients reveals that we can reject the null hypothesis of equality at a 5% level ($p = .021$). This suggests that the gambling for resurrection effect is stronger than the house money effect on an individual level and this may explain why only past losses remain significant when looking at the aggregate data. We also find that the following factors are associated with a higher individual demand for credit: zero past profits ($p < 1\%$); belief in a high return ($p < 1\%$); larger collateral ($p < 1\%$); belief in a higher interest rate ($p < 1\%$).

Columns 4-6 show the results for IE. Patterns are similar to the market economy with a few exceptions. Comparing ME and IE, we find that the two environments are characterized by similar behavioral traits. In particular, the gambling for resurrection effect and the house-money effects, as well as optimistic beliefs, are present in both market mechanisms. Focusing on the final specifications in columns 3 and 6, we observe no significant differences in terms of gambling for resurrection and house-money effects at the 5% level. Similarly, there are no significant differences in the belief-channel at the 5% significance level. This suggests that these biases are not themselves generated by the market environment.

[Table 3 about here.]

The measure of demand for credit we use in this section consists of both a quantity and interest-rate component. We also investigate the determinants of each individual demand component using a simultaneous equation estimation approach (3SLS) in the Appendix. Although the results are unaffected by this change in estimation procedure, we find that the effects we document below work to a larger extent through the quantity demanded, rather than through the interest rate subjects are willing to pay.

### 3.4 Credit constraints

We now investigate how credit constrained subjects are and how it evolves over the course of the experiment. We compute the ratio of their credit demand using the definition of the previous section to collateral. A higher ratio means that their credit constraint is closer to be binding. We compute the proportion of subjects among those who obtained credit who have a ratio above .7.[4] Figure 5 shows how this measure evolves over time for low and high credit supply. The figure also displays the equilibrium price.

In case of low supply, credit constraints increase over time. This is natural since subjects make losses on average and their collateral thus decreases. As a consequence, they become more and more credit constrained. Interestingly, credit constraints reach their peak shortly after the interest rate peaks. This suggests that the interest rate stops increasing because subjects feel that they are too close to becoming constrained and thus decrease their credit demand. A Kruskall-Wallis test on the fraction of binding constraints before and after the peak under low supply suggests a significant difference at a 1% level. In case of high credit supply, credit constraints are more volatile and it is difficult to identify a pattern.

[Figure 5 about here.]

### 3.5 Determinants of Beliefs

Our results indicate that credit demand increases when subjects are more optimistic, that is, when they believe in a high return realization and when they believe in a higher equilibrium interest rate. In this section, we investigate the determinants of these beliefs.

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

Next, we run various regressions to analyze the determinants of beliefs on project returns. Table 4 presents the results. Columns 1-3 show the results for ME. Column 1 shows random effect

[4] We also varied this threshold value to magnitudes from 0.6 to 0.8, leaving our results –qualitatively– unchanged.

estimates, column 2 shows estimates using a panel-probit specification and column 3 uses a logit specification. We find that larger past losses significantly increase the likelihood that subjects believe in a high return. This suggests that subjects adapt their belief in a way consistent with their desire to resurrect. Furthermore, subjects who experience a high return realization are more likely to believe in a subsequent low return. The sign of the relevant coefficient is negative and significant at a 5% level. This is consistent with the gambler's fallacy [Kahneman and Tversky, 1974]. Finally, we find that more pessimistic beliefs follow larger collateral. In some specifications, older subjects hold significantly more pessimistic beliefs. Experience makes subjects more pessimistic, suggesting that they improve on their ability to understand random processes. Columns 4-6 show the results for IE. Past profits and wealth do not correlate with beliefs anymore. The evidence is still consistent with the gambler's fallacy.

[Table 4 about here.]

We now analyze the data on interest rate beliefs. In principle, it could be that prices in the market economies differ from the island economies simply because subjects are confused. This is natural since this environment is more complex and the outcomes for subjects depend in a non straightforward way on the behavior of other agents. However, we find that price forecasts of our subjects are quite accurate. Figure 6 shows the distribution of nominal deviations of forecasts from actual interest rates under low and high supply. Both distributions have their corresponding modes around zero. The average forecast deviation under low supply is only $-.0065$. We cannot reject the null hypothesis that the average and median forecast deviations per session are zero (t-test: $p = .45$, rank test: $p = .32$). In other words, subjects were aware of the fact that prices are high, predicted them to be high and still pursued their purchasing behavior. Testing forecast accuracies under high supply is more difficult since actual prices reached the lower bound, generating a bias towards rejecting the null hypothesis unless *all* participants did indeed predict interest rates accurately. Nevertheless the mode of forecast distribution is again around zero and the average deviation is .025, still suggesting fairly accurate price forecasts.

[Figure 6 about here.]

# 4 A Simple Investment Model with a Resurrection Motive

To summarize, we find that bubbles can arise in this credit market environment and that larger average losses in the economy lead to higher interest rates, consistent with a gambling for resurrection motive. In this section, we show that a simple model of investment in which investors have such a resurrection motive can generate the boom-bust pattern we observe in the experiments. The conditions for this boom-bust pattern to emerge are that credit supply should be low, also consistent with our findings.

### 4.1 Baseline Model

Along the lines of the experimental design 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 $t = 1, ..., T$. The project generates returns $A_1 > 0$ with probability $\pi$ and $A_2 < 0$ with probability $1-\pi$ in period $t$, and we denote its expected return by $\bar{A} > 0$. We assume that project returns are independently and identically distributed over time and across agents.

To make investments of size $I_t^i$ in period $t$, investor $i$ has to take out one-period loans of the same magnitude, paying a competitive market interest rate $r_t$ given an exogenous supply of credit $S$ in every period. 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:

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

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 previous 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. Previous 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 $(1 + \bar{A})S$.

## 4.2 Gambling for resurrection

Next, we introduce a resurrection motive into the investor's objective function. The gambling for resurrection effect asserts that agents become more risk-seeking after facing larger losses. We formalize this idea by assuming that investors attach a weight $\lambda(R_{t-1})$ on their potential gains, where $R_{t-1} = (\bar{A} - r_{t-1})S$ is the average past profit. To capture a resurrection motive, we further assume $\lambda'(R_{t-1}) < 0$ and $\lambda(R_{t-1}) > 1$ 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. While a weight that depends on individual rather than average past profit would be preferable, 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.[5]

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 resurrection 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

[5] We also ran numerical simulations with heterogeneous agents in which $\lambda$ depended on individual rather than average past profit. Bubble patterns survive in this environment. We omit the presentation of these simulations for the sake of brevity but the results can be made available upon request.

point, both collateral and the interest rate remain constant.

Introducing a resurrection motive in a simple model of investment can rationalize several of our experimental results. If credit supply is small, prices evolve according to a hump shaped pattern. With prices initially above the project's expected return agents accumulate losses, aggravating their desire to break even. The upward spiral between losses, prices and break even motives comes to an end if wealth evaporates sufficiently. As the budget constraint binds prices crash. Importantly, as discussed in the previous sections, we also observe in our data that the fraction of binding budget constraints increases significantly as prices peak in our low supply treatment. Moreover, our data also suggests that the fraction of binding constraints remains high during the subsequent crash. Put differently, we can reconcile various stylized features of our data in our model, after incorporating a resurrection motive. The model also predicts that credit supply has a significant effect on price dynamics. If credit supply is large, prices are low and eventually converge to the expected returns from below. While we indeed observe different price dynamics in our data under different credit supplies, we do not observe convergence from below in our experiments under high supply. Instead, prices tend to stay at the lower bound. However, the latter effect could eventually vanish by increasing the trading horizon.

# 5 Conclusion

Our work provides new insights into the sources of experimental asset price bubbles. First, we show that both the evidence and a simple model suggest that gambling for resurrection can generate bubbles. Second, we show that the market plays a crucial role as it amplifies the resurrection motive because larger prices increase average losses and thus reinforce the resurrection motive. This suggests that markets do not correct behavioral biases. This result is in line with the importance of strategic complementarity in how individual irrationality can have effects on aggregate outcomes.

A remaining unanswered question is how the forces we identify would play in a more realistic asset market in which assets are longer-lived and in which capital gains become possible. The concept of losses becomes more complicated in this environment since they do not only stem from low dividend realizations but also from forgone capital gains or from capital losses. We leave this question for future research.

# References

Nicholas Barberis, Ming Huang, and Tano Santos. Prospect theory and asset prices. *The Quarterly Journal of Economics*, 116(1):1–53, 2001.

Aleix Calveras, Juan-Jose Ganuza, and Esther Hauk. Wild bids. gambling for resurrection in procurement contracts. *Journal of Regulatory Economics*, 26(1):41–68, 2004.

Paolo Crosetto and Antonio Filippin. The bomb risk elicitation task. *Journal of Risk and Uncertainty*, 47(1):31–65, July 2013. ISSN 0895-5646. doi: 10.1007/s11166-013-9170-z.

George W Downs and David M Rocke. Conflict, agency, and gambling for resurrection: The principal-agent problem goes to war. *American Journal of Political Science*, pages 362–380, 1994.

M. Dufwenberg, T. Lindqvist, and E. Moore. Bubbles and experience: An experiment. *American Economic Review*, 95(5):1731–1737, 2005.

Ernst Fehr and Jean-Robert Tyran. Individual irrationality and aggregate outcomes. *Journal of Economic Perspectives*, pages 43–66, 2005.

Ernst Fehr and Jean-Robert Tyran. Limited rationality and strategic interaction: the impact of the strategic environment on nominal inertia. *Econometrica*, 76(2):353–394, 2008.

Urs Fischbacher. z-Tree: Zurich Toolbox for Ready-made Economic Experiments. *Experimental Economics*, 10(2):171–178, 2007.

Ben Greiner. An Online Recruitment System for Economic Experiments. *Forschung und wissenschaftliches Rechnen*, 63:79–93, 2003.

E. Haruvy, Y. Lahav, and C. N. Noussair. Traders' expectations in asset markets: Experimental evidence. *American Economic Review*, 97(5):1901–1920, 2007.

Peter Heemeijer, Cars Hommes, Joep Sonnemans, and Jan Tuinstra. Price stability and volatility in markets with positive and negative expectations feedback: An experimental investigation. *Journal of Economic Dynamics and Control*, 33(5):1052 – 1072, 2009. ISSN 0165-1889. doi: http://dx.doi.org/10.1016/j.jedc.2008.09.009. URL http://www.sciencedirect.com/science/article/pii/S0165188909000293. Complexity in Economics and Finance.

Daniel Kahneman and Amos Tversky. Subjective probability: A judgment of representativeness. In *The Concept of Probability in Psychological Experiments*, pages 25–48. Springer, 1974.

M. Kirchler, J. Huber, and T. Stoeckl. Bubble measures in experimental asset markets. *Experimental Economics*, 13:284–298, 2010.

M. Kirchler, J. Huber, and T. Stoeckl. Thar she bursts: Reducing confusion reduces bubbles. *American Economic Review*, 102(2):865–883, 2012.

V. Lei and F. Vesely. Market efficiency: Evidence from a no-bubble asset market experiment. *Pacific Economic Review*, 14(2):246–258, 2009.

V. Lei, C. N. Noussair, and C. R. Plott. Nonspeculative bubbles in experimental asset markets: Lack of common knowledge of rationality vs. actual irrationality. *Econometrica*, 69(1):831–859, 2001.

Jean-Charles Rochet. *Why are there so many banking crises?: the politics and policy of bank regulation*. Princeton University Press, 2009.

R. J. Shiller. *Irrational Exuberance*. Princeton: Princeton University Press, 2000.

V. Smith, G. L. Suchanek, and A. Williams. Bubbles, crashes, and endogenous expectations in experimental spot asset markets. *Econometrica*, 56(5):1119–1151, 1988.

V. Smith, M. v. Boening, and C. Wellford. Dividend timing and behavior in laboratory asset markets. *Economic Theory*, 16(3):567–583, 2000.

R.H. Thaler and E.J. Johnson. Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management Science*, 36(6):643–660, 1990.

# 6 Appendix

In this section we decompose individual demand for loans into the quantity ($I_t^i$) and interest rate ($r_t^i$) component. We suggest a system of simultaneous equations of the form (variables are defined as above):

$$I_t^i = \alpha_0 + \bar{\alpha} r_t^i + \alpha_1^+ Pr\bar{o}fits_{i,t-1}^+ + \alpha_1^- Pr\bar{o}fits_{i,t-1}^- + \alpha_1^0 Profits_{i,t-1}^0 + \alpha_2 Collateral_{i,t} + \alpha_3 ProjectBelief_{i,t} + ... \tag{1}$$
$$... + \alpha_4 Supply_i + \alpha_5 X_i + \epsilon_i^1 + \eta_{i,t}^1,$$

and

$$r_t^i = \beta_0 + \bar{\beta} I_t^i + \beta_1^+ Pr\bar{o}fits_{i,t-1}^+ + \beta_1^- Pr\bar{o}fits_{i,t-1}^- + \beta_1^0 Profits_{i,t-1}^0 + \beta_2 InterestBelief_{i,t} + \beta_3 ProjectBelief_{i,t} + ... \tag{2}$$
$$... + \beta_4 Supply_i + \beta_5 X_i + \epsilon_i^2 + \eta_{i,t}^2.$$

Note that we assume that $InterestBelief_{i,t}$ only affects the interest rate component and that $Collateral_{i,t}$ primarily affects the quantity component of demand. A Durbin-Wu Hausmann test suggests that we indeed face a simultaneity bias for both our market and the island economies ($p - values < 0.001$ for both), rendering OLS estimates of the parameters in (1) and (2) biased. We therefore use a 3SLS approach to estimate the underlying structural parameters. The results from this estimation, using our market-economy data, are shown in columns (1) and (2) of Table (5). Columns (3) and (4) show the results using data from the island economies.

[Table 5 about here.]

First of all, we observe that quantity and interest rates are positively correlated in both treatments and that the house money and break even effects are primarily driven by adjustments in the size of the loan. As a matter of fact, the structural estimates suggest that subjects adapt offered interest rates into the opposite direction as suggested by the two behavioral biases. But note that this "structural perspective" does not take joint effect of making losses on the offered interest rate into account since the effect of losses on interest rates is not simply given by $\beta_1^-$ but by $\bar{\beta}\alpha_1^- + \beta_1^-$ since quantity and interest rates correlate positively. A similar argument holds for the coefficients which describe previous gains in (1) and (2). The joint effects of previous gains and losses on the individual demand components, estimated via reduced forms of (1) and (2), are given in Table 6. The reduced form coefficients show that previous gains and losses have no significant effect on offered interest rates (they may already be high or low) but rather affect the size of the loan demand and thereby affect the market interest rate. The estimated coefficients, using loan-size as dependent variable, are very similar to the ones presented in the main text in which we use the value of demand as dependent variable.

[Table 6 about here.]

To summarize, independently of whether we look at a summary statistic of individual demand –as in the main text– or if we decompose the demand we observe the house money and the break even effect in the individual data. We again observe an asymmetry of these effects on the size of the loan demanded in ME and a symmetry of these effects in IE. Overall, from a qualitative point of view, the change in estimation strategy has no significant effect on the interpretations provided in the main text and are presented here for the sake of completeness.

# Tables

| First set of experiments | | | | |
|---|---|---|---|---|
| Session | Price mechanism periods 1-20 | Price mechanism periods 21-40 | Supply periods 1-20 | Supply 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 |
| Second set of experiments | | | | |
| Session | Price mechanism periods 1-20 | Price mechanism periods 21-40 | Supply periods 1-20 | Supply periods 21-40 |
| 1 | ME | IE | 100 | 100 |
| 2 | ME | IE | 100 | 100 |
| 3 | ME | IE | 200 | 200 |
| 4 | ME | IE | 200 | 200 |
| 5 | IE | ME | 100 | 100 |
| 6 | IE | ME | 100 | 100 |
| 7 | IE | ME | 200 | 200 |
| 8 | IE | ME | 200 | 200 |
| Subjects p. Session | 10 | | | |
| Taler-Euro | | | | |
| Conversion Rate | 30:1 | | | |

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 market clearing mechanism and varied supply across sequences of 20 periods (within subject). In the second set of experiments we fixed supply and varied the price setting mechanism within subject after 20 periods.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $r_t$ | $r_t$ | $r_t$ | $r_t$ | $r_t$ | $r_t$ (Supply $\leq$ 200) |
| $\overline{Profits}^{+}_{s,t-1}$ | -0.00121 | -0.00110 | -0.00095 | -0.00095 | | -0.00175 |
| | (0.201) | (0.195) | (0.293) | (0.293) | | (0.129) |
| $\overline{Profits}^{-}_{s,t-1}$ | -0.00315** | -0.00315** | -0.00300** | -0.00300** | | -0.00352** |
| | (0.018) | (0.018) | (0.032) | (0.032) | | (0.050) |
| $\overline{Profits}_{s,t-1}$ | | | | | -0.00187** | |
| | | | | | (0.016) | |
| Trend | -0.00201 | -0.00199 | -0.00175 | -0.00175 | -0.00184 | -0.00174 |
| | (0.333) | (0.361) | (0.416) | (0.416) | (0.401) | (0.471) |
| $\overline{Collateral}_{s,t}$ | | -0.0000915 | -0.0000132 | -0.0000132 | 0.00000101 | 0.000343 |
| | | (0.838) | (0.769) | (0.769) | (0.826) | (0.948) |
| $\overline{ProjectBelief}_{s,t}$ | | | 0.102*** | 0.102*** | 0.102*** | 0.114*** |
| | | | (0.005) | (0.005) | (0.005) | (0.003) |
| Risk Seeking | | | | 0.0481*** | 0.0465*** | 0.0462*** |
| | | | | (0.000) | (0.000) | (0.000) |
| Skill | | | | 0.0458*** | 0.0458*** | 0.0313 |
| | | | | (0.003) | (0.008) | (0.197) |
| Age | | | | 0.0307*** | 0.0302*** | 0.0303*** |
| | | | | (0.000) | (0.000) | (0.000) |
| Gender | | | | 0.121 | 0.171 | 0.132 |
| | | | | (0.438) | (0.270) | (0.465) |
| Inexperience | 0.114*** | 0.114*** | 0.107*** | 0.107*** | 0.110*** | 0.118*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Supply200 | -0.211*** | -0.209*** | -0.207*** | -0.207*** | -0.206*** | -0.206*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Supply300 | -0.132*** | -0.128*** | -0.119*** | -0.119*** | -0.116*** | |
| | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) | |
| Supply400 | -0.295*** | -0.291*** | -0.281*** | -0.281*** | -0.279*** | |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | |
| Session FE | yes | yes | yes | yes | yes | yes |
| $N$ | 429 | 429 | 429 | 429 | 429 | 370 |
| $R^2$ | 0.77 | 0.77 | 0.78 | 0.78 | 0.78 | 0.76 |

$p$-values in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 2: **Determinants of Market Interest Rates**. This Table presents nested random effects models. Standard errors are clustered on a within-session level (20 consecutive periods). The left-hand side variable is the market interest rate, $r_{s,t}$, in period $t$ and session $s$. The right-hand side variables are: $\overline{Profits}^{+}_{s,t-1}$, is a vector which contains average positive profits from the previous period of session $s$, if positive average profits were observed in session $s$ in the previous period and is zero otherwise. $\overline{Profits}^{-}_{s,t-1}$, is a vector which contains average negative profits from the previous period of session $s$, if negative average profits were observed in session $s$ in the previous period and is zero otherwise. $\overline{Profits}_{s,t-1}$ is a vector which contains average profits (positive and negative) from the previous period of session $s$. $\overline{Collateral}_{s,t}$ is the average collateral at the beginning of period $t$ of session $s$. $\overline{ProjectBelief}_{s,t}$ is the average project belief in session $s$, given at the beginning of period $t$ (before interest rates are realized). Risk Seeking is a vector, which contains the average measure of risk aversion elicited in session $s$ - the higher the measure the more risk seeking the subjects in a given session. Skill is a discrete variable, ranging from 1 - 10, which measures the average self perceived math skills of subjects who participated in session $s$. Age is the average age of subjects in session $s$. Gender is the average fraction of female subjects in session $s$. SupplyX is a dummy variable which takes the value of 1 if the supply in session $s$ has been X. Session FE indicates that we included dummy variables for individual sessions.

| | (1) ME | (2) ME | (3) ME | (4) IE | (5) IE | (6) IE |
|---|---|---|---|---|---|---|
| $Profits^{+}_{i,t-1}$ | 0.150** | 0.146** | 0.127** | 0.245** | 0.250** | 0.252** |
| | (0.0741) | (0.0669) | (0.0642) | (0.109) | (0.109) | (0.109) |
| $Profits^{-}_{i,t-1}$ | -0.517*** | -0.464*** | -0.430*** | -0.368*** | -0.337*** | -0.335*** |
| | (0.0983) | (0.100) | (0.105) | (0.111) | (0.112) | (0.112) |
| $Profits^{0}_{i,t-1}$ | 8.130*** | 7.880*** | 7.060*** | 8.268*** | 8.729*** | 8.716*** |
| | (1.377) | (1.307) | (1.346) | (2.169) | (2.111) | (2.114) |
| $Collateral_{i,t}$ | 0.175*** | 0.183*** | 0.188*** | 0.216*** | 0.211*** | 0.210*** |
| | (0.0307) | (0.0299) | (0.0295) | (0.0363) | (0.0355) | (0.0351) |
| Risk Seeking | 0.0905 | 0.123 | 0.112 | 0.594** | 0.715*** | 0.717*** |
| | (0.199) | (0.189) | (0.191) | (0.286) | (0.260) | (0.258) |
| Skill | -0.966 | -0.947 | -0.970 | 0.381 | 0.257 | 0.299 |
| | (0.664) | (0.682) | (0.689) | (0.856) | (0.900) | (0.889) |
| Age | -0.196 | -0.323 | -0.330 | 0.0394 | -0.110 | -0.098 |
| | (0.246) | (0.246) | (0.259) | (0.153) | (0.163) | (0.163) |
| Gender | 1.480 | 1.023 | 1.002 | 3.901 | 2.189 | 2.330 |
| | (2.351) | (2.318) | (2.353) | (3.260) | (3.232) | (3.213) |
| Supply200 | -10.68*** | -10.44*** | -4.954** | -12.23 | 0.276 | -3.363 |
| | (2.758) | (2.671) | (2.376) | (12.66) | (11.92) | (12.64) |
| Supply300 | -9.815** | -8.699* | -4.309 | | | |
| | (5.002) | (4.468) | (4.589) | | | |
| Supply400 | -18.21*** | -16.80*** | -9.307** | | | |
| | (5.010) | (4.882) | (4.578) | | | |
| Inexperience | 14.00*** | 12.87*** | 9.691*** | -9.081 | -13.05 | -16.38 |
| | (2.376) | (2.259) | (2.154) | (10.96) | (10.99) | (11.33) |
| $ProjectBelief_{i,t}$ | | 19.54*** | 19.26*** | | 14.80*** | 14.89*** |
| | | (1.840) | (1.830) | | (2.008) | (2.004) |
| $InterestrateBelief_{i,t}$ | | | 33.53*** | | | 11.87 |
| | | | (6.890) | | | (8.275) |
| Session FE | yes | yes | yes | yes | yes | yes |
| $N$ | 4290 | 4290 | 4290 | 1560 | 1560 | 1560 |
| $R^2$ | 0.37 | 0.44 | 0.44 | 0.45 | 0.46 | 0.48 |

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: **Determinants of individual credit demand.** This Table presents nested random effects models. Standard errors are clustered on an individual level. The left hand side variable for the first three columns is the demand for credit of individual $i$ in period $t$ (see text) in the market economy. The left hand side variable in the last three columns is the demand for credit of individual $i$ in period $t$ (see text) in the island economy. The right hand side variables are: $Profits^{+}_{i,t-1}$, is a vector which contains positive profits from the previous period of individual $i$, if positive profits were observed for individual $i$ in the previous period and is zero otherwise. $Profits^{-}_{i,t-1}$, is a vector which contains negative profits from the previous period of individual $i$, if negative profits were observed for individual $i$ in the previous period and is zero otherwise. $Profits^{0}_{i,t-1}$ is a dummy vector which is one if a subject made zero profits (did not receive or demand loan) in the past period. $Collateral_{i,t}$ is the collateral in period $t$ of individual $i$. $ProjectBelief_{i,t}$ is the project belief of individual $i$, given at the beginning of period $t$ (before interest rates are realized). Risk Seeking is a vector, which contains the measure of risk aversion elicited for individual $i$ - the higher the measure the more risk seeking the subject. Skill is a discrete variable, ranging from 1 - 10, which measures the self perceived math skill of a subject. Age and Gender are self explanatory. SupplyX is a dummy variable which takes the value of 1 if the supply in session $s$ has been X. Inexperience is a dummy variable which takes a value of 1 in the first 20 periods. Session FE indicates that we included dummy variables for individual sessions.

| | (1) ME: RE | (2) ME: Probit | (3) ME: Logit | (4) IE: RE | (5) IE: probit | (6) IE: Logit |
|---|---|---|---|---|---|---|
| $Project_{i,t-1}$ | -0.0658** | -0.203*** | -0.338*** | -0.135*** | -0.466*** | -0.791*** |
| | (0.011) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $Profits^{+}_{i,t-1}$ | 0.000778 | 0.00241 | 0.00390 | 0.000953 | 0.00346 | 0.00575 |
| | (0.346) | (0.222) | (0.239) | (0.362) | (0.438) | (0.457) |
| $Profits^{-}_{i,t-1}$ | -0.00161** | -0.00573** | -0.0108** | 0.0000991 | -0.000482 | -0.00144 |
| | (0.041) | (0.017) | (0.012) | (0.932) | (0.926) | (0.872) |
| $Profits^{0}_{i,t-1}$ | 0.0121 | 0.0548 | 0.0901 | -0.0346 | -0.109 | -0.179 |
| | (0.609) | (0.360) | (0.369) | (0.379) | (0.400) | (0.419) |
| $Collateral_{i,t}$ | -0.000408** | -0.00134*** | -0.00227*** | 0.0000712 | 0.000177 | 0.000161 |
| | (0.025) | (0.001) | (0.001) | (0.801) | (0.863) | (0.927) |
| Risk Seeking | -0.00153 | -0.00672 | -0.0117 | -0.00801* | -0.0271 | -0.0459 |
| | (0.615) | (0.575) | (0.564) | (0.051) | (0.202) | (0.207) |
| Skill | -0.000949 | -0.00173 | -0.00240 | 0.00932 | -0.00229 | -0.000392 |
| | (0.933) | (0.964) | (0.970) | (0.524) | (0.969) | (0.997) |
| Age | 0.00669 | 0.0321** | 0.0545** | 0.0103*** | 0.0475** | 0.0841** |
| | (0.110) | (0.030) | (0.030) | (0.000) | (0.018) | (0.017) |
| Gender | 0.0252 | 0.108 | 0.176 | 0.116** | | |
| | (0.590) | (0.480) | (0.495) | (0.044) | | |
| Inexperience | 0.0584* | 0.195*** | 0.323*** | 0.0854 | 0.271 | 0.466 |
| | (0.054) | (0.001) | (0.001) | (0.490) | (0.553) | (0.552) |
| Session FE | yes | yes | yes | yes | yes | yes |
| Supply FE | yes | yes | yes | yes | yes | yes |
| $N$ | 4290 | 4290 | 4290 | 1560 | 1560 | 1560 |
| $R^2$ | 0.04 | | | 0.08 | | |
| Wald-$chi^2$-p-value | | $< 0.001$ | $< 0.001$ | | $< 0.001$ | $< 0.001$ |

$p$-values in parentheses $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 4: **Determinants of Project Beliefs.** This Table presents random effects, probit and logit models. Standard errors are clustered at an individual level. In the first three columns the left hand side variable is the belief of the project realization of individual $i$ in period $t$ (see text) in the market economy. It is a dummy variable which takes the value 1 if the belief is "good" (100%). In the last three columns the left hand side variable is the belief of the project realization of individual $i$ in period $t$ (see text) in the island economy. It is a dummy variable which takes the value 1 if the belief is "good" (100%). The right hand side variables are: $Project_{i,t-1}$, is the vector of past, actual project realizations. $Collateral_{i,t}$ is the collateral in period $t$ of individual $i$. Risk Seeking is a vector, which contains the measure of risk aversion elicited for individual $i$ - the higher the measure the more risk seeking the subject. Skill is a discrete variable, ranging from 1 - 10, which measures the self perceived math skill of a subject. Age and Gender are self explanatory. SupplyX is a dummy variable which takes the value of 1 if the supply in session $s$ has been X. Inexperience is a dummy variable which takes a value of 1 in the first 20 periods. Session FE indicates that we included dummy variables for individual sessions.

| | Market Economy | | Island Economy | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Dependent Variable: | $I_t^i$ | $r_t^i$ | $I_t^i$ | $r_t^i$ |
| $r_t^i$ | 6.085 | | 11.510 | |
| | (0.271) | | (0.291) | |
| $I_t^i$ | | 0.0004*** | | 0.001*** |
| | | (0.000) | | (0.005) |
| $Profits^+_{i,t-1}$ | 0.255*** | -0.0004*** | 0.367*** | -0.0001** |
| | (0.000) | (0.037) | (0.000) | (0.015) |
| $Profits^-_{i,t-1}$ | -0.589*** | 0.0006*** | -0.494*** | 0.0151** |
| | (0.000) | (0.001) | (0.000) | (0.000) |
| $Profits^0_{i,t-1}$ | 6.615*** | -0.044*** | 11.781*** | -0.008*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| $ProjectBelief_{i,t}$ | 14.345*** | 0.061*** | 7.873*** | 0.098*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| $Collateral_{i,t}$ | 0.164*** | | 0.166*** | |
| | (0.000) | | (0.000) | |
| $InterestBelief_{i,t}$ | | 0.700*** | | 0.387*** |
| | | (0.000) | | (0.000) |
| Risk Seeking | 0.078 | 0.001*** | 0.492*** | 0.0003 |
| | (0.153) | (0.135) | (0.000) | (0.664) |
| Skill | -1.05*** | 0.003*** | 0.243 | -0.001 |
| | (0.000) | (0.000) | (0.334) | (0.521) |
| Age | -0.236*** | -0.0004 | 0.137 | -0.0012*** |
| | (0.000) | (0.511) | (0.854) | (0.001) |
| Gender | -0.55 | 0.007** | 2.312** | -0.0073 |
| | (0.434) | (0.034) | (0.019) | (0.236) |
| Inexperience | 12.70*** | -0.012 | 0.259 | -0.015 |
| | (0.000) | (0.512) | (0.964) | (0.594) |
| Session FE | yes | yes | yes | yes |
| Supply FE | yes | yes | yes | yes |
| $N$ | 4290 | 4290 | 1560 | 1560 |
| $R^2$ | 0.636 | 0.710 | 0.687 | 0.610 |

$p$-values in parentheses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

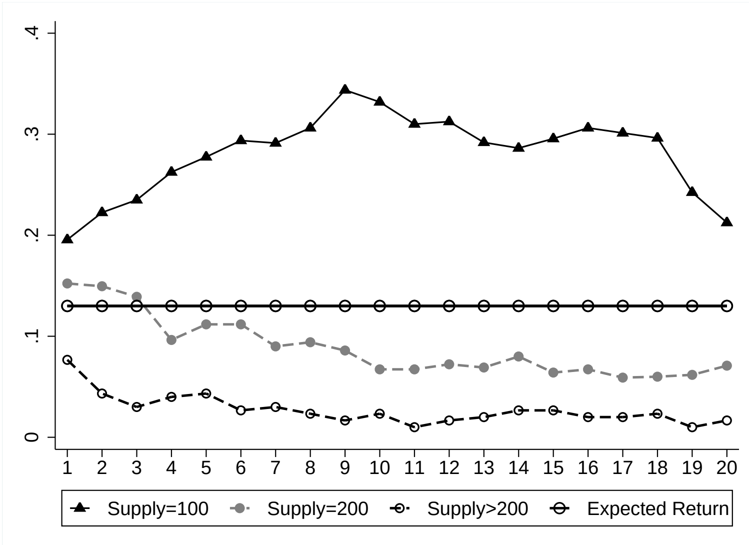
Table 5: **Determinants of Individual Credit Demand, Structural Estimation.** This Table presents results from our 3SLS regressions. Standard errors are clustered on an individual level. The left hand side variable is the demand for credit of individual $i$ in period $t$ decomposed into quantity and price (see text) in the island economy and the market economy. The right hand side variables are: $Profits^+_{i,t-1}$, is a vector which contains positive profits from the previous period of individual $i$, if positive profits were observed for individual $i$ in the previous period and is zero otherwise. $Profits^-_{i,t-1}$, is a vector which contains negative profits from the previous period of individual $i$, if negative profits were observed for individual $i$ in the previous period and is zero otherwise. $Profits^0_{i,t-1}$ is a dummy vector which is one if a subject made zero profits (did not receive or demand loan) in the past period. $Collateral_{i,t}$ is the collateral in period $t$ of individual $i$. $ProjectBelief_{i,t}$ is the project belief of individual $i$, given at the beginning of period $t$ (before interest rates are realized). Risk Seeking is a vector, which contains the measure of risk aversion elicited for individual $i$ - the higher the measure the more risk seeking the subject. Skill is a discrete variable, ranging from 1 - 10, which measures the self perceived math skill of a subject. Age and Gender are self explanatory. SupplyX is a dummy variable which takes the value of 1 if the supply in session $s$ has been X. Inexperience is a dummy variable which takes a value of 1 in the first 20 periods. Session FE indicates that we included dummy variables for individual sessions. Instruments are discussed in the text.

| | Market Economy | | Island Economy | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Dependent Variable: | $r_t^i$ | $I_t^i$ | $r_t^i$ | $I_t^i$ |
| $Profits_{i,t-1}^{+}$ | -0.000173 | 0.133** | -0.000190 | 0.178** |
| | (0.000115) | (0.0536) | (0.000369) | (0.0850) |
| $Profits_{i,t-1}^{-}$ | 0.000202 | -0.426*** | 0.000668 | -0.244*** |
| | (0.000183) | (0.103) | (0.000465) | (0.0795) |
| $Profits_{i,t-1}^{0}$ | -0.0179*** | 6.600*** | -0.0349** | 6.646*** |
| | (0.00530) | (1.131) | (0.0145) | (1.650) |
| $Collateral_{i,t}$ | 0.000105** | 0.163*** | 0.000161** | 0.153*** |
| | (0.0000435) | (0.0310) | (0.0000780) | (0.0310) |
| Risk Seeking | 0.000506 | 0.0781 | 0.000673 | 0.559*** |
| | (0.000762) | (0.157) | (0.00141) | (0.214) |
| Skill | 0.00335 | -0.914 | -0.000947 | 0.371 |
| | (0.00230) | (0.577) | (0.00489) | (0.720) |
| Age | -0.00105* | -0.304 | -0.00138 | -0.0386 |
| | (0.000585) | (0.226) | (0.000982) | (0.148) |
| Gender | 0.00584 | 0.323 | -0.00522 | 1.815 |
| | (0.00857) | (1.998) | (0.0177) | (2.633) |
| Inexperience | 0.0142* | 8.293*** | 0.0918 | 11.90** |
| | (0.00822) | (1.842) | (0.0673) | (5.759) |
| $ProjectBelief_{i,t}$ | 0.0734*** | 16.14*** | 0.110*** | 10.98*** |
| | (0.00749) | (1.587) | (0.0139) | (1.588) |
| $InterestBelief_{i,t}$ | 0.694*** | 13.79*** | 0.353*** | 0.515 |
| | (0.0401) | (5.189) | (0.0563) | (5.870) |
| Session FE | yes | yes | yes | yes |
| Supply FE | yes | yes | yes | yes |
| $N$ | 4290 | 4290 | 1560 | 1560 |
| $R^2$ | 0.599 | 0.449 | 0.313 | 0.450 |

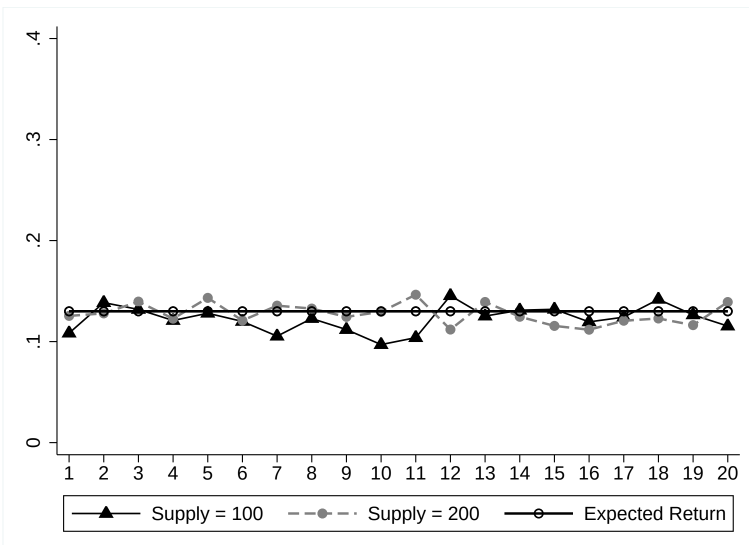
$p$-values in parentheses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: **Determinants of Demand, Reduced Form Estimation**. This Table presents reduced form results on our demand estimates. Standard errors are clustered on an individual level. The left hand side variable is the demand for credit of individual $i$ in period $t$ - either quantity or price (see text) in the island economy and the market economy. The right hand side variables are: $Profits_{i,t-1}^{+}$, is a vector which contains positive profits from the previous period of individual $i$, if positive profits were observed for individual $i$ in the previous period and is zero otherwise. $Profits_{i,t-1}^{-}$, is a vector which contains negative profits from the previous period of individual $i$, if negative profits were observed for individual $i$ in the previous period and is zero otherwise. $Profits_{i,t-1}^{0}$ is a dummy vector which is one if a subject made zero profits (did not receive or demand loan) in the past period. $Collateral_{i,t}$ is the collateral in period $t$ of individual $i$. $ProjectBelief_{i,t}$ is the project belief of individual $i$, given at the beginning of period $t$ (before interest rates are realized). Risk Seeking is a vector, which contains the measure of risk aversion elicited for individual $i$ - the higher the measure the more risk seeking the subject. Skill is a discrete variable, ranging from 1 - 10, which measures the self perceived math skill of a subject. Age and Gender are self explanatory. SupplyX is a dummy variable which takes the value of 1 if the supply in session $s$ has been X. Inexperience is a dummy variable which takes a value of 1 in the first 20 periods. Session FE indicates that we included dummy variables for individual sessions. Instruments are discussed in the text.

# Figures

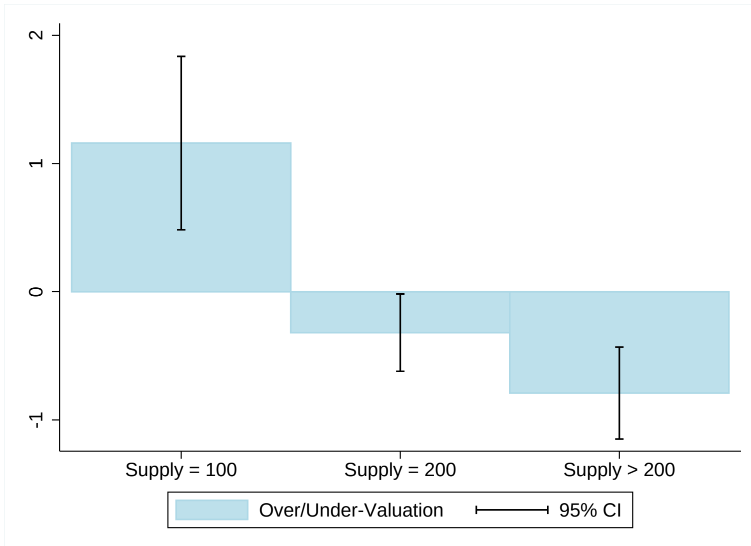



(a) Market prices

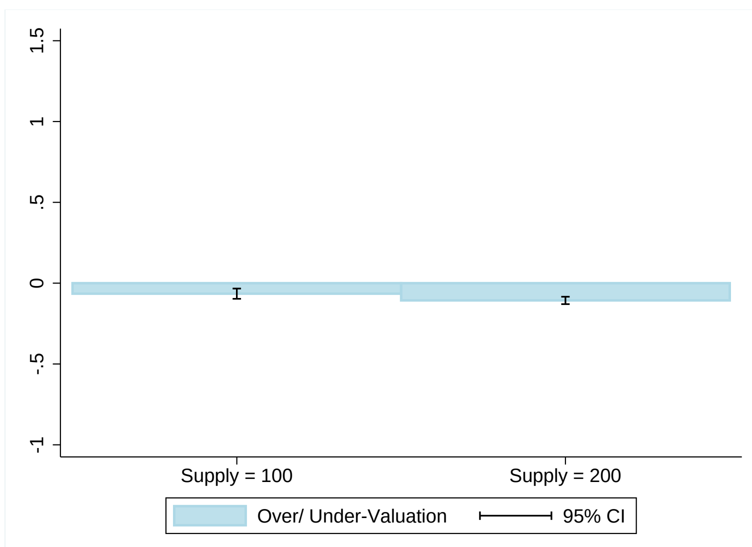



(b) Island prices

Figure 1: **Interest rates** Panel (a) shows the average call market prices, conditional on supply. Panel (b) shows the average prices paid by subjects in our island economy treatment.

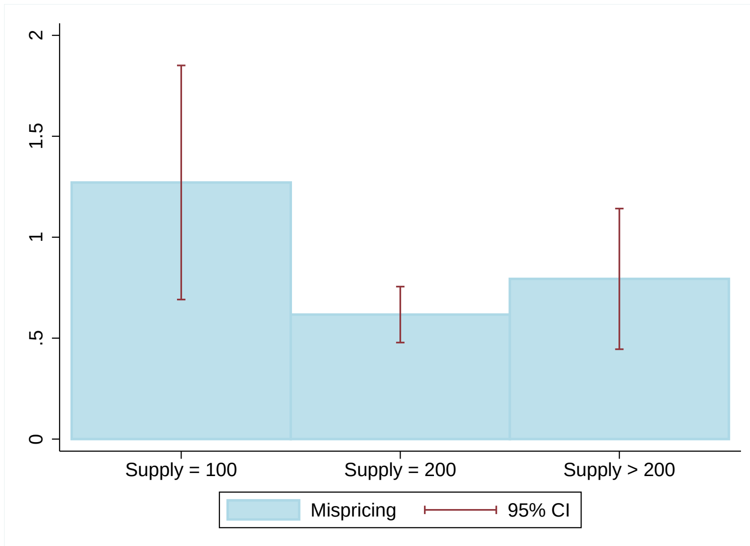



(a) Market RD

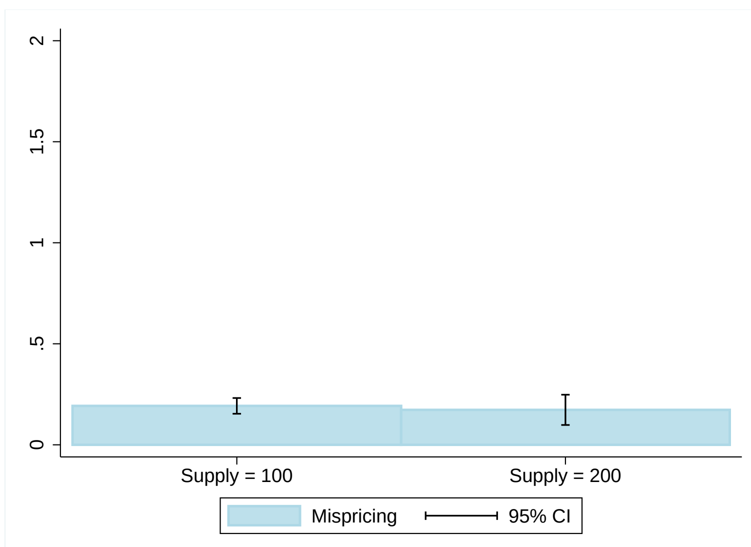



(b) Island RD

Figure 2: **Overvaluation** Panel (a) shows the average RD ($RD = \frac{1}{20}\sum_{t=1}^{20}\frac{r_t - FV}{FV}$) for ME conditional on supply. Panel (b) shows the average RD for IE conditional on supply. The Figures also show 95% confidence intervals.

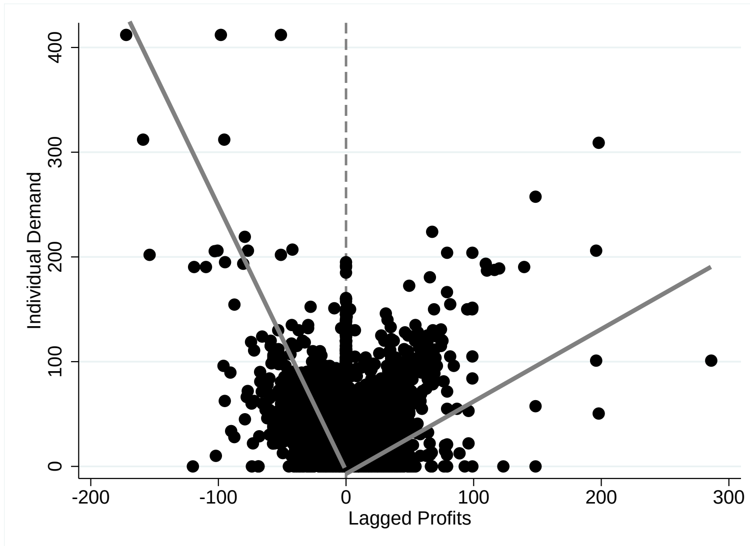



(a) Market RAD

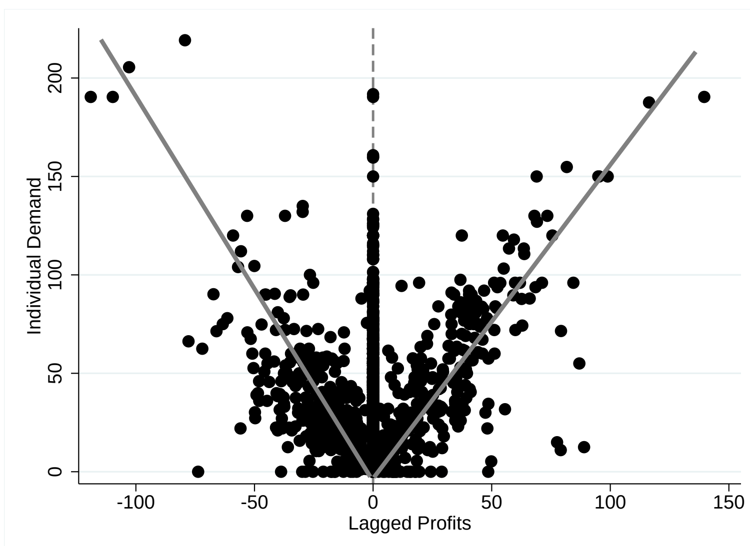



(b) Island RAD

Figure 3: **Mis-pricing** Panel (a) shows the average RAD ($RAD = \frac{1}{20}\sum_{t=1}^{20}\frac{|r_t - FV|}{FV}$) for ME conditional on supply. Panel (b) shows the average RD for IE conditional on supply. The Figures also show 95% confidence intervals.

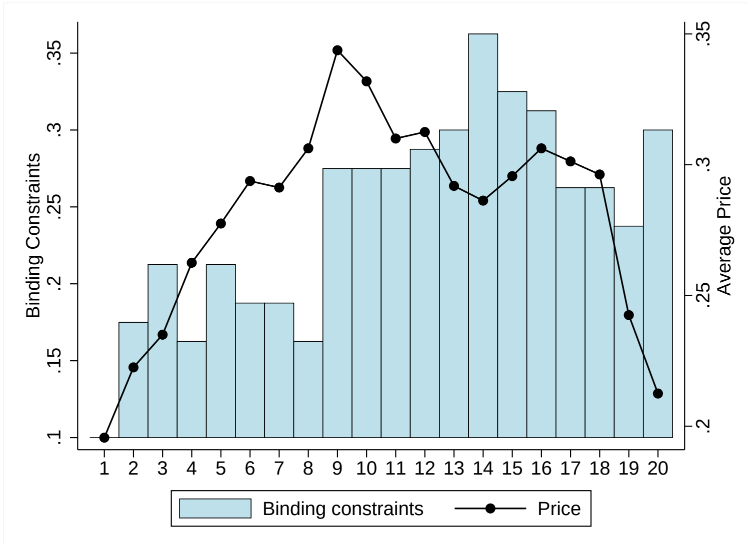



(a) Market Economy

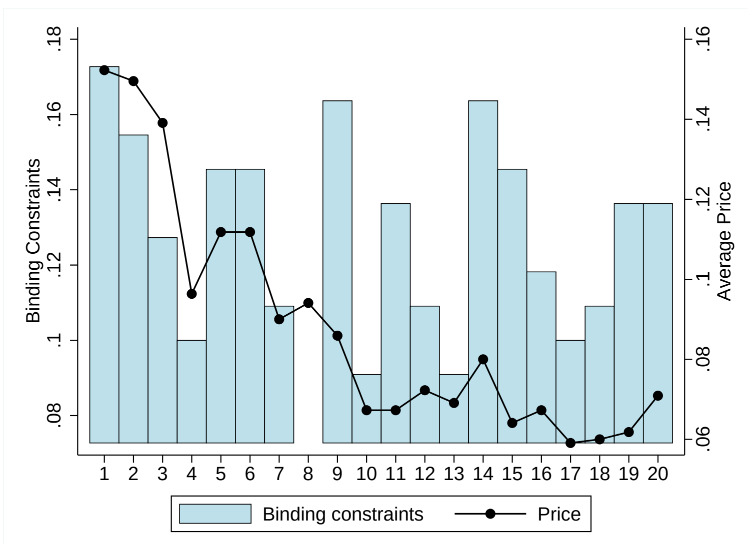



(b) Island Economy

Figure 4: **Individual Credit Demand and Past Profits.** We compute individual demand in period $t$ as $Demand_{i,t} = I_t^i r_t^i$. and relate them to profits and losses from the previous period for each individual.




(a) Low Credit Supply Economy




(b) High Credit Supply

Figure 5: **Credit constraints and market interest rates.** We compute credit constraints in period $t$ as the ratio between $Demand_{i,t}$ and $C_{i,t}$. A higher ration indicates a more credit-constrained subject.

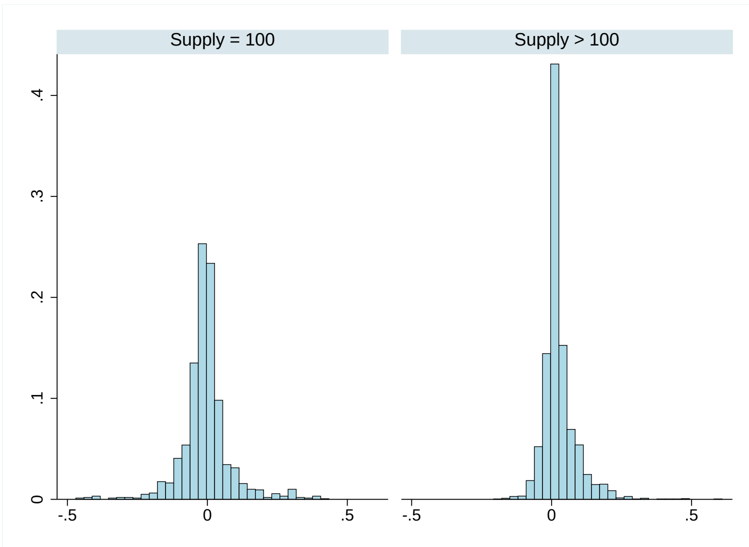



Figure 6: **Market Rate Forecast Accuracy**. We compute the forecast accuracy as $(\mathbb{E}^i_{t-1}(r_t) - r_t)$; i.e. nominal deviation of individual forecasts of interest rates $\mathbb{E}^i_{t-1}(r_t)$ from realized interest rates.

## Recent Issues

| | | |
|---|---|---|
| No. 103 | Massimiliano Caporin, Loriana Pelizzon, Francesco Ravazzolo, Roberto Rigobon | **Measuring Sovereign Contagion in Europe** |
| No. 102 | Iñaki Aldasoro, Iván Alves | **Multiplex interbank networks and systemic importance: An application to European data** |
| No. 101 | Marcel Grupp | **On the Impact of Leveraged Buyouts on Bank Systemic Risk** |
| No. 100 | Marcel Grupp | **Taking the Lead: When Non-Banks Arrange Syndicated Loans** |
| No. 99 | Marcel Grupp, Christian Rauch, Marc Umber, Uwe Walz | **The Influence of Leveraged Buyouts on Target Firms' Competitors** |
| No. 98 | Tobias Niedrig, Helmut Gründl | **The Effects of Contingent Convertible (CoCo) Bonds on Insurers' Capital Requirements Under Solvency II** |
| No. 97 | Tobias Niedrig | **Optimal Asset Allocation for interconnected Life Insurers in the Low Interest Rate Environment under Solvency Regulation** |
| No. 96 | Jens-Hinrich Binder | **Banking Union and the Governance of Credit Institutions – A Legal Perspective** |
| No. 95 | Loriana Pelizzon, Marti G. Subrahmanyam, Davide Tomio, Jun Uno | **Sovereign Credit Risk, Liquidity, and ECB Intervention: Deus Ex Machina?** |
| No. 94 | Claudia Lambert, Felix Noth, Ulrich Schüwer | **How Do Banks React to Catastrophic Events? Evidence from Hurricane Katrina** |
| No. 93 | Shafik Hebous, Tom Zimmermann | **Revisiting the Narrative Approach of Estimating Tax Multipliers** |
| No. 92 | Christoph Hambel, Holger Kraft, Eduardo S. Schwartz | **Optimal Carbon Abatement in a Stochastic Equilibrium Model with Climate Change** |