Liquidation policy and credit history in financial contracting: An experiment

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Liquidation Policy and Credit History in Financial Contracting: An Experiment

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Abstract

In the presence of contract incompleteness and asymmetric information, liquidation policy plays an important role in financial contracting. Liquidation is a double-edged sword. It deters borrowers from defaulting strategically, but it could be harsh to borrowers experiencing short-term liquidity problems. This paper presents an experimental analysis of the impacts of (1) liquidation policy on borrowers' incentive to engage in strategic default and (2) disclosure of credit history information on lending relationships and borrowers' behaviors. We show that liquidation policy deters borrowers from defaulting strategically. The availability of credit information softens the liquidation policy when the equilibrium liquidation policy is relatively lenient and helps to reduce strategic defaults.

Keywords: Strategic Default, Liquidity Default, Liquidation Policy, Credit History, Lab Experiments

J.E.L. Classification: C70, C91, G14, G33

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1 Introduction

Loan contracts are typically accompanied by covenants stipulating the rights and obligations of lenders and borrowers and actions that lenders can take under various contingencies. As complete as these contracts can be, there will always be unforeseen contingencies that cannot be covered in the contracts. When these contingencies arise, both parties may potentially end up in a protracted dispute requiring a third party to adjudicate. A borrower may opportunistically claim that she is facing financial distress and is unable to repay the loan, and then ask for financial leniency from the lender despite being actually financially sound. The incentive to engage in such a strategic act is exacerbated in the presence of asymmetric information between the borrower and the lender. It would be difficult for the lender to find out whether the default occurs due to financial distress (liquidity problem) or opportunistic behavior (strategic default).[1]

In the absence of the assignment of control rights, borrowers can strategically default on the loan, placing lenders in a vulnerable position. In anticipation of this possibility, lenders might be unwilling to fund projects even if these projects are profitable. This insight was first developed by Grossman and Hart (1986) and subsequently by Hart and Moore (1990 and 1998) and Aghion and Bolton (1992). Following the spirit of Aghion and Bolton (1992), Dewatripont and Tirole (1994) build a theoretical model based on the premise that the optimal financial contract should correlate income rights and control rights. It goes beyond the framework of Aghion and Bolton (1992), which addresses the potential conflicting goals between the manager and the single investor, by introducing managerial moral hazard and multiple outside investors holding diverse securities. Dewatripont and Tirole (1994) state that the optimal loan contract calls for appropriate

[1] Bolton and Scharfstein (1990 and 1996) coined these two default cases as, respectively, liquidity default and strategic default.

course of actions by outside investors following the firm's realization of profits. Bolton and Scharfstein (1996) extend the Aghion and Bolton state-contingent loan contract to examine the role of liquidation policy as a tool to transfer control rights from borrowers to lenders when no-repayment occurs. Liquidation policy can be designed optimally to exert disciplinary muscle over errant borrowers with high propensity to commit strategic default.[2] Bolton and Scharfstein (1996) argue that the optimal liquidation policy calls for probabilistic liquidation; borrowers will be liquidated with positive probability if they fail to repay the loan regardless of the underlying reason for default.

A number of mechanisms are documented in the empirical banking literature to address the issues such as adverse selection and moral hazard resulted from information asymmetry between borrowers and lenders. For instance, lenders could require borrowers to pledge collateral, which could alleviate moral hazard problems and thus acts as a disciplinary tool in theory. However, empirical evidence suggests that collateralized loans sometimes are associated with higher default rates (Jiménez and Saurina, 2004; Berger et al., 2016). Besides collateralized loans, relationship banking is another powerful tool (see Boot, 2000 for an excellent review). Long-term relationships could enhance market welfare (Boot and Thakor, 1994) and deter misbehavior (Brown et al., 2004; Fehr and Zehnder, 2009).

In addition, empirical evidence has shown that liquidation is a widely used disciplinary instrument. Banks exercise foreclosure rights in the event of missed mortgage payments (Gerardi et al., 2013; Gerardi et al., 2015). In the United States bankruptcy code, Chapter 7 liquidation allows the borrower's assets to be sold to pay creditors' claims. Chapter 7 liquidation is not an uncommon type of bankruptcy filings for businesses (Bris et al., 2006; Altman and Hotchkiss,

[2] See also Hotchkiss et al. (2008) for a thorough survey of literature on corporate bankruptcy and liquidation.

2011). We believe the insights provided by Bolton and Scharfstein (1996) have some empirical relevance. Kahl (2002) shows that the dynamic liquidation strategy may explain why financial distress tends to be long-term in nature. Dynamic liquidation proposed in Kahl (2002) and probabilistic liquidation outlined in Bolton and Scharfstein (1996) share similarities in spirit as liquidation involves uncertainty in the process in both frameworks. Cleary et al. (2007) adopt a similar setup as Bolton and Scharfstein (1996) and set liquidation to be stochastic. They propose a theory suggesting a U-shape relationship between internal funds and a firm's investment. Their theoretical predictions find strong empirical support.

This paper delves into the role of liquidation policy in debt contracting. In particular, this paper adopts Bolton and Scharfstein's framework of probabilistic liquidation policy as the centerpiece and presents an experimental analysis of the impact of liquidation policy on borrowers' incentive to engage in strategic default. Through a series of laboratory experiments, we investigate how the liquidation policy is set, what factors influence the harshness of the liquidation policy and how this liquidation policy affects borrowers' incentive to engage in opportunistic behavior. In addition, this paper evaluates the role of credit history in lending relationship. Specifically, we compare the incidence of strategic default and the choice of the liquidation policy when information on borrowers' credit history is provided to all lenders. Similar to liquidation policy, information on credit history could play an important disciplinary role in deterring borrowers from defaulting strategically.[3]

With regards to the role of credit history, our study is closely related to the strand of literature on credit information sharing. In the presence of adverse selection and moral hazard, credit

[3] See Jappelli and Pagano (2006) for an excellent survey on the role and effects of sharing credit information among lenders on lending relationships.

information sharing attenuates the problem and reduces strategic default rate (Pagano and Jappelli, 1993; Padilla and Pagano, 1997, 2000). The sharing of credit information among lenders would open up an opportunity for borrowers to develop a good reputation. This, in turn, would lessen the extent of conflict of interest between lenders and borrowers (Diamond, 1989). On the empirical front, Jappelli and Pagano (2002) find evidence that credit information sharing is associated with lending expansion and reduced credit risk. Djankov et al. (2007) show that credit information sharing improves borrowers' access to credit using aggregate cross-country data. A host of other papers have shown that credit information sharing improves credit market performance by fostering lending and reducing default rates (e.g., Brown et al., 2009; de Janvry et al., 2010; Doblas-Madrid and Minetti, 2013; Degryse et al., 2016).

Our study contributes to the literature on financial contracting and credit information sharing in two ways. First, to the best of our knowledge, this is the first experimental study focusing on the interplay between the liquidation policy and borrowers' strategic behavior. The challenge of studying strategic defaults is that they are "*de facto unobservable events*" (Guiso et al., 2013; Mayer et al., 2014). The experimental methodology makes it possible to study factors that would be unobservable in empirical studies (see, e.g., Davydenko and Strebulaev, 2007). In our study, the experiments allow us to clearly distinguish between strategic default and liquidity default, which would be difficult, if not impossible, to study using existing empirical data.

Second, to the best of our knowledge, our study is one of only a handful of experimental studies exploring the effects of the disclosure of credit information on lending relationships and credit market performance (e.g., Brown and Zehnder, 2007). By having both liquidation policy and credit information sharing within the same experimental framework, we are able to study the interaction between them such as how credit information sharing affects the liquidation policy and how credit information sharing influences strategic defaults under different liquidation policies. Credit information sharing significantly reduces the problem of information asymmetry between lenders and borrowers. As such, there might be less need for lenders to impose a harsh liquidation policy if default occurs. Our experiment provides a direct test of this speculation.

The rest of the paper is organized as follows. Section 2 introduces the theoretical framework, and Section 3 presents our experimental design and procedure. The results are presented in section 4. Section 5 concludes the paper.

2 Theoretical Framework

We begin by introducing the probabilistic liquidation framework proposed in Bolton and Scharfstein (1996). It is a two-period model of a lending relationship between a bank and a firm that has no initial wealth. At time $t = 0$, the firm borrows an initial investment K from the bank to implement a project with uncertain payoff (e.g., cash flow). At time $t = 1$, the project is successful with probability θ, generating a cash flow x or fails with probability $(1 - \theta)$, generating a cash flow 0. Both the bank and the firm are assumed to be risk neutral.

Similar to other incomplete contract models (e.g., Grossman and Hart, 1986), cash flow is assumed to be *observable* by both parties, but *not verifiable* by a third party (e.g., a court). Consequently, the loan contract cannot be made contingent on the realization of cash flow, and instead it should specify the allocation of control rights over assets in case defaults happen. More specifically, the loan contract specifies that if the firm repays an amount of R_x (i.e., the repayment when the cash flow is x), the bank has the right to liquidate the firm's assets with probability β_x. If the firm repays an amount of R_0 (i.e., the repayment when the cash flow is 0), the bank has the right to liquidate the firm's assets with probability β_0. The repayment and liquidation decisions take place at the end of period $t = 1$. Essentially, if the liquidation takes place, the control rights over the firm's assets are transferred from the firm to the bank. If the firm survives liquidation at period $t = 1$, the firm proceeds to period $t = 2$ and receives the continuation cash flow of y with certainty. The firm's expected payoffs can be expressed as,

$$\theta[x - R_x + (1 - \beta_x)y] + (1 - \theta)[0 - R_0 + (1 - \beta_0)y]. \tag{1}$$

The bank's expected payoffs can be expressed as

$$\theta(R_x + \beta_x L_x) + (1 - \theta)(R_0 + \beta_0 L_0) - K, \tag{2}$$

where L_x and L_0 represent the liquidation value of assets when cash flow is x and 0, respectively.

Given that the firm has no initial wealth, the repayment at period $t = 1$ cannot exceed the amount of funds available, which implies that $R_0 \leq 0$ and $R_x \leq x$. Under the risk neutrality assumption, the loan contract is designed to be incentive compatible to ensure that the manager has an incentive to repay R_x rather than R_0 when cash flow is x. The incentive constraint can then be expressed as,

$$x - R_x + (1 - \beta_x)y \geq x - R_0 + \beta_0 S + (1 - \beta_0)y, \tag{3}$$

where S refers to the utility that the firm's manager receives by paying R_0 when the actual cash flow is x and the assets are subject to liquidation.

In addition to satisfying the incentive constraint above, the optimal contract must give an incentive for the firm to repay R_0 rather than R_x when cash flow is 0. However, it is straightforward that this constraint is not binding because the firm cannot repay a positive amount of R_x when cash flow is 0. Finally, at the optimum, the bank's payoffs from lending must be non-negative.

$$\theta(R_x + \beta_x L_x) + (1 - \theta)(R_0 + \beta_0 L_0) - K \geq 0. \tag{4}$$

It is optimal to set $R_0 = 0$ and $\beta_x = 0$. That is, when the cash flow is 0, the repayment amount must also be 0. When the firm repays R_x given that the cash flow is x, the firm should not be liquidated. It is straightforward to establish that the incentive constraint and the non-negative profit constraint must be binding. Substituting $R_0 = 0$ and $\beta_x = 0$ into (3) yields

$$R_x = \beta_0(y - S). \tag{5}$$

Substituting (5) to (4) and assuming that (4) is binding yields

$$\beta_0[\theta(y - S) + (1 - \theta)L_0] - K = 0. \tag{6}$$

The optimal β_0 can then be derived as

$$\beta_0 = \frac{K}{\theta(y - S) + (1 - \theta)L_0}. \tag{7}$$

β_0 is increasing in the amount of investment outlay K and decreasing in the continuation cash flow y at period $t = 2$, and the liquidation value of assets L_0 when cash flow is 0. Under some parameter values, there will be a strictly positive probability of liquidation when the repayment is R_0. This implies that regardless of the reason (whether it is due to liquidity constraint or strategic behavior) for the lack of repayment, the bank will liquidate the firm with some probability β_0.

3 Experimental Design and Procedures

Our experiment has two goals. First, we investigate factors influencing the optimal liquidation policy. Second, we evaluate the role of liquidation policy and credit history disclosure in deterring the firm from engaging in strategic default.

3.1 Experimental Design

The Benchmark Optimal Liquidation Probability

To investigate if the findings are sensitive to the value of β_0, we conducted the experiment with a low beta (β_{0_low}) and a high beta (β_{0_high}). For the purposes of our experiment, we assigned the following parameter values to the above model: $K = 14$, $x = 30$, $(y - S)_{low} = 64$, $(y - S)_{high} = 24$, $R_{x\_low} = 19.2$, $R_{x\_high} = 16.8$, $L_0 = 12$ and $\theta = 2/3$. It is straightforward to verify that these values satisfy (5) and (6), and thus there exists a feasible solution for β_{0_low} and β_{0_high}. Substituting these parameter values to (7) yields the following optimal probability of liquidation when the borrower fails to repay.

$$\beta_{0\_low} = 0.3. \tag{8}$$

$$\beta_{0\_high} = 0.7. \tag{9}$$

The Game Structure

The game used in the experiment followed the structure in Bolton and Scharfstein (1996). At the beginning of each round, each bank has an initial endowment to lend. The firm receiving the loan will use the funds to cover its capital outlay K. The project may succeed with probability 2/3 yielding 30 points or fail with probability 1/3 yielding 0 points. If the project succeeds, the firm can either repay the bank with 19.2 (low beta treatments) or 16.8 (high beta treatments) points[4] covering the amount loaned to the firm and the interest payment or default on the loan.

If default occurs regardless of the reason, the bank is entitled to liquidate the firm and sell its assets. The bank will do so with some probability agreed upon earlier between both parties and

[4] These points are the amount of money available to banks from their interest earned minus their cost of funds (e.g., the principal and the interest payments to depositors).

stated in the loan contract. If the firm repays the loan, the bank cannot liquidate the firm. The bank obtains 12 points if the matched firm is liquidated for defaulting. The game ends when liquidation occurs. Otherwise, the game proceeds to $t = 2$. If the firm survives liquidation and proceeds to $t = 2$, it obtains a sure second period payoff of 64 (low beta treatments) or 24 (high beta treatments) points. Both banks and firms have complete information on the project status in period 1 (i.e., whether or not the project is successful).

Banks must use up the available 14 points for the loan in each round if they intend to lend. If they decide not to get involved in a lending relationship, they will have to sit out that particular round and will only receive 6 points.[5] Figure 1 illustrates the game tree.

[Enter Figure 1 Here]

The Experimental Treatments[6]

We employed the 2 × 2 design and varied two dimensions, i.e., the equilibrium beta and the presence of credit history. For the equilibrium beta dimension, the low and high equilibrium beta is set to be 0.3 and 0.7 correspondingly. This is achieved by adjusting the repayment amount and the second period payoff. As for the credit history dimension, the credit history of firms in previous rounds is revealed to banks before banks decide whether to engage in a lending relationship with any specific firm. The credit history profile includes information on the number

[5] One way to motivate this setup is to think of the 6 points as the bank's non-interest based revenue after subtracting the cost of funds and some administrative costs. We set this payoff following two considerations. It has to be small enough to encourage banks to get matched and has to be large enough to give unmatched banks a decent payoff. It could be viewed as the payoff from banks' outside option. It is not uncommon in the literature that payoff from the outside option is different from that from entering the game (Rapoport et al., 2000; Zwick and Rapoport, 2002; Croson et al., 2003; Schmitt, 2004; Charness and Dufwenberg, 2006; Rigdon, 2009; Cox et al., 2010). Though our setup is not to mimic the financial institutions in real world, the insights gained from the experiment could still be useful to test the empirical relevance of theories proposed to understand real world issues (Dufwenberg, 2015).

[6] The experiment was conducted in a framed context. Though the neutral context is more ideal, it runs the risk of confusing subjects. Use of "framed" contexts in such experiments is not uncommon in the literature (see, e.g., Brown and Zehnder, 2010; Cole et al., 2015; Brown and Serra-Garcia, 2017).

of successful projects, the times of defaults while the project is successful, the number of failed projects, the times of defaults while the project fails in all previous rounds.

Like the no-credit-history treatments, interactions in the credit-history treatments are one-shot in nature. We reassign temporary identifications to firms in every matching cycle so that the credit history profile and the firm's identity are not connected. Lenders choose borrowers based on the beta offer and the credit history without knowing if they have had interactions with specific borrowers before. That is to say, we exclude the possibility of relationship banking.

There were 4 treatments in total: the *low beta no-credit-history (Low_NCH)* treatment, the *low beta credit-history (Low_CH)* treatment, the *high beta no-credit-history (High_NCH)* treatment and the *high beta credit-history (High_CH)* treatment. Banks and firms play in pairs and have to go through a matching process. We introduce competition to attract borrowers among banks by having more banks than firms. This competition would theoretically drive the non-negative constraint to 0 and eliminate the bargaining power of banks.[7]

3.2 Predictions

We formulate our predictions based on the two treatment variations, i.e., the beta value dimension and the credit history dimension.

In the *low beta no-credit-history (Low_NCH)* and the *high beta no-credit-history (High_NCH)* treatments, lenders choose borrowers based on the beta offers and that no reputation building is possible. According to the incentive constraint (3), $\beta_0 \geq R_x/(y - S)$ holds. In other words, the predicted beta is increasing in the ratio of the repayment and the second period payoff. We vary this ratio so that there are "*low beta*" and "*high beta*" conditions across treatments. Given that

[7]In order to provide enough incentive to participants playing the role of the bank in our experiment, we need to ensure that they would on average obtain positive earnings from the experiment. We achieve this by using a combination of the show-up fee and the earnings from the experiment.

the incentive constraint (3) and the non-negative constraint (4) are both binding, the theoretical predictions for the agreed beta are 0.3 for the Low_NCH treatment and 0.7 for the High_NCH treatment. Note that the prediction is based on the assumption of risk neutrality and rationality specified in the model. Considering that those assumptions might not be fully realistic, our goal is not to make point predictions of the beta agreed on. Treatment effects are our primary interests. Therefore, we expect higher beta in the High_NCH treatment compared to the Low_NCH treatment.

Hypothesis 1. The agreed beta in the High_NCH treatment is higher than that in the Low_NCH treatment.

Though the effect of credit history is not directly captured in the probabilistic liquidation model, credit history may affect the continuation value of the business, which is the second period payoff (y) in the model. In general, credit history has impacts on one's future access to credits. For instance, credit card providers decide one's credit limit and interest rate based on the borrower's credit profile. A business with a good repayment history is more likely to get loans than those without. In other words, a borrower with a good credit history is likely to receive favorable treatments from lenders. Since the interest rate, the loan size and the second period payoff are exogenously given in the probabilistic liquidation framework, the favorable treatment is likely to be in a form of a lower liquidation probability.

An alternative approach to understanding why there might be lower liquidation probabilities when the credit history is available is to think of liquidation as a disciplinary device. Brown and Zehnder (2007) find that credit reporting is a powerful disciplining instrument when the alternative device relationship banking is not available. It has little effect when relationship banking is available. Credit information sharing and liquidation are both disciplining devices and that they are both available in the credit-history treatments. As a result, the harsh liquidation policy as an additional disciplining tool will not be in strong demand when the other tool credit reporting is in place.

Hypothesis 2. The agreed beta is lower in the credit-history treatments than that in the no-credit-history treatments.

Following the discussion in Brown and Zehnder (2007), we assume there are two types of non-distinguishable borrowers: the social type and the payoff-maximizing type. The social type borrower suffers a psychological cost a if she does not repay the loan when the project is successful. For the payoff-maximizing type borrowers, we have $\beta_0 = \frac{K}{\theta(y-S)+(1-\theta)L_0}$ as specified in equation (7). For the social type borrowers, the borrower's incentive constraint becomes $x - R_x + (1-\beta_x)y \geq x - R_0 + \beta_0 S + (1-\beta_0)y - a$ and the lender's non-negative payoff constraint remains the same. The equilibrium beta is specified as $\beta_0^S = \frac{K-\theta a}{\theta(y-S)+(1-\theta)L_0}$. It is straightforward to infer that the social type borrower tends to have a lower equilibrium beta in theory when the type is observable by both parties. When it is not observable, borrowers can potentially use their offer of β to signal their type. Good borrowers can offer a higher value of β to separate themselves from bad borrowers. In our experimental setup without credit history, the borrowers' types are unobservable by banks, we expect good borrowers to have higher beta values.

Hypothesis 3 In the no-credit history treatments where the borrower's type is not distinguishable, good borrowers signal their type through higher beta values. In the credit-history treatments, borrowers with good credit histories tend to end up with a lower beta (i.e., more lenient liquidation policy).

When future loan conditions are dependent on the credit history, borrowers have strong incentive to maintain a good credit history. Through field experiments, Karlan and Zinman (2009) find that borrowers default significantly less when future loan offers are contingent on past repayment behaviors. Credit information sharing is often associated with improved access to credit and reduced credit risk (e.g., Diamond, 1989; Pagano and Jappelli, 1993; Padilla and Pagano, 1997, 2000; Jappelli and Pagano, 2002; Djankov et al., 2007; Brown et al., 2009; de Janvry et al., 2010; Doblas-Madrid and Minetti, 2013; Degryse et al., 2016). Therefore, we expect the strategic default rate to be lower in the credit-history treatments than that in the no-credit-history treatments.

Hypothesis 4. The availability of credit history information reduces strategic default in the credit-history treatments compared to that in the no-credit-history treatments.

3.3 Procedures

The Matching Process

The matching process between borrowers and banks takes place at the beginning of each round. The process can be described as follows. Firms require funds K from banks to implement a project. Firms post their desired liquidation probability β_i for all banks to observe. Banks then decide which firm to select.[8] If a firm is selected by only one bank, the pair is matched successfully and the agreed β_i will be incorporated in the loan contract. If a firm is selected by multiple banks, a random draw decides which bank is going to be matched with the firm. This completes one matching cycle. Unmatched firms and banks after the first matching cycle enter

[8]We opt for a setup whereby firms make an offer of β_i to banks to be in line with the assumption that firms have stronger bargaining power than banks. There are more banks than firms, and we do not allow multiple banking relationships, so there will be some banks that will not get matched and miss out on the opportunity to earn higher payoffs. Banks compete to attract firms and since firms know this, they would in theory offer β_i which will just make the non-negative profit constraint of banks binding. Letting banks make an offer of β_i to firms would in theory not alter the results.

the next cycle and repeat the matching process all over again. We allow for up to 5 matching cycles in the matching process. If they remain unmatched after 5 matching cycles, they will have to be inactive until a new round begins. An unmatched bank would earn 6 points and an unmatched firm would earn 0 points.[9]

The experiment was conducted in the lab at Nanyang Technological University (NTU) in Singapore. Participants were NTU undergraduate students from various academic backgrounds[10] The experiment was programmed in Z-tree (Fischbacher, 2007). The between-subject design was adopted. There were 3 sessions for each treatment with 21 subjects per session, totaling 252 subjects in 12 sessions. In addition, we had 3 independent clusters within every session and that matching only happened within the cluster. That is to say, there were 9 independent matching groups and therefore 9 independent group-level observations for every treatment. In each matching cluster, there were 3 firms and 4 banks.

We provided paper instructions,[11] which were read aloud at the beginning of each session. Subjects had to answer all control questions correctly before proceeding to the experiment. Subjects played the game for 10 rounds anonymously without knowing the total number of rounds beforehand. They were randomly assigned the role of firms or banks and that the role stayed fixed during the course of the experiment. 1 out of 10 rounds was randomly selected for payment. The points were converted into Singapore dollars (SGD) at the exchange rate of 1 point = 0.2 SGD (firms) or 1 point = 0.8 SGD (banks). After the 10 rounds, there was a risk elicitation

[9]Alternatively, we could choose different payoff magnitude for the unmatched banks. The choice of 6 points is to provide banks with a bit of bargaining power albeit much lower than that of firms, and it allows them to have on average some reasonable earnings from the experiment. We believe that changing this payoff magnitude would not qualitatively alter the results of our experiment.

[10] If one is concerned about the representativeness of student subjects, it is perhaps worth noting that it is common in the experimental literature that student subjects are used to study topics in financial markets. Cornée et al. (2012) find that commercial bank professionals and students show comparable behavioral patterns.

[11] Experimental instructions are provided in the supplementary appendix.

stage. We used a method similar to Holt and Laury (2016). Subjects were asked to choose between a sure payoff (safe choice) and a lottery (risky choice). Table 1 shows the 10 choices in the risk elicitation stage. Subjects were not shown the payoff difference. It is expected that subjects would switch from option A to option B at some point. A risk neutral agent would switch in line 6. The later she switches, the more risk averse she is. 1 out of 10 lines was selected for payment. The payment for the experiment included earnings in the binding round for the main experiment, earnings in the binding line for risk elicitation and the 5 SGD show-up fee. Subjects had to fill in a questionnaire before seeing their final payment. The average duration of one session was around 90 mins and that the average payment was around 17 SGD (equivalent to around 12.3 US dollars). Subjects were paid in cash privately at the end of the experiment.

[Enter Table 1 here]

4 Experimental Results

In this section, we start with the summary statistics. Then, we present an analysis of the choice of β including the effects of the credit history information on the choice of β. Subsequently, we investigate borrowers' incentive to engage in strategic default.

4.1 The Summary Statistics

The frequency with which the borrowers defaulted (γ) when their project is successful gives us a measure of the borrowers' propensity to engage in misbehavior by committing strategic default. This can be expressed as

$$\gamma = \frac{\sum(Default|Success)}{\sum Success}. \tag{10}$$

Table 2 presents the summary statistics of all treatments. To be consistent with the theoretical framework of Bolton and Scharfstein (1996), which assumes that the banking sector is perfectly competitive, we have more banks than the potential borrowers, i.e., 3 firms and 4 banks. Consequently, in every round, at least one of the banks would fail to match with a borrower and therefore has to be inactive in that particular round. The number of matching pairs in the second column of table 2 only includes successfully matched pairs out of the maximum possible number of matched pairs, which is 270, in every treatment. Thus, roughly over 95% of the times, a pair is successfully formed.

The average mutually agreed liquidation probability (β) in all treatments shown on the third column of table 2 falls into the range of 0.4 and 0.5. It is above the predicted equilibrium beta 0.3 in the low beta treatments and is below the predicted equilibrium beta 0.7 in the high beta treatments. There seems to be little difference in the agreed β between the no-credit-history treatments and the credit-history treatments. This is true for both the low beta and the high beta treatments. The last column on the right is calculated according to equation (10). It shows the percentage of misbehavior. Overall, there is a substantially higher proportion of strategic defaults in the high beta treatments than that in the low beta treatments. In addition, the percentage of strategic defaults is lower in the credit-history treatments than that in the no-credit-history treatments. This finding is universal regardless of the equilibrium beta value. The difference is more pronounced in the high beta treatments (42.4% vs 69.0%) than that in the low beta treatments (29.9% vs 32.6%).

[Enter Table 2 Here]

4.2 The Optimal Choice of Liquidation Policy

Figure 2 shows the evolution of the mutually agreed β over time. The average mutually agreed β is roughly stable over time in most of the treatments except that there is a mild decaying trend in the low beta credit-history treatment. In the equilibrium β value dimension, there is no significant difference in the agreed β between the low beta treatment and the high beta treatment when credit history is absent (two-sided Mann Whitney test[12], p = 0.69). Hypothesis 1 does not find its support. The difference becomes marginally significant in the presence of credit history (two-sided Mann Whitney test, p = 0.07). As for the credit history dimension, the agreed β is not significantly different between the no-credit-history treatments and the credit-history treatments. This is universal regardless of the equilibrium β value (two-sided Mann Whitney test, Low_NCH vs Low_CH, p = 0.251; High_NCH vs High_CH, p = 0.566).[13] The evidence does not support hypothesis 2.

[Enter Figure 2 Here]

The average β in the low beta treatments roughly lies in the range of 0.35-0.5, which is above the equilibrium β at 0.3. On the contrary, the average β in the high beta treatments roughly falls into the range of 0.45-0.55, which is below the equilibrium β at 0.7. There could be numerous

[12] The matching cluster average is used as independent observations. Unless otherwise stated, the same rule applies to all the non-parametric tests in the paper.

[13] The distribution of beta values in all treatments are available in appendix A (Figure A3 and A4). For the low beta condition, the top 3 common beta values in the no-credit-history treatment are 0.4, 0.5 and 0.3, which account for 68%. The top 3 common beta values in the credit-history treatment are 0.3, 0.5 and 0.2, which account for 62%. For the high beta condition, the top 3 common beta values are 0.5, 0.6 and 0.4, which account for 68% in the no-credit-history treatment and account for 58% in the credit-history treatment. Though the mean values of beta are similar across treatments and that the non-parametric tests find no significant difference, we do observe some difference in the distribution of beta. On the beta value dimension, if we compare the top 3 common beta values (0.4, 0.5 and 0.3 in Low_NCH vs 0.5, 0.6 and 0.4 in High_NCH), beta values are slightly lower in the low beta treatment. On the credit history dimension, if we again compare the top 3 common beta values (0.4, 0.5 and 0.3 in Low_NCH vs 0.3, 0.5 and 0.2 in Low_CH), beta values are slightly lower in the credit-history treatment for the low beta condition. Such a difference in beta is not observed for the high beta condition. This is consistent with econometric analysis in table 3, where the Low_CH treatment dummy is negatively significant and the High_CH treatment dummy is not significant.

factors explaining why the observed β deviates from the equilibrium β. It is beyond this paper's intention to exhaust all those reasons. We endeavor to explore some of those factors in the following discussions.

In general, the average β is in proximity to 0.5, which may serve as a focal point. Since the equilibrium β in our experiment is not so straightforward without sophisticated calculations, it is possible that subjects are not sure which β to start with. 0.5 seems to be a natural focal point. They may then agree on betas around that anchor. As shown in figure 2, the average β in period 1 is indeed very close to 0.5. However, the agreed β fails to increase to the high equilibrium β or decrease to the low equilibrium β in the corresponding treatments.

Our findings, to some degree, share similar spirit with findings in Isaac et al. (1989). Isaac et al. (1989) study contributions in threshold public goods game with high, medium and low provision points. There is a salient equilibrium among the multiple equilibria in each game. It is found that the mean contribution is above the salient equilibrium in the public goods game with a low provision point. It is below the salient equilibrium in the ones with medium and high provision points. As the salient equilibrium requires large individual contributions when the provision point is high, there could be a high risk of being at the receiving end of an opportunistic behavior by others. Likewise, a high β means a high risk of being liquidated if liquidity default happens beyond the agent's control. Therefore, firms might be reluctant to offer high β especially when they have some bargaining power as in our experiment. This could be one of the reasons why the observed β is below the equilibrium β in high beta treatments.

Besides saliency, another possible factor contributing to the no-difference result in the beta dimension could be risk attitudes. Firms are subject to liquidation according to the agreed probability in case of project failure, which is expected to happen one third of the times and is beyond their control. As a result, the firm might be reluctant to offer high betas if one is risk-averse. This effect might be more pronounced for firms in the high beta treatments. Though the agreed beta overall is not much different between the low beta and high beta conditions, the treatment effect might be present for some risk attitude categories. Our results show that all types of risk attitudes exist among firms[14] and there seems to be difference in beta between the low beta and high beta conditions for some categories of risk attitudes[15]. For the risk-loving type in the no-credit-history treatments and the risk-averse type in the credit-history treatments, the average beta value appears to be higher in the high beta treatments than that in the low beta treatments.

Table 3 reports the multilevel mixed-effects linear estimates of the determinants of β. The dependent variable is the mutually agreed liquidation probability (β), which also captures the severity of the liquidation policy. We have separate regressions for the low beta treatments and the high beta treatments, respectively. Separate regressions have the advantage of directly capturing the effect of credit history on β for the low beta and the high beta conditions.

The independent variables are as follows: a treatment dummy (*Low_CH*) with the Low_NCH treatment being the baseline, a treatment dummy (*High_CH*) with the High_NCH treatment being the baseline, *Round*, the proportion of strategic defaults for the firm in previous rounds (*Firm PreSdefault Percent*) and its interaction with the treatment dummy (*Low_CH*×*Firm PreSdefault Percent, High_CH*×*Firm PreSdefault Percent*); the number of cycles needed to get matched for the firm in the previous round (*Firm Cycles (t-1)*), the number of safe choices chosen in the risk elicitation stage (*No of Safe Choices*), a set of indicator variables representing

[14] See figure A5 in appendix A for the distribution of firms' risk attitudes. Those who chose more than 6 safe choices could be classified as risk-averse. Those with less than 6 safe choices could be classified as risk-loving and those with 6 safe choices could be considered as risk-neutral.

[15] See table A1 and table A2 in appendix A for the mean beta value by risk attitudes.

the gender composition of the pair with mixed gender pairings (*Gender Pair (Mix)*) and two-male pairings (*Gender Pair (Male)*), the average age of the pair (*Age Pair*), a set of indicator variables representing whether the pair has attended economics/finance classes with one of the pair having attended such classes (*EconExperience_Pair (M)*) and both having attended such classes (*EconExperience_Pair (Y)*). The similar definition applies to the variable representing the subjective report on whether they understand probability (*Probability Pair (Y)*) and the variable representing whether they have participated economics experiments before (*ExpExperience Pair (M), ExpExperience Pair (Y)*). The baseline of the gender variable is the two-female pairing, of the economics experience variable is that neither of the pair has economics exposure, of the probability variable is that only one of the pair reports understanding of probability and of the experiment experience variable is that neither of the pair has economics experiment experience.

[Enter Table 3 Here]

Panel A presents the analysis of the Low_NCH and the Low_CH treatments. Panel B presents the comparison of the High_NCH and the High_CH treatments. The treatment dummy *Low_CH* is negatively significant. It suggests that the presence of credit history decreases the agreed β value compared to the case where credit history is absent. This is intuitive because credit history itself tells something about the firm's propensity to engage in strategic default. As a result, the matched bank on average may not require a severe liquidation policy, i.e., a high β, as an insurance to lend. However, the presence of credit history seems to only affect β in the low beta treatments. Such effects are not observed in the high beta treatments as indicated by the insignificance of the treatment dummy *High_CH*. When credit history is absent, the more the firm strategically defaults, the lower the β would be. This applies to both the low beta and the high beta treatments as shown by the negative sign of the variable *Firm PreSdefault Percent*.

This is consistent with the signaling effect.[16] The results support hypothesis 3. Besides the direct effects captured by the treatment dummy, credit history exerts indirect effects on β captured by the interaction between the treatment dummy and the proportion of the firm's strategic defaults (*Low_CH* × *Firm PreSdefault Percent* and *High_CH* × *Firm PreSdefault Percent*). The positive sign of the interaction variable indicates that when the credit profile worsens (i.e., there is a higher proportion of strategic defaults in the past), there would be an upward pressure on the value of β when the credit history is present. In other words, when a firm has a bad credit history and the credit history is revealed to creditors, the creditors may require the firm to commit to a more severe liquidation policy (higher β) to persuade creditors to lend. The effect is more pronounced in the low beta treatments than that in the high beta treatments.

Note that, *Firm Cycles (t-1)* can be interpreted as a measure of toughness of the firm in the negotiation process. Longer firm matching cycles imply that the firm initially offers a low β, and no bank is willing to accept the offer, and the firm is reluctant to revise its offer upward in the early matching cycles. The effect of *Firm Cycles (t-1)* is negatively significant. It suggests that the tougher the firm is in the matching process, the lower β it achieves. Since firms have more bargaining power than banks, it is not surprising that being tough helps firms gain better β deals. Risk attitude does not have any significant effects in the low beta treatment while it does in the high beta treatments. The larger number of safe choices chosen indicates a more risk averse attitude. Being more risk averse drives down β in the high beta treatments.

As shown in model (2) and (4), results are qualitatively the same after socio-demographics are included. The socio-demographic variables mostly have differential effects in the low beta and

[16] Figure A6 in appendix A depicts the relationship between the average propensity of strategic default and the agreed beta. Figure A6 shows that good borrowers tend to have higher beta, which is consistent with results in table 3.

the high beta treatments except for gender. The presence of male in the pair drives up β, which is true for both beta level conditions. The matched pair having economics exposure or understanding probability has some positive effects on β while the economics experiment experience tends to drive down β. Those effects are only observed in the high beta treatments.

4.3 The Incidence of Strategic Defaults

Figure 3 presents the strategic default rate conditional on the value of the mutually agreed β in all treatments. In general, the percentage of strategic defaults goes down as the liquidation policy becomes more severe (i.e., β becomes higher). Overall, for the low beta treatments, the strategic default rate is not significantly different between the no-credit-history treatment and the credit-history treatment (two-sided Mann Whitney test, p=0.757). As for the high beta treatments, the strategic default rate in the no-credit-history treatment is significantly higher than that in the no-credit history treatment (two-sided Mann Whitney test, p=0.003). One possible reason might be that due to our parameter settings, the second period payoff if one survives liquidation is much higher in the low beta treatments than that in the high beta treatments (64 vs 24). As a result, one might be more tempted to take the risk to default strategically in the low beta treatment despite that credit history is revealed. In other words, our results suggest that the presence of credit history alone is not enough to offset the payoff temptation to default strategically in the low beta treatments. The magnitude of payoff when one survives liquidation and the probability of liquidation are also important, as they determine whether or not the borrowers should gamble by strategically defaulting. However, when the payoff of doing so is not so large and the probability of liquidation is sufficiently large as in the high beta treatments, it might be better to behave well to maintain a good credit history.

[Enter Figure 3 Here]

When the agreed β is lower than the equilibrium β, the incentive constraint is not satisfied. That is to say, in cases where $\beta < 0.3$ in the low beta treatments or $\beta < 0.7$ in the high beta treatments, firms, in theory, have no incentive to repay the loan even if the project is successful as the expected payoff from defaulting on the loan is higher than that from repayment. However, we do not observe 100% strategic default in those cases in both treatments. Thus, interestingly, firms show some degree of intrinsic trustworthiness even if it is not payoff maximizing to do so.

As shown in figure 3, when β is low, i.e., $\beta \leq 0.3$ for the low beta treatment or $\beta \leq 0.5$ for the high beta treatments, the strategic default rate in the credit-history treatment is lower than that in the no-credit-history treatment. The result holds for both the low beta treatments and the high beta treatments. The availability of credit history dampens borrowers' incentive to default strategically in the low beta range. In other words, when the credit history is available, borrowers have less incentive to default strategically even when the incentive compatibility constraint is violated.

Our results show that severe liquidation policy in case of defaults and information sharing discourage strategic default to some degree. This finding contributes to the literature on borrowers' strategic default behavior. Foote et al. (2008) suggest that homeowners' default decisions are related to the relative weight of mortgage and income from keeping the house. Borrowers' repayment decisions could be also related to lenders' ability to exclude defaulted borrowers from their current income source (Brown and Serra-Garcia, 2017), moral and social factors (Fay et al., 2002; Gross and Souleles, 2002; Karlan, 2005; Guiso et al., 2013), and mortgage modification programs (Mayer et al., 2014).

Table 4 reports the multilevel mixed-effects probit estimates of the determinants of strategic default. The dependent variable strategic default is a binary variable taking value 1 if the firm does not repay the loan when the project is successful and 0 otherwise. The independent variables are the mutually agreed β (*Beta*), the dummy variable taking value 1 if credit history is revealed and 0 otherwise (*CH*), the interaction between the credit history dummy and the mutually agreed β (*CH_Beta*), the accumulated times of liquidation in previous rounds (*AccumPreviousLiquidation*), Round number (*Round*), the number of cycles needed for the firm to get matched (*Firm Cycles*), the number of safe choices in the risk elicitation stage (*No of Safe Choices*), gender taking value 1 for males and 0 otherwise (*Gender*), age (*Age*), a dummy variable taking value 1 for foreigners and 0 otherwise (*Nationality*), a dummy variable representing whether one has attended economics/finance related classes (*EconExperience*), a dummy variable indicating the subjective report on whether one understands probability (*Probability*), a binary variable indicating whether one has participated economics experiments before (*ExperimentExperience*).

[Enter Table 4 Here]

The agreed beta value has negatively significant effects on the firm's propensity to default strategically. That is to say, as the liquidation policy becomes more severe (i.e., the agreed β goes up), it is less likely that the firm will default strategically. This is in line with results in figure 3. It is straightforward that the cost of strategic default rises as the agreed β increases, which deters strategic default to some degree. The presence of credit history exerts negative and significant influence on strategic default. Therefore, making credit history available could be an effective disciplinary tool to discourage strategic default. Hypothesis 4 finds its support. The firm's liquidation experience in the past and the toughness of the firm in the matching process do not have any significant effects. Risk attitude has negatively significant effects. A larger number of safe choices represents a more risk adverse attitude. The more risk averse the agent is; the less likely strategic default will happen. This is intuitive as strategic default imposes the risk of the firm being liquidated. The more risk averse agents would be more reluctant to take such risks. The socio-demographic variables have no effects on strategic default.

5 Concluding Remarks

In this paper, we present an experimental analysis of the impacts of bank liquidation policy and credit history information on borrowers' incentive to commit strategic default. Our experimental design is motivated by the Bolton and Scharfstein model of optimal liquidation policy in an incomplete contracting framework (Bolton and Scharfstein 1996). Bolton and Scharfstein (1996) show that the optimal financing contract is characterized by a probabilistic liquidation policy. Whenever the borrower fails to repay the loan—regardless of the reason—the borrower would be liquidated with some positive probability.

Our experimental setting incorporates the important elements of Bolton and Scharfstein (1996). There exists an equilibrium liquidation probability in the incomplete contracting setting. To investigate how credit history affects liquidation policy and strategic behavior, we vary the credit-history dimension. As a result, we have the no-credit-history and the credit-history treatments. Since we are also interested to know if the effects are sensitive to the equilibrium β value, we have the low beta and the high beta treatments.

The results show that credit history has different impacts on the agreed liquidation probability in the low beta and the high beta treatments. It tends to drive down the agreed liquidation probability when the equilibrium beta is low. It does not affect the agreed β when the equilibrium beta is high. In terms of the effects on strategic behavior, the availability of credit history deters strategic default. It is a more effective disciplinary tool when the liquidation policy is relatively lenient. This is universal regardless of the equilibrium beta value. The possibility of liquidation itself discourages strategic default. The more severe the liquidation policy is, the less likely the firm misbehaves.

This paper sheds light on the effects of credit history on liquidation policy and on strategic behavior. It adds to the burgeoning literature on credit information sharing in financial contracting settings. We find some interesting results in our experiments. That being said, there is still much to be explored. For example, the agreed β deviates from the equilibrium β in our experiments. One direction for possible future research would be to explore what the contributing factors are. The anchoring effect is one possible factor. Since the optimal liquidation probability is not so obvious, 0.5 becomes a salient point naturally. Another reason why 0.5 is attractive might be because people think it is a fair liquidation probability. Since the firm is subject to liquidation in the case of genuine liquidity constraints (i.e., the project fails), one may feel it is fair to liquidate the firm with 50% chance. In other words, social preferences could have implications on the selection of beta. In addition, we made major adjustments to the second period payoff and minor adjustments to the repayment amount to vary the theoretical beta value across treatments. The second period payoff only concerns the firm's payoff. It does not change the incentive structure for the bank side across treatments. This specific way of parameter specification might have contributed to the results as well. One could explore the contributing factors along those directions for future research. One could also study if changing the size of the matching cluster, the competitiveness among banks/firms and the matching process affect the results. Another line for future research could be comparing strategic behavior under endogenously decided β and exogenously decided β. β is endogenous in our study, it would be intriguing to study if firms behave differently when β is exogenously given.

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Tables and Figures

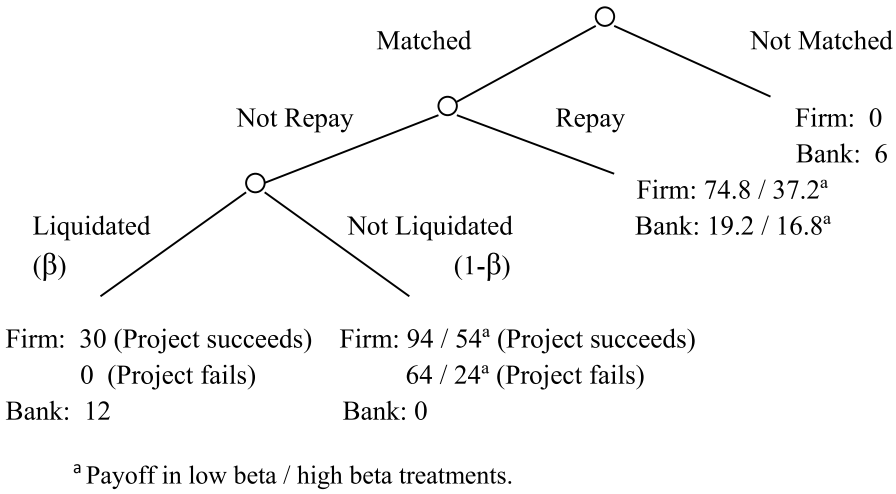

Figure 1. The game tree

Table 1. Risk elicitation

Line	Option A	Option B	Expected payoff difference
1	\$3	10% of \$5, 90% of \$0.1	2.41
2	\$3	20% of \$5, 80% of \$0.1	1.92
3	\$3	30% of \$5, 70% of \$0.1	1.43
4	\$3	40% of \$5, 60% of \$0.1	0.94
5	\$3	50% of \$5, 50% of \$0.1	0.45
6	\$3	60% of \$5, 40% of \$0.1	-0.04
7	\$3	70% of \$5, 30% of \$0.1	-0.53
8	\$3	80% of \$5, 20% of \$0.1	-1.02
9	\$3	90% of \$5, 10% of \$0.1	-1.51
10	\$3	100% of \$5, 0% of \$0.1	-2

Table 2. The Summary Statistics by Treatment

Treatment	Number of matching pairs[a]	Average β (Std. Dev.)	Number of successful project	Number of strategic defaults	Propensity to default strategically (γ)
Low_NCH	264	0.45 (0.15)	175	57	32.6%
Low_CH	266	0.4 (0.20)	177	53	29.9%
High_NCH	263	0.48 (0.16)	184	127	69.0%
High_CH	256	0.49 (0.19)	170	72	42.4%

Notes: a. One pair with a valid agreed β is considered as 1 observation. Matching failure is excluded.

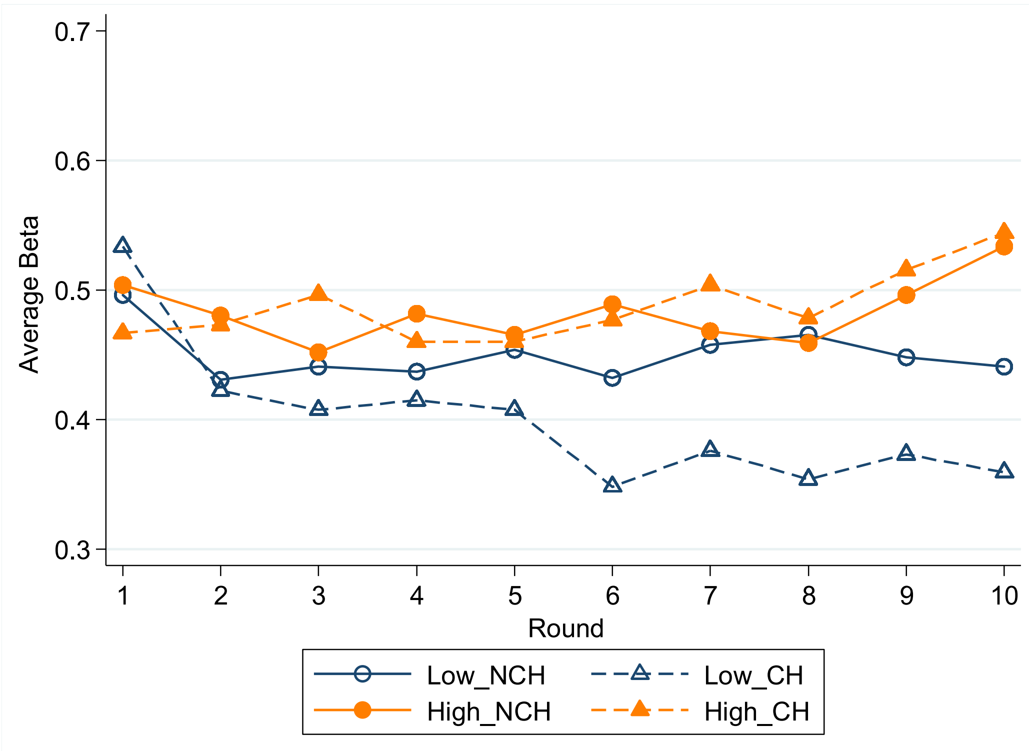

Figure 2. The average mutually agreed β across rounds

Table 3. Determinants of β: multilevel mixed-effects linear estimation

	Dependent variable: the agreed β			
	Panel A Low Beta		Panel B High Beta	
	(1)	(2)	(3)	(4)
Low_CH	-0.107**	-0.109**		
	(0.0472)	(0.0496)		
High_CH			-0.0311	-0.0582
			(0.0456)	(0.0404)
Round	-0.00291	-0.00270	0.00720**	0.00663**
	(0.00273)	(0.00264)	(0.00305)	(0.00284)
Firm PreSdefault Percent	-0.0959***	-0.119***	-0.0455	-0.0808**
	(0.0346)	(0.0343)	(0.0371)	(0.0357)
Low_CH × Firm PreSdefault Percent	0.137***	0.153***		
	(0.0467)	(0.0471)		
High_CH × Firm PreSdefault Percent			0.0369	0.0812*
			(0.0514)	(0.0487)
Firm Cycles (t-1)	-0.0184***	-0.0174***	-0.0226***	-0.0186***
	(0.00690)	(0.00672)	(0.00742)	(0.00699)
No of Safe Choices	0.00349	0.00473	-0.00926*	-0.0107**
	(0.00547)	(0.00535)	(0.00560)	(0.00534)
Gender Pair (Mix)		0.0863***		0.0453**
		(0.0208)		(0.0223)
Gender Pair (Male)		0.0765***		0.0728***
		(0.0233)		(0.0259)
Age Pair		-0.00576		0.00837
		(0.00688)		(0.00578)
EconExperience_Pair (M)		0.0166		0.0158
		(0.0219)		(0.0267)
EconExperience Pair (Y)		0.0374		0.0606**
		(0.0250)		(0.0295)
Probability Pair (Y)		-0.0187		0.165***
		(0.0286)		(0.0336)
ExpExperience Pair (M)		0.00127		-0.159***
		(0.0341)		(0.0248)
ExpExperience Pair (Y)		-0.0340		-0.123***
		(0.0346)		(0.0282)
Constant	0.507***	0.579***	0.568***	0.304**
	(0.0532)	(0.164)	(0.0491)	(0.143)
Observations	434	434	431	431

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

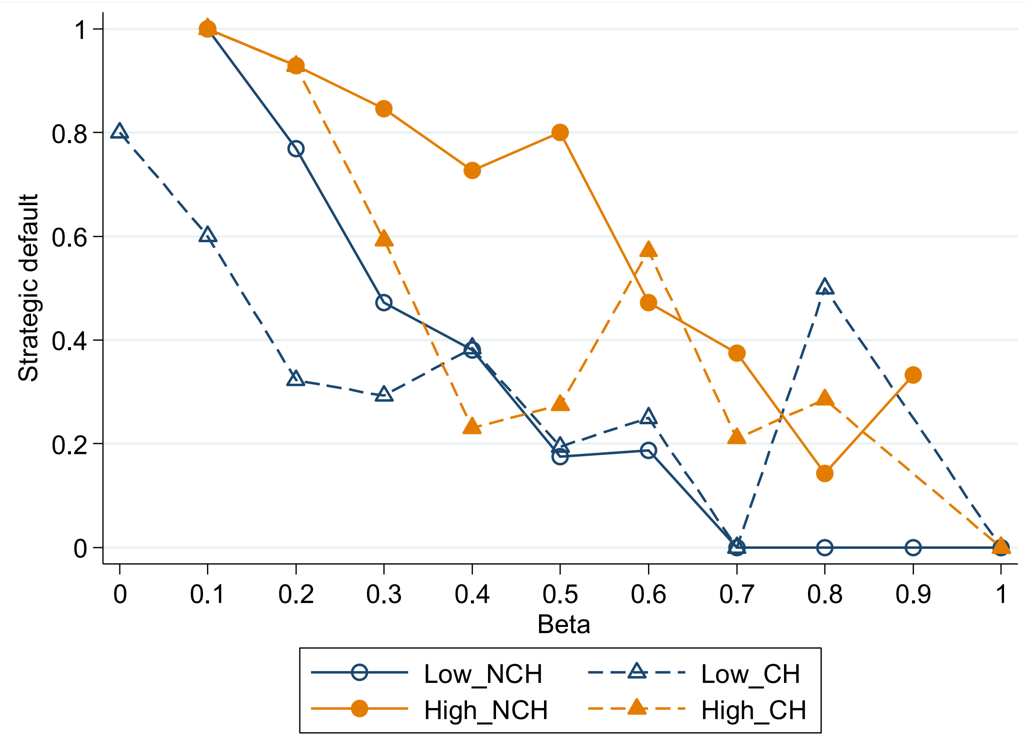

Figure 3. The strategic default rate conditional on the mutually agreed β

Table 4. Determinants of strategic default: multilevel mixed-effects probit estimation

	Dependent variable: Strategic default		
	(1)	(2)	(3)
Beta	-5.343***	-5.816***	-5.852***
	(0.802)	(0.906)	(0.908)
CH	-1.421**	-1.660**	-1.638**
	(0.604)	(0.658)	(0.664)
CH_Beta	1.761*	2.404**	2.362**
	(1.016)	(1.097)	(1.095)
AccumPreviousLiquidation		0.00371	-0.00572
		(0.0933)	(0.0923)
Round		-0.00393	-0.00279
		(0.0355)	(0.0353)
Firm Cycles		0.00310	0.00874
		(0.0668)	(0.0671)
No of Safe Choices		-0.184**	-0.192***
		(0.0727)	(0.0717)
Gender			0.386
			(0.256)
Age			-0.0212
			(0.0611)
Nationality			0.350
			(0.252)
EconExperience			0.208
			(0.272)
Probability			-0.178
			(0.543)
ExperimentExperience			0.0213
			(0.284)
Constant	2.418***	3.792***	3.944**
	(0.461)	(0.722)	(1.549)
Observations	706	634	634

*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

Appendix A. Additional results

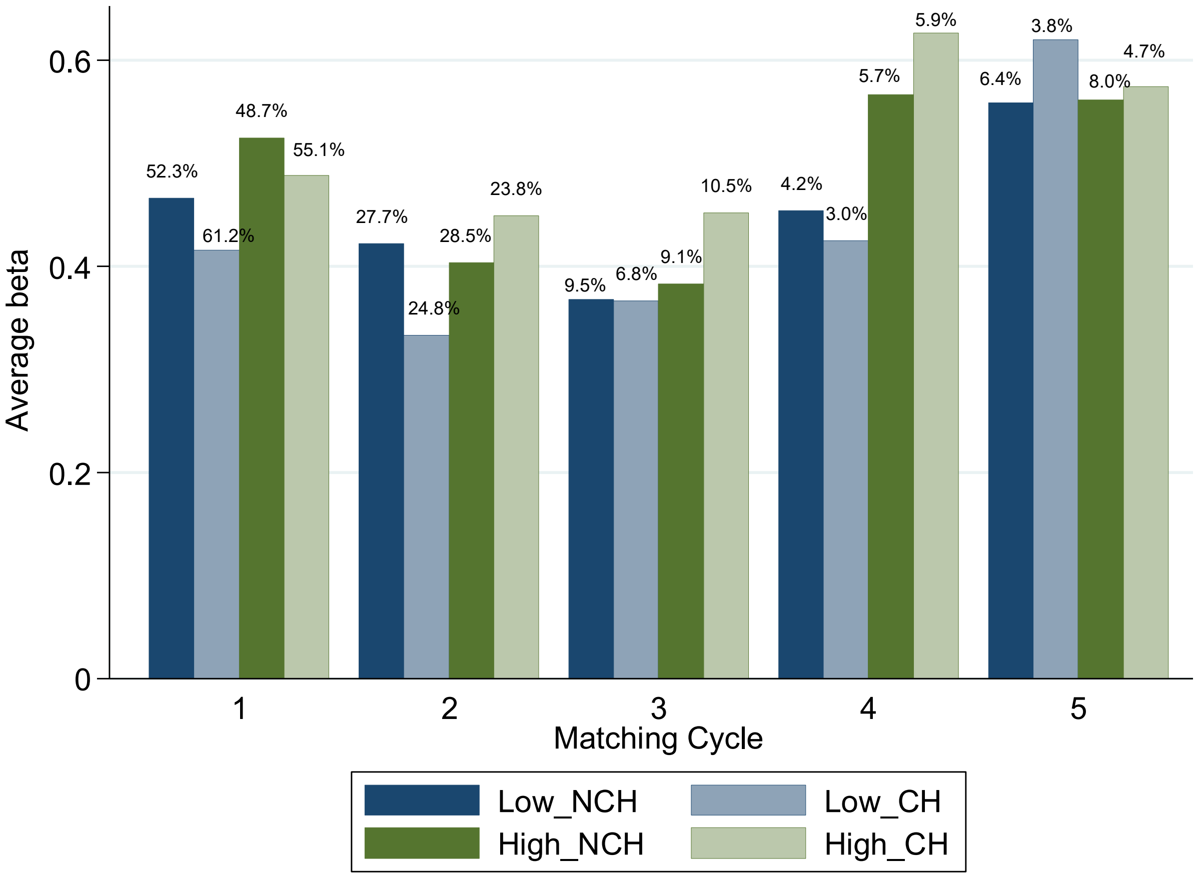

Figure A1. The average accepted beta across matching cycles

Notes: The number on the top of bars indicates the percentage of pairs who reach an agreement on the specified beta in that particular matching cycle.

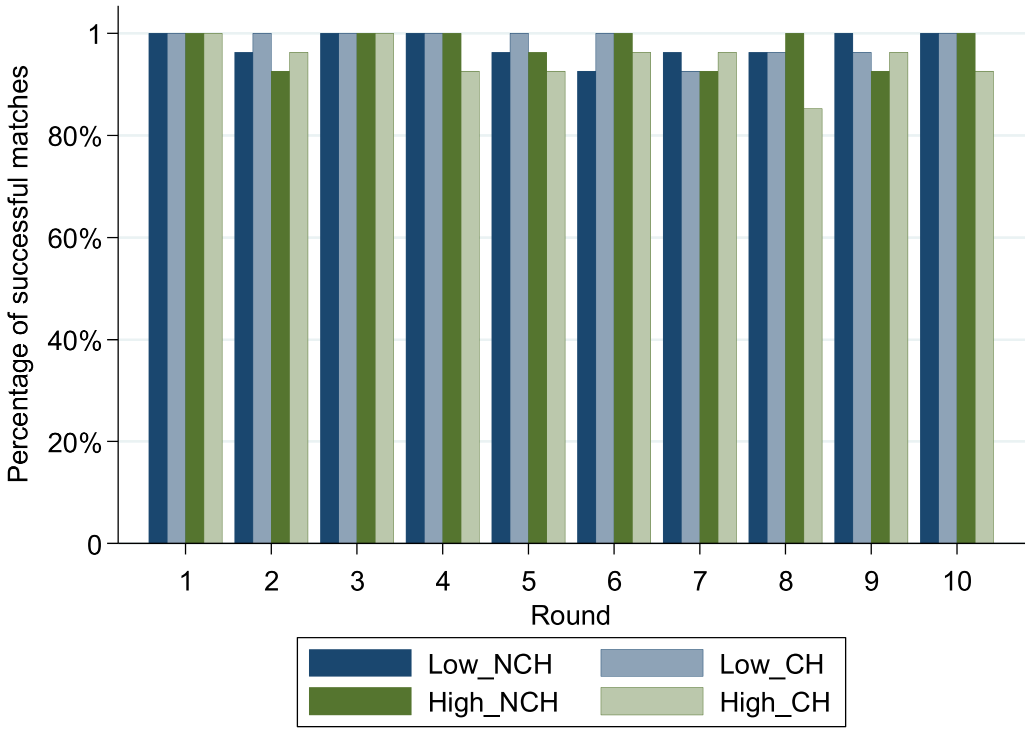

Figure A2. The percentage of successful matches over time

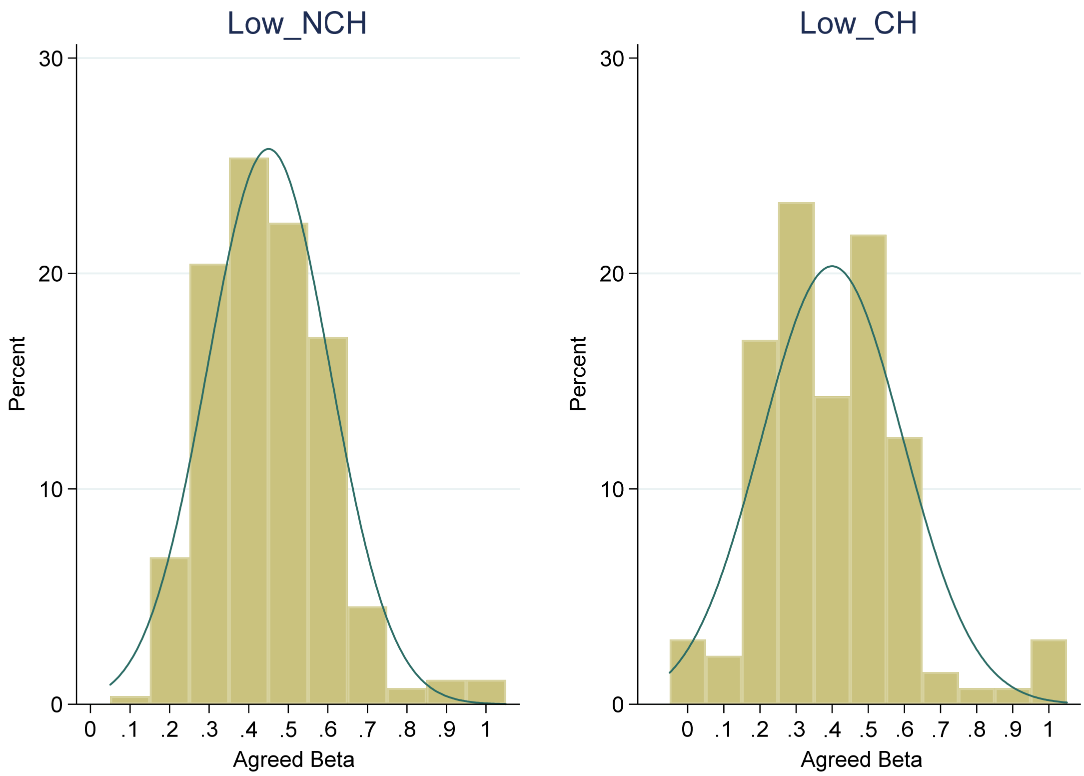

Figure A3. Histogram of the agreed beta in the low beta treatments

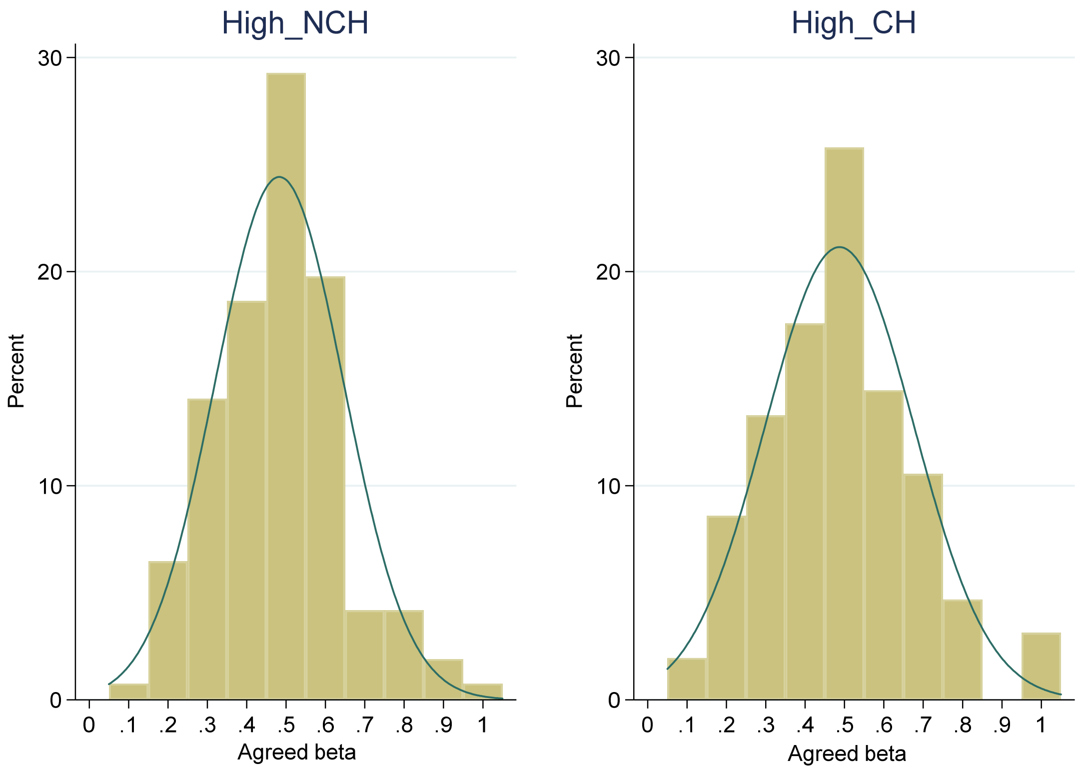

Figure A4. Histogram of the agreed beta in the high beta treatments

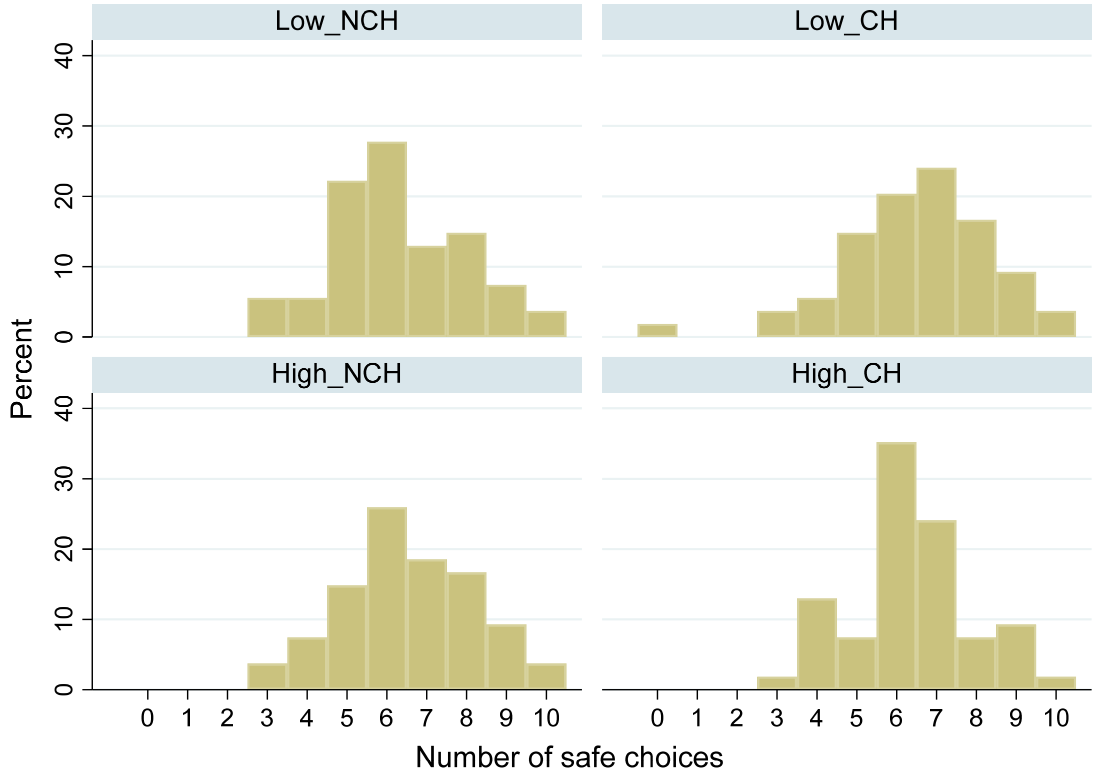

Figure A5. Distribution of firms' risk attitudes

Table A1. Average beta by risk attitude in the no-credit-history treatments

	Low_NCH		High_NCH	
Number of safe choices	percentage of observations	Mean beta (std. dev.)	percentage of observations	Mean beta (std. dev.)
0	0.00%	NA	0.00%	NA
1	0.00%	NA	0.00%	NA
2	0.00%	NA	0.00%	NA
3	7.20%	0.34(0.16)	7.60%	0.57(0.18)
4	7.58%	0.38(0.06)	7.60%	0.59(0.19)
5	22.35%	0.50(0.18)	11.41%	0.57(0.09)
6	29.17%	0.41(0.14)	25.48%	0.47(0.15)
7	15.15%	0.46(0.15)	14.83%	0.46(0.18)
8	11.36%	0.44(0.07)	18.25%	0.42(0.16)
9	7.20%	0.61(0.13)	11.03%	0.41(0.13)
10	0.00%	NA	3.80%	0.56(0.14)

Table A2. Average beta by risk attitude in the credit-history treatments

	Low_CH		High_CH	
Number of safe choices	percentage of observations	Mean beta (std. dev.)	percentage of observations	Mean beta (std. dev.)
0	0.00%	NA	0.00%	NA
1	0.00%	NA	0.00%	NA
2	0.00%	NA	0.00%	NA
3	3.76%	0.25(0.07)	0.00%	NA
4	11.28%	0.48(0.17)	14.45%	0.49(0.20)
5	22.18%	0.49(0.18)	10.55%	0.42(0.19)
6	7.52%	0.29(0.20)	48.44%	0.50(0.18)
7	14.66%	0.42(0.30)	15.23%	0.46(0.14)
8	26.32%	0.38(0.14)	3.52%	0.54(0.19)
9	10.53%	0.33(0.13)	7.81%	0.53(0.26)
10	3.76%	0.31(0.10)	0.00%	NA

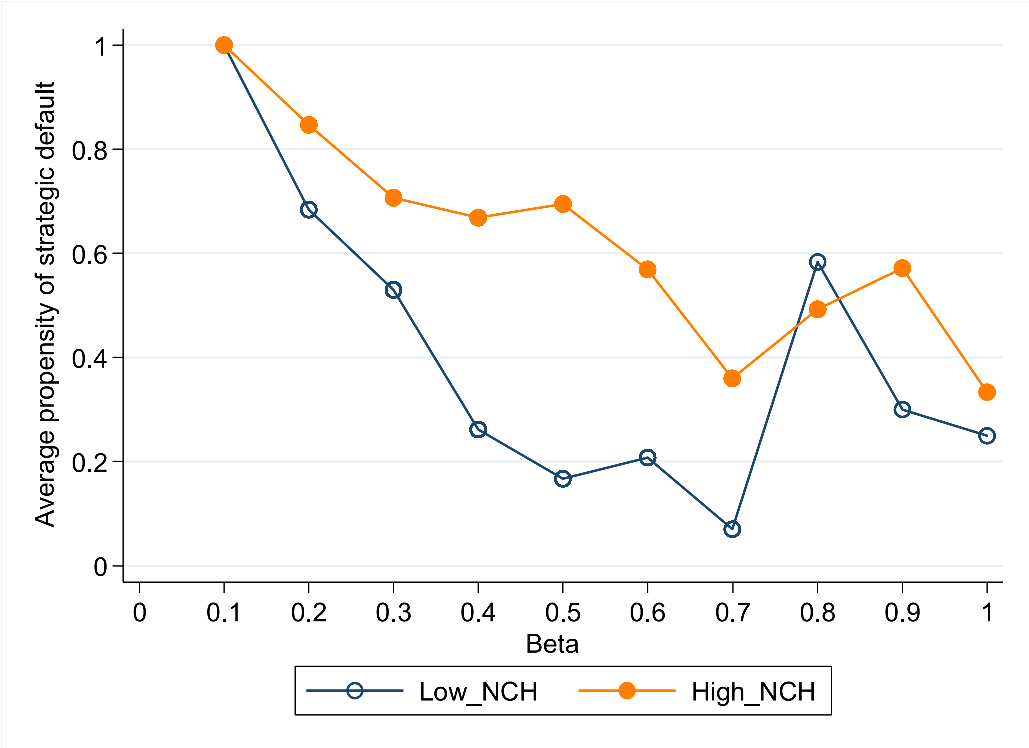

Figure A6. Average propensity of strategic default and the agreed beta in no-credit-history treatments

Notes: Propensity of strategic default measures the quality of firms. Higher propensity of strategic default indicates the firm has a history of high percentage of strategic default.