That's how we roll: an experiment on rollover risk

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Abstract

We design a continuous-time experiment to study how different short-term credit maturities interact with the state of the economy. We find that, when the economy is in a boom, long maturities stabilize the credit market. Yet, when in a downturn, such maturities increase the likelihood of credit freezes. This result has important regulatory implications, as it suggests that a policy aimed at reducing maturity mismatch in short-term credit markets might backfire during a recession.

Keywords: Experiment, Financial Crisis, Continuous-Time, Short-Term Credit

JEL Codes: C92, C91, G01, GO2, G21

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1 Introduction

While a relevant segment of the literature agrees on placing a run on short-term credit as one of the most destabilizing events of the recent financial crisis (e.g. Brunnermeier (2009), Krishnamurthy (2010), Bernanke (2008, 2009a,b)), there is much less consensus on how to prevent another panic from happening. One policy that has been widely discussed consists in limiting the maturity mismatch of firms. Brunnermeier et al. (2009) suggests extending the maturity of short-term credits to help stabilize the market for credit, while Farhi and Tirole (2012) advocates for putting a cap on the total amount of short-term debt that firms can issue. Malherbe (2014), on the other hand, warns about the unintended consequences of limiting maturity mismatch.

This disparity of recommendations reflects the difficulty in studying markets for short-term credit, as maturities are endogenous, and field experiments not easily feasible. In this paper, we overcome these problems by bringing short-term credit markets into the lab. Our intention is to study the interplay between different maturity lengths and the state of the economy in a market for Asset Backed Commercial Paper (ABCP).[1] To do so, we will draw on the model by He and Xiong (2012), where a firm finances its long-term investment by issuing short-term debt to a continuum of creditors with staggered maturities. [2]

Our main result is that there is a strong interaction between a) the decision to roll-over credit, b) the state of the economy, and c) the length of the maturities. As we show below, when the economy is in a good state, contracts with long maturities are more likely to be rolled over. However, when the economy is in a downturn, long maturities are more likely to trigger a credit dry-up. The intuition is the following: During good times there is little uncertainty about the performance of firms, which makes long maturities attractive, thus helping stabilize the credit market. Yet, when the economy is in a dip, creditors will shy away from long- term commitments, and will only want to extend credit with very short maturities. If these are not available, then a credit freeze will ensue.

[1] Asset Backed Commercial Paper (ABCP), is a specific type of short-term credit in which, if the issuing firm does not fulfill its promises, the holder of the ABCP can seize the posted collateral.

[2] It is important to understand that the objective of this paper is *not* to test experimentally the predictions of He and Xiong (2012), but rather to use experimental methods to explore questions that are hard to answer with field data.

Our result, therefore, suggests that the best policy would be counter-cyclical, limiting maturity mismatch during booms, but favoring it during downturns.

In the experiment we also observe a significant number of runs on firms that are solvent and have enough liquidity to repay all creditors in case of a fire-sale. This type of runs do not arise in one-shot simultaneous move models such as Diamond and Dybvig (1983) or Goldstein and Pauzner (2005), as there can be no coordination failure on a bank that can pay back in full every sinlge depositor even after liquidating its assets. Otherwise, in He and Xiong (2012), because rollover decisions are asynchronous and the firm fundamentals are time-varying, creditors have to evaluate both today's as well as tomorrow's values whenever deciding whether to roll-over their credit. This triggers a "rat race" between creditors, who try to preemptively stop rolling-over their credit before other creditors do so.[3] This type of runs were a surprising development during the recent crisis and major financial institutions were not prepared for them (see (Bernanke (2008)).[4]

2 Our Experiment in the Context of the Experimental Literature

Continuous-time experiments started with the working papers of Cheung and Friedman, and Brunnermeier and Morgan around 2003/04 (later published as Cheung and Friedman (2009) and Brunnermeier and Morgan (2010)), and have taken off with Oprea et al. (2009), Anderson et al. (2010), Friedman and Oprea (2012), or more recently, Calford and Oprea (2017), and Tasneem et al. (2017). While none of these continuous-time experiments directly addresses any of the questions of our paper, our design and data analysis was

[3]In Diamond and Dybvig (1983), if a firm is liquid and has strong fundamentals, even if all other creditors decide to run, not running is still the optimal strategy. Yet, because in He and Xiong (2012), because the decisions to roll-over are asynchronous (i.e., different creditors have maturities at different times), and the fundamental value is time-varying, maturing creditors must consider both today and tomorrow's value of the firm. In other words, at each maturity point, creditors must consider the risk of rolling over, given that tomorrow the value of the firm will have changed and a new set of creditors will be deciding whether or not to rollover their credit.

[4]In a 2008 speech Bernanke said: "One of the key events in financial markets in recent months was the near-bankruptcy (. . .) [of] Bear Stearns. The collapse was triggered by a run of its creditors and customers, analogous to the run of depositors on a commercial bank. This run was surprising, however, in that Bear Stearns's borrowings were largely secured (. . .) Bear Stearns's contingency planning had not envisioned a sudden loss of access to secured funding, so it did not have adequate liquidity to meet those demands for repayment"Bernanke (2008).

inspired by many of their ideas.

Closer to our purposes is the literature on experimental bank runs. In it, we find two different strands: The first one is centered on “single shot” designs close to the Diamond and Dybvig (1983) model (e.g., Madies (2006); Arifovic et al. (2013)), while the second favors a more “dynamic” approach that allows experimental subjects multiple opportunities to withdraw their deposits (e.g., Garratt and Keister (2009) or Schotter and Yorulmazer (2009)). The important difference between these two strands resides in the extra information contained in the past actions of other depositors. For example, Schotter and Yorulmazer (2009) show that the more information subjects have of their counterpart’s past actions, the more likely it is that they will defer their withdrawals. Garratt and Keister (2009), on the other hand, find that the more opportunities an experimental subject is given to withdraw, the more likely it is that she will do so. In a similar vein, Kiss et al. (2012) conclude that observability of other subjects’ actions can be considered as a partial substitute for deposit insurance. Chakravarty et al. (2014) and Brown et al. (2017), study contagion across banks, and show that when the fundamentals of two banks are correlated, observing a run in a bank increases the probability of a run in the other. Interestingly, Brown et al. (2017) note that this contagion is due to a fear of other subjects running rather than of the bank having weak fundamentals. Finally, it is worth mentioning that Kiss et al. (2014) study the effects of networks on bank runs, concluding that, while observability influences the likelihood of bank runs, it is the actions being observed, and the position of the subject in the network, what ultimately determines the outcome.

There is also a large literature studying experimental credit markets. For example, Baghestanian and Massenot (2016) have subjects borrow at a certain market-determined interest rate in order to invest in a risky project. They show that even in a transparent market with full information and no aggregate shocks, credit cycles can arise endogenoulsy. Brown and Zehnder (2007) study the effects of banks sharing the “credit history” of creditors; their result is that while sharing this information increases repayment rates in one-shot interactions, these effects disappear when creditors and banks interact repeatedly. In a more recent paper, Brown and Zehnder (2010) conclude that it is the level of symmetry in the information what determines whether the “credit history” is shared between banks. In Barboni et al. (2013) even if creditors have full information on the credit history of borrowers, risk aversion turns out to be the driving force behind multiple lending relationships. Finally, Cason et al. (2012) compare peer monitoring to lender monitoring, and shows that when peer monitoring is cheaper than lender monitoring, then the former results in more loan frequency and higher repayment rates. However, this effect disappers when both monitoring costs are the same. A good summary of the experimental credit market literature can be found in Christie (2013).

In conclusion, while there exists a dense experimental literature on both banking panics and credit markets, no paper focuses on short-term markets or maturity mismatch.[5] Our contribution is to use continuous-time techniques to bring both of these topics into the laboratory, and to study their interaction with the state of the economy.

3 Theoretical Benchmark

Our experiment is inspired on the continuous-time model by He and Xiong (2012) (HX henceforth). In it, a firm finances its long-term investment by issuing short-term debt to a continuum of creditors (assume this credit to be of \$1). The value of the firm follows a geometric Brownian motion, and is perfectly observable by all creditors.[6] The Brownian motion can be written as:

$$\frac{dy}{y} = \mu dt + \sigma dZ \tag{1}$$

Where y_t is the value of the firm, μ is the drift, σ the volatility, and Z the standard Brownian motion.

Each creditor's debt matures with the arrival of an independent Poisson shock of intensity $\kappa > 0$, creating a uniform distribution of the maturities, with all contracts having an expected duration of $1/\kappa$ at any point in time. If within the time interval $[t, t+dt]$ enough creditors decide to stop rolling over their credit, then the firm draws from its cash reserves (ϑ) and survives, on average, an extra $1/\vartheta\kappa$ units of time.[7] Once the firm runs

[5] For a more detailed summary of the existing literature on experimental finance and their contributions see Heinemann (2012) or Dufwenberg (2015).

[6] We will assume that the firm's only investment is on the long-term asset, so the value of the long-term asset is the total value of the firm.

[7] He and Xiong (2012) describe ϑ as unreliable credit lines that the firm may tap, which is why the

out of reserves it goes bankrupt and liquidates its assets at a discount value $\alpha < 1$, so the value of the asset is $\alpha F(y_t)$, where $F(y_t)$ is the present discounted value of the firm.

As payoffs, creditors receive a stream of interests r until $\tau = \min[t_m, t_b, t_d]$ which is the earliest of three possible events. The first event (t_m) is the maturing of the long-term investment of the firm, in which case the creditor gets back either the full principal of the credit, or whatever the firm can pay back, but never more than the original \$1 credit (i.e., $\min(1, y_{t_m})$). The second possible event (t_b) is the bankruptcy of the firm, in which case the creditor gets back either the entire principal or the liquidation value ($min[1, \alpha F(y_t)]$). Finally, the individual short-term credit of the creditor can mature (t_d), at which point she will decide whether or not to rollover her credit. She will do so if the continuation value $V(y_{t_d}; y*)$ is higher than getting the principal back (\$1), where y_{t_d} is the value of the firm at the maturity point t_d, and $y*$ is the stopping threshold of other agents. The continuation value is thus:

$$\begin{aligned} V(y_t; y*) &= E_t\Big\{ \int_t^\tau e^{-\rho(s-t)} r ds + e^{-\rho(\tau-t)} \Big[\min(1, y_\tau)\mathbf{1}_{\tau=t_m} + \\ &\min\left(1, \alpha F\left(y_\tau\right)\right)\mathbf{1}_{\tau=\mathrm{t_b}} + \max_{\text{rollover or stop}} \left\{0, 1-\mathrm{V}\left(\mathrm{y}_\tau; \mathrm{y}*\right)\right\}\mathbf{1}_{\tau=\mathrm{t_d}}\Big]\Big\} \end{aligned} \tag{2}$$

Where ρ>0 is the discount value of the creditor, and $\mathbf{1}_{\{.\}}$ is an indicator function which takes value 1 whenever the subscript is true, zero otherwise. By evaluating the change in the continuation value (2) over a small time interval $[t, t+dt]$ the Hamilton-Jacobi-Bellman equation can be written as:

$$\begin{aligned} \rho V(y_t; y*) &= \mu y_t V_y + \frac{\sigma^2}{2} y_t^2 V_{yy} + r + \phi\left[\min\left(1, y_t\right) - V\left(y_t; y*\right)\right] + \\ &\kappa\delta \mathbf{1}_{\{y_t < y*\}}\left[\min\left(1, \alpha F\left(y_\tau\right)\right) - V\left(y_t; y*\right)\right] + \delta \max_{\text{rollover or stop}} \left\{0, 1-\mathrm{V}\left(\mathrm{y_t}; \mathrm{y}*\right)\right\} \end{aligned} \tag{3}$$

In equation 3 the left-hand side represents the required return to the creditor, while the first two terms on the right-hand side evaluate the fluctuation in the value of the firm. The remaining terms are the continuation values of each of the three outcomes (long-term maturity, bankruptcy, short-term maturity) weighted by each one's probability.

extra time is a function of the contract length. We believe that describing ϑ as cash reserves is more intuitive for our experimental purposes.

HX show that agents will rollover the credit *if and only if* $V(y_t; y*) > 1$. This results in a unique symmetric equilibrium determined by the condition $V(y*; y*) = 1$, at which point no creditor rolls over credit to a firm whose value is below $y*$, but always does if the value is above $y*$.

4 Experimental Implementation

4.1 Basic Design

Our experiment implements groups of 4 subjects whose composition stays the same during all 60 rounds of a session. In each round, subjects must make one and only one decision: whether stop rolling over their credit to a firm or not. The credit is valued in $1 and it is automatically extended, at the beginning of each round, by all members of the group to the same firm. The firm uses this money to finance a long-term investment which doubles as collateral for the credit. The value (y_t) of this long-term investment is dynamic such that, at every "tick" (1/5 of a second), it can either go up $(1 + 0.07) * (y_t)$ or down $(1 - 0.07) * (y_t)$ with probabilities $P = 0.5001$ and $1 - P = 0.4999$ respectively.[8] Each round has a random ending governed by a Poisson process, with an expected length of 30 seconds (150 ticks). At this point the long-term investment matures and the firm ceases to exist.

If at any point during a round a subject decides to stop rolling over her credit, the decision is final, and that round is over for her. If two subjects decide not to rollover their credit during the same round, then the firm will continue to run for a fixed number of ticks (θ) before it goes bankrupt and has to liquidate its assets at a fire-sale value. This "extra time" is a linear function of the duration of the short-term contracts, and can be interpreted as the cash reserves of the firm.[9]

Subjects play sixty rounds per session, but are paid for only ten of them.[10] The payoffs

[8]This is a Binomial approximation to the geometric Brownian motion of HX, as described in Anderson et al. (2010).

[9]This parameter comes directly from HX where they show that it holds some non-monotonic properties. While not crucial for our experimental design, we kept it in because we want to test the effects of changing θ in future experiments.

[10]Subjects are informed about this, and are aware that the selection of rounds to be paid is random.

come from two sources: a flow payoff and an end-of-round status. The flow payoff can be interpreted as the interest payments on the credit, and the end-of-round status as the "state of the world" which will determine the proportion of the principal that the subject gets back. To be precise:

1. *Flow payoff*: For each tick that a subject keeps her credit with the firm she receives $0.004 (i.e., $0.6 for every 30 seconds invested).

2. *End-of-round status*:

   (a) Exit: if a subject exits the project at time t_e, then she gets back her initial investment of $1, independently of the value of the firm ($y_{(t_e)}$) at that point.

   (b) Bankruptcy: if at time t_b a firm goes bankrupt it will sell its assets at a fire sale value of $\alpha F(y_{t_b})$, and pay subjects with outstanding credits $Min[1, \alpha F(y_{t_b})]$.

   (c) Natural Ending: If the firm reaches its random "natural" ending t_n without going bankrupt, it pays subjects with outstanding credits $Min[1, y_{t_n}]$.[11]

During each round subjects see a screen as in Figure 1. In it, they can keep track of both the firm's value (y_t, green jagged line), and of the fire-sale value ($\alpha F(y_t)$, golden jagged line with dots). Additionally, they can see the values at which subjects in the group decided to stop rolling over their credit in the previous 15 periods (upper right box), the $1 threshold under which the principal they get back would be <$1 (horizontal red line), and the moment they asked to stop rolling over their credit if they decided to do so (green vertical line).

4.2 Credit Rollover and Credit Maturities

The asynchronous maturities of the experiment are one of its unique aspects, and presented some implementation problems. Since having subjects decide whether to roll over their credit every few seconds is too cumbersome, we implement an "automatic rollover"

[11] Recall that subjects are creditors, not investors, therefore, whatever the value of the collateral at the end of the round, a subject will never get back more than $1 (plus the flow payoffs).

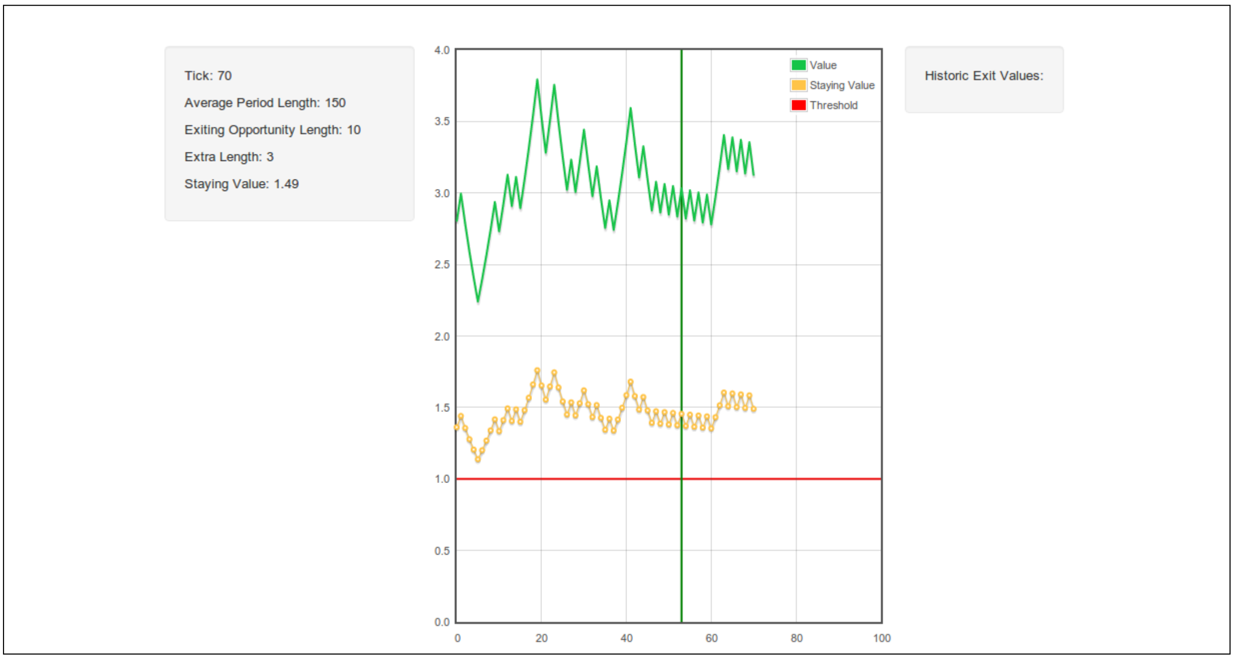

Figure 1: Screen-shot

system. In it, credits are rolled over automatically unless the subject decides otherwise. To stop the automatic rollover, she just needs to hover from left to right over three consecutively numbered buttons that appear on the screen, and the credit will stop being rolled-over at the next maturity point. The hovering idea comes from Brunnermeier and Morgan (2010), who introduce this mechanism to avoid subjects making inferences from the clicking sounds made by other subjects. We add the requirement that the hovering should follow a certain direction (from left to right), to avoid accidental stopping orders, a prevalent problem reported in Brunnermeier and Morgan (2010).

Since we are interested in the endogenous values at which subjects decide to stop rolling over their credit, and not in the exogenous maturity point we impose, we hide these maturity points. By hiding this information we avoid turning maturities into focal points and, thereby, we keep the focus on the values of the collateral that will trigger credit freezes, our value of interest.[12] To implement this "hidden maturities" system we fix the length of the contracts to be δ ticks long, and have the computer (randomly) assign to each subject an initial maturity point within the first δ ticks of each round. After that, for each subject, the maturities will happen every δ ticks. So, for example, for subject

[12]After all, in financial markets, even if at a certain date one individual credit contract does not mature, many others (of potentially similar creditors) do.

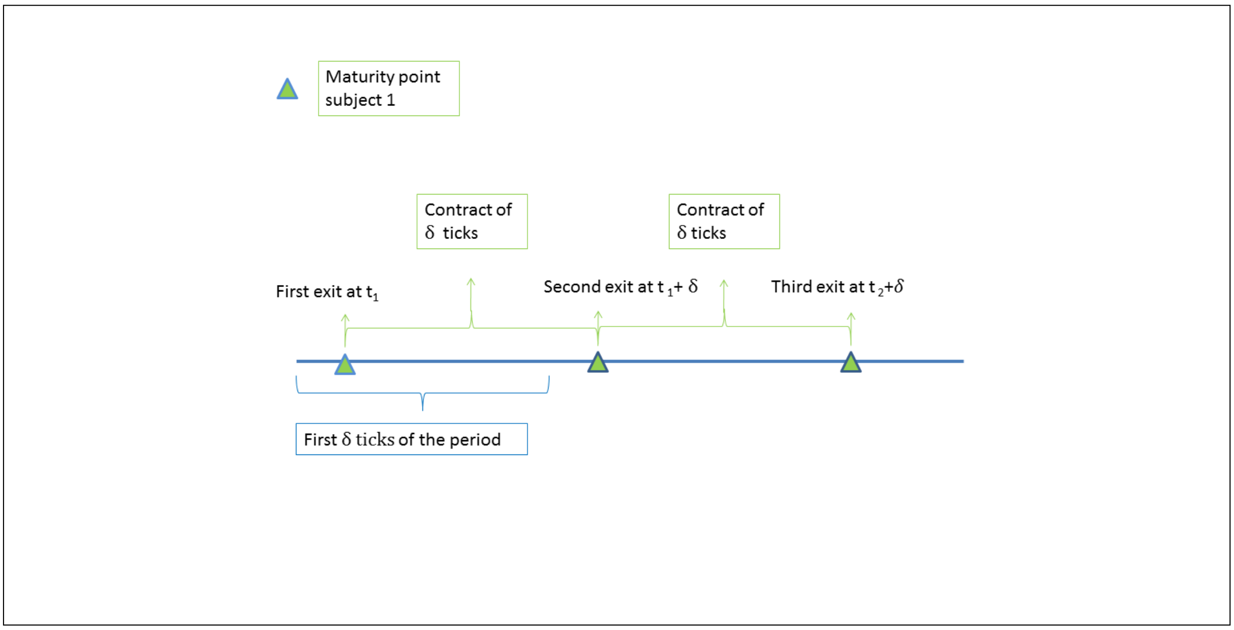

Figure 2: Image of random maturity mechanism

i in round j her first maturity point will be a random number $t_{1ij} \epsilon [0, \delta]$, the second one ($t_{2ij}$) at $t_{2ij} = t_{1ij} + \delta$, the third one ($t_{3ij}$) at $t_{3ij} = t_{2ij} + \delta$, and so on (see Figure 2). As a result, at every point in time the expected maturity of every subject is $\delta/2$ ticks away, akin to a Poisson shock of intensity $\delta/2$.

Additionally, as in Anderson et al. (2010), we let every round play until its random ending and do not provide subjects with any information on what other members of the group are doing. So, a firm might have gone bankrupt due to the actions of other subjects, but this will not be communicated to the group until the end of the round, when they are presented with the end-of-round screen (Figure 3). In it subjects can see other subjects' (and one's own) requests to exit (green vertical lines), other subjects' (and one's own) actual exit (orange vertical line), as well as a bankruptcy point if there was one (red vertical line). The screen also provides subjects with other information such as round length, and their individual payoffs for the round (table to the left of the screen). The idea of hiding the actions of other group members until the end of the round comes from Anderson et al. (2010) who call it the "semi-strategy method," and it allows us to collect more data per round.[13]

[13]Imagine that a certain subject i has its threshold at a value y_i. Then, if we did not use the "semi-strategy method" we would never be able to observe her threshold if at least two other members of the group (j, k) had stopping thresholds above hers (i.e., $y_{j,k} > y_i$). Additionally, because these are groups of four, each individual subject carries a disproportionate weight, so we feared any (visible) withdrawal

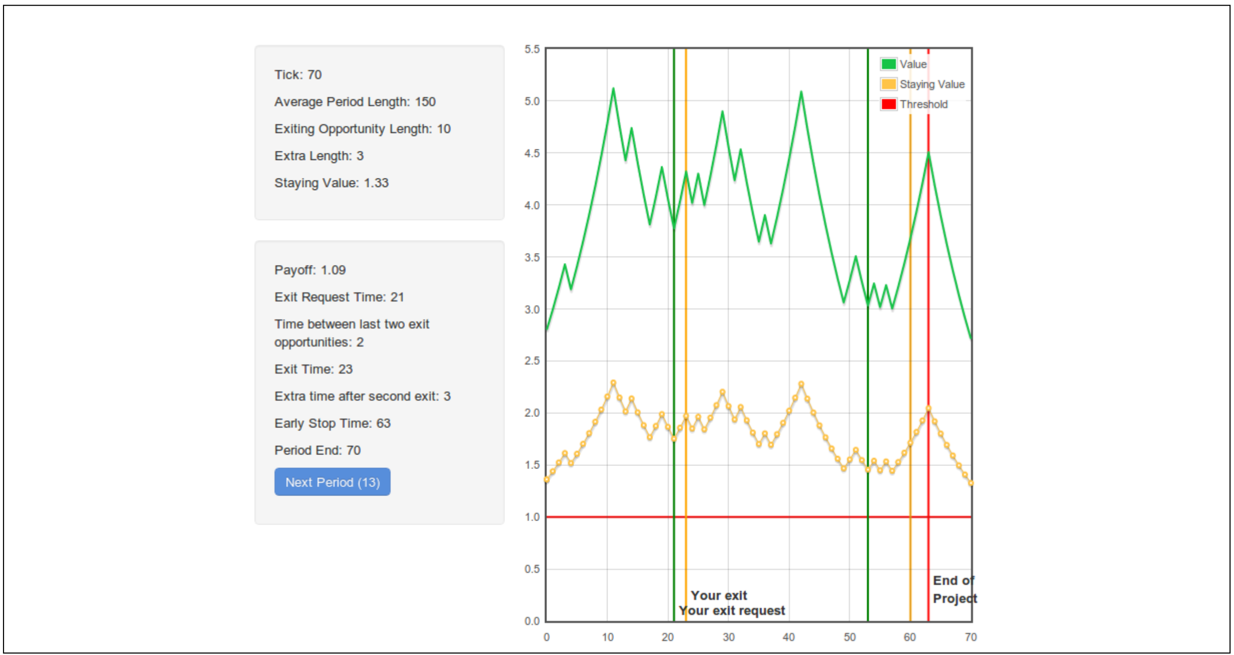

Figure 3: Pseudo-Strategy Method Screen

4.3 Parameters

Since we are interested in comparing the effects of short and long maturities on the rollover decisions of our subjects, we setup two treatments: Long and Short. In the Long Treatment each contract is eight seconds long ($\delta = 40$ ticks) and cash reserves last fifteen extra ticks. In the Short Treatment each contract is two seconds long ($\delta = 10$ ticks) and cash reserves last for for three ticks. These treatments were chosen to maximize the distance between the two rollover thresholds predicted by He and Xiong (2012) given our parameters (see Table 1).

Parameter	Long Contract	Short Contract	Comment
δ	40 ticks	10 ticks	Contract Length
θ	15 ticks	3 ticks	Cash reserves
μ	0.0024	0.0024	Drift of the GBM
r	\$0.004 per tick	\$0.004 per tick	Per-tick flow payoff
σ^2	1.1	1.1	Volatility

Table 1: Parameter Values

In HX, the threshold differences arise because when a creditor decides whether or not to roll over her credit, she must take into account the present value of the firm *and*

would automatically trigger an immediate run by all other members of the group.

the length of the contracts. Everything else being equal, longer credit maturities have two opposing effects: on the one hand, rollover decisions are less frequent, so the firm is less likely to fail if its investment drops in value, while on the other, the creditor's own maturity is longer so there are more chances for other creditors to stop rolling over their credit. Which of the two effects prevails will depend on the remaining parameters of the model. In our experiment, the former effect dominates, so the threshold for the Long Treatment ($y_L* = \$1.65$) is lower than that for the Short Treatment ($y_S* = \$1.82$).

5 Experimental Results

5.1 Description

All sessions were run at the LEEPS lab of the University of California at Santa Cruz, all subjects were undergraduates from this institution, and none played the game twice. In total 92 subjects participated in the experiment, spread into 9 different sessions.[14] The first seven sessions took place during the summer of 2012, the other two in the spring of 2013. Subjects earned, on average, \$16 and each session lasted a bit over one hour. Demographic details of the participants can be found in Appendix A.

In each session we had either 12 or 8 subjects for a total of 5,520 decisions (60 rounds × 92 subjects).[15] Unfortunately, a number of subjects did not understand the experimental setup and were trying to "sell [the asset] at high values", as was reported by one of them in the post experimental questionnaire. To take care of these distorted values, we will ignore all stopping decisions for a value above \$4, which leaves us with 5,274 observations. We pick the value of \$4 because at it, it is impossible to lose money in the Short Treatment, and the probability of doing so in the Long Treatment is $<0.1\%$.[16]

To have a first quick view of the experimental results, we plot the cumulative density functions of all the observed stopping values for both treatments, along with their respective theoretical stopping thresholds (vertical dotted lines) in the left pane of Figure 4. It

[14] 12 groups participated in the Short Treatment and 11 in the Long Treatment.

[15] Each session begins with some practice rounds whose results are not used in the analysis.

[16] Because subjects receive a flow payoff for every tick that they are locked in the contract, rolling over for any value above \$4 is a dominant strategy.

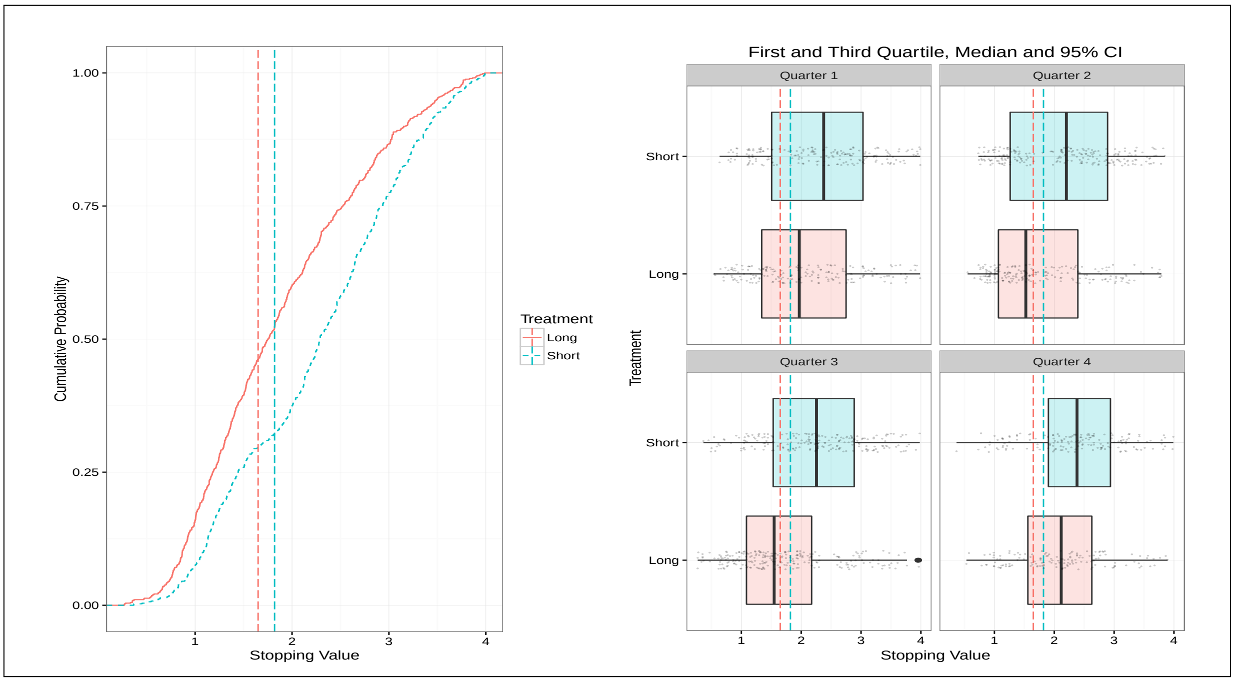

Figure 4: Left pane: CDF plotting the value of the firm at the stopping values for both treatments (dashed blue line representing the Short Treatment). Right pane: Box plots of each quarter with the observed stopping values for each treatment (vertical dotted lines).

is apparent from Figure 4 that there is a treatment effect as the CDF's are clearly separated, with Short Treatment stopping values being higher than in the Long Treatment.[17] Additionally, in the right pane of Figure 4 we divide the experiment into quarters (15 periods each) and plot the median stopping value (vertical dark line), the bounds comprised between the second and third quartile (colored box), along with the 95% confidence interval (horizontal line) and the individual decisions within each round (soft grey dots).

Next, in Figure 5, we plot the fire-sale value ($\alpha F(y_t)$) at which subjects stopped their credit in both treatments. All stopping decisions to the right of the dashed black line correspond to the case when the firm had "solid fundamentals" (i.e., $E\left[Min[1, \alpha F(y_{(t_{(b+\theta)})})] \geq 1\right]$), so, it turns out that the "frantic runs" predicted by HX take place quite often. Consequently we can state the following result:

- Result: *Frantic runs occur often: Approximately* 67%(55%) *of the decisions to stop rolling over a credit in the Short (Long) Treatment are made when firms have strong fundamentals.*

[17] An Epps-Singleton test comparing the median choice for each group across the whole session confirms this (p-value<0.001) (see Figure 8 in Appendix B).

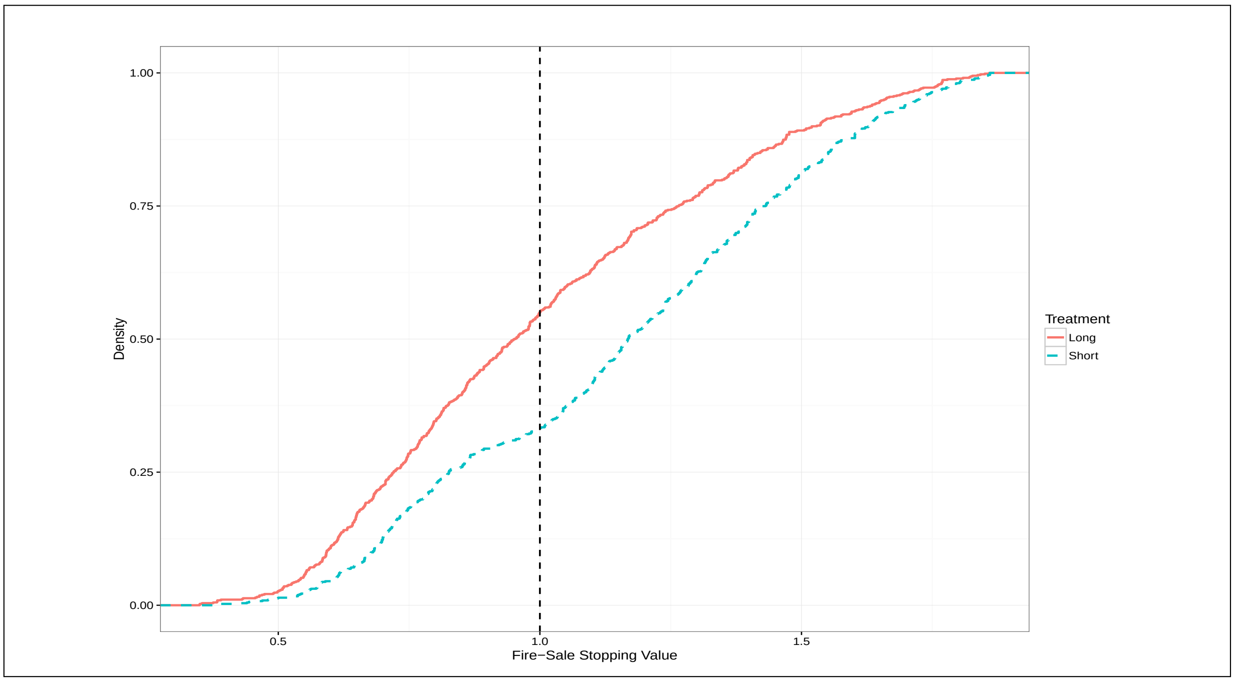

Figure 5: CDF plotting the fire-sale value of the firm at the stopping values for both treatments (dashed blue line representing the Short Treatment).

We are also interested in understanding how past actions affect present ones. To do so, in the first column of Table 2 we present the results of a random effects probit. In it, the binary outcome is whether a subject stopped rolling her credit, and the dummy for the treatment variable (*Short*) shows no differences in the likelihood of stopping the credit. However, the minimum value that the collateral reached (*MinVal*) is highly significant and negative; the intuition being that the lower the value within a round, the more likely it is that a subject will stop rolling over her credit.[18] It can also be observed that neither having stopped rolling over the credit in the previous period (*Stop-1*), nor having observed a bankruptcy (*Bankruptcy-1*) seem to have an effect on the subjects' decisions.

In the second column of Table 2 we show the results of a random effects model where the dependent variable is the value at which subjects decide to stop rolling over their credit. In this case, conditional on having decided to stop rolling over, subjects in the Short Treatment do so at higher values of the firm. Surprisingly having seen a bankruptcy in the last period again has no effect, but having stopped the previous period does makes subjects stop at higher values. Column 3 has the results of a random effects probit, where

[18]Recall that one of the reasons for using the "semi-strategy method" was to have a wider set of values for y_t in each round.

the binary variable is whether, conditional on having stopped rolling over, the stopping decision is a "frantic run" or not. The treatment variable shows that it is more likely to be part of such runs in the Short Treatment than in the Long Treatment. Additionally, having stopped rolling over in the past period makes it more likely that a subject is part of a "frantic run" this period. For completeness we plot the time series of the subjects' decisions in Figure 9 of Appendix B.

	(1) Stop Binary	(2) Stop Value	(3) Frantic Binary
Short	-0.180	0.294***	0.762***
	(0.208)	(0.106)	(0.251)
MinVal	-0.567***	0.880***	2.201***
	(0.0853)	(0.0547)	(0.167)
Quarter 2	-0.0855	-0.0814**	-0.117
	(0.0696)	(0.0357)	(0.137)
Quarter 3	-0.0616	0.0993**	0.289**
	(0.0807)	(0.0498)	(0.132)
Quarter 4	-0.227***	-0.0830	-0.0489
	(0.0824)	(0.0538)	(0.140)
Bankruptcy-1	0.0844	-0.00618	-0.117
	(0.0565)	(0.0398)	(0.146)
Stop-1	-0.0201	0.114***	0.388***
	(0.0706)	(0.0369)	(0.116)
Constant	0.169	0.816***	-2.855***
	(0.172)	(0.0914)	(0.245)
N	4970	1408	1408

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

Table 2: Column one is a random effects Probit on the decision to run. Column two a random effects model with the stopping value as the dependent variable. Column three is a random effects Probit, where the dependent variable is whether a decision to stop rolling over is a "frantic run" decision or not.

However, the results shown in columns 2 and 3 of Table 2, as well as Figure 4, should be interpreted with caution as they ignore the information captured in a subject's decision *not* to stop rolling over her credit. When, in any period, a subject does not stop rolling over her credit, she is *de facto* telling us that her "stopping threshold" is below the minimum value achieved by the firm in that period. Therefore, by only using the observed stopping values, we are ignoring the set of censored observations corresponding to those subjects with the lowest stopping thresholds.[19] To correct for this censoring we follow Oprea et al. (2009) and use, in the next section, the Product Limit Estimator (Kaplan and Meier (1958)), also known as the Kaplan-Meier estimator.

5.2 Hazard Rates and the Value of the Firm

The Product Limit Estimator (Kaplan and Meier (1958)) is a non-parametric Maximum Likelihood Estimator of the distribution that is adapted to dealing with censored data, and allows us to calculate the hazard function of the data. This function can be understood as the "probability" that a subject that has not stopped rolling her credit will do so for each possible (lower) value of the firm, thus allowing us to study the interaction between the value of the firm, and the different contract lengths.[20]

In Figure 6 we present the hazard function (right pane) along the Nelson-Aalen cumulative hazard estimates (left pane) for each treatment.[21] As expected, in both treatments we see that as the value of the firm falls (notice that the horizontal axis is inverted), subjects are more "likely" to stop rolling over their credit (i.e., the hazard increases). More interesting is the clear interaction between the treatment hazard estimates and the value

[19]To be clear; imagine that for a given round j, subject i has threshold (t_{ij}). If the sequence of values of the firm (y_j) never gets below the threshold (i.e., $Min[y_j] \geq t_{ij}$), then we will never be able to observe subject i stopping its credit rollover.

[20]Actually, the hazard function is the ratio between the probability density function of the event (stopping the rollover) and the survivor function. To be more precise, the instantaneous hazard rate $(h(y))$ is a measure of the probability that a subject will decide to stop rolling over her credit within the (limiting) interval $\triangle y$ of collateral values, conditional on her not having already stopped rolling over her credit. Formally:

$$h(y) = \lim_{\triangle y \to 0} \frac{e[y, y + \triangle y]/N(y)}{\triangle y} \tag{4}$$

Where $e[y, y + \triangle y]$ is the number of observed rollover stops in the interval $[y, y + \triangle y]$, and $N(y)$ is the number of subjects at risk for the value of the collateral y. From equation 4 it is clear that if we do not take into account the censored observations, then $N(y)$ would be too high, bringing down the real hazard rate for the infinitesimal value of the collateral $\triangle y$, consequently biasing the hazard curve.

[21]The Nelson-Aalen cumulative hazard estimate is an estimation of the cumulative hazard for each of the values of the firm. Because this is a cumulative measure, the estimate can go above the value of 1. A way to interpret this is that for those values above one, subjects would stop rolling their credit more than once if it were possible.

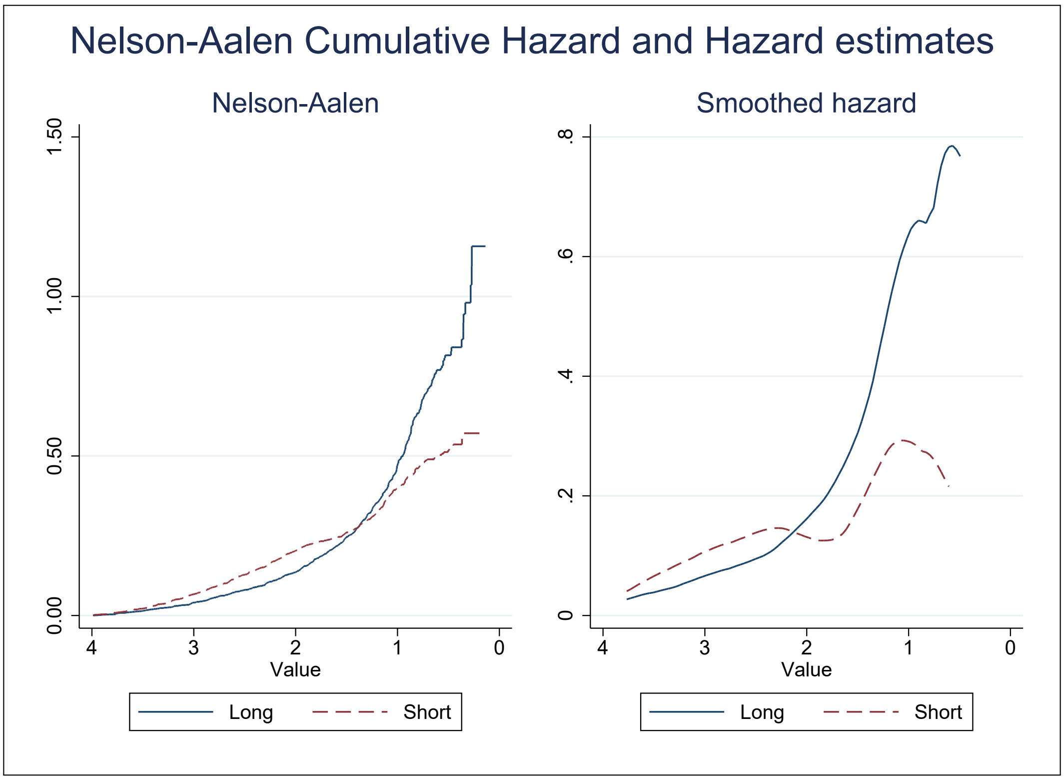

Figure 6: Cumulative hazard and hazard estimates for both treatments. Notice that the horizontal axis has the values reversed.

of the firm. While for high values of a firm Long contracts are more likely to be rolled over (i.e., lower hazard), when the firm value falls, the hazard estimates flip, and Long contracts are much more likely to drive the economy into a credit dry-up. This interaction between contract length and the value of the firm is a key result of this experiment, and suggests that exogenously reducing the maturity mismatch in markets for short-term credit (i.e., imposing long contracts) can have different effects depending on the "state of the economy." An implication of this is that the optimal regulation for short-term credit should be "counter-cyclical," favoring longer contracts (lower maturity mismatch) when the economy is in good shape, while allowing for shorter-term contracts (higher maturity mismatch) when the economy is in a recession.

The intuition behind the result is this: imagine that you are an investor deciding whether or not to roll over your credit to a company. If the collateral offered by a company has a low value, then you would only extend credit with very short maturities. But if doing so is impossible due to legal limitations, then you might decide not to lend at all. Conversely, if the value of a collateral is high, then you would be more willing to sign a long credit contract since it is more unlikely that the collateral loses all its value before the end of the contract. This result is qualitatively robust across the whole experiment as can be seen in Figure 7 where we decompose Figure 6 into quarters. [22]

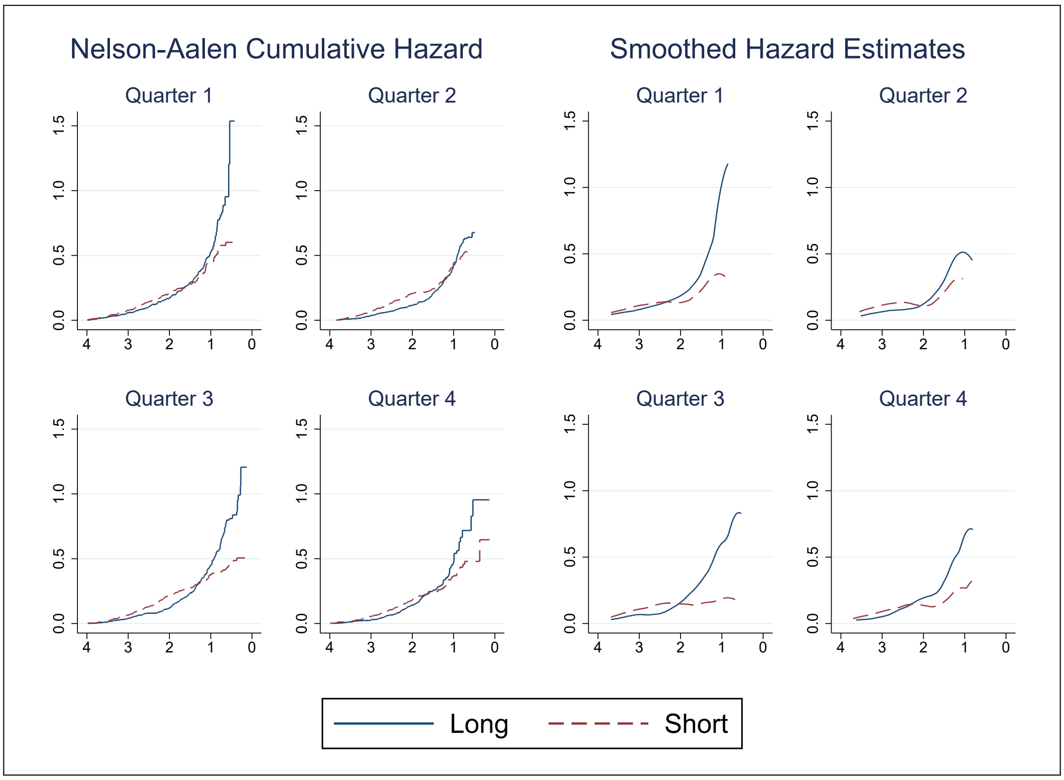

Figure 7: Nelson-Aalen cumulative hazard and smoothed hazard estimates per quarter

Finally, to confirm the last result we test whether or not the hazard functions are statistically different across treatments. To do so, we cannot simply compare the mean of each treatment through a t-test, as the hazard functions might be very similar for some values of the firm, but very different for others. To overcome this problem, survival analysis generally uses the log-rank test, which gives the same weight to all observations independently of the value of the firm. Unfortunately, we cannot use the log-rank test as our data do not satisfy the proportional hazards assumption required for it (Fleming et al. (1980)). [23] To find out what is the best weight function to be applied in our statistical

[22]The robustness of the behavior observed across the whole experiment suggests that the lack of (financial) expertise of the experimental subjects does not seem to unduly condition their decisions. This would add support to the external validity of our experiment. An analysis of this question is beyond the scope of our paper and we refer readers to Fréchette (2016) for a detailed discussion of it.

[23]In our case, the proportional hazards assumption would hold if the relation between both hazard curves in our experiment could be described for all values of the collateral as $H_L = \theta H_S$ where θ is any

analysis we follow Gaugler et al. (2007). It turns out that a modified Peto and Peto (1972) and Prentice (1978) gives us the most consistent p-values across all combinations of weights, showing that the hazard functions are significantly different (p-value<0.001) for all weight combinations except the most extreme cases (see Appendix C for details). This confirms that our subjects behave very differently depending on the length of the debt contract and the state of the economy and, thus, we can state:

- Result: *There is a strong interaction between the state of the economy and the behavior of the experimental subjects towards different credit maturities. While for a healthy economy long contracts are more likely to be rolled over, when the economy is in a downturn, long contracts are more likely to provoke a credit dry-up.*

6 Conclusion

The goal of the paper has been to study the effects of different maturities in the market for short-term credit, and their interactions with the state of the economy. As a result, we contribute to the literature on, both, financial coordination games and the regulation of maturity mismatch. Our analysis is based on a continuous-time experiment that mimics a market for Asset Backed Commercial Paper. We show that there is a strong interaction between the subjects' decisions to rollover their credit, the state of the economy, and the maturity length. To be more precise, we observe that when the economy is in a good state, longer maturities are rolled over more often, helping to stabilize the credit market. Yet, when the economy is in a downturn, these longer maturities increase the likelihood of a credit freeze. This result casts its weight in the debate about whether short maturities should be prohibited in a downturn by suggesting a counter-cyclical policy that limits maturity mismatch during booms, but relaxes this requirement during the low cycles of the economy.

The experiment also confirms the predictions of He and Xiong (2012) that creditors might not be willing to extend loans even to firms that can post enough collateral. This

constant, and H_L and H_S the hazard functions for the Long and Short treatments, respectively. That is, if the ratio between both hazard curves were the same across all values of the collateral. As it is clear from Figure 6, this is not the case. For a lengthier discussion on the proportional hazards assumption see Suciu et al. (2003).

happens because when a subject is considering whether to rollover a credit, in both their model and in our experiment, she must evaluate both today's as well as tomorrow's value of the firm. This leads to a "rat race" in which subjects preemptively stop rolling over their credit even for firms that present solid fundamentals. This is an interesting result as it reproduces the runs on secured debit that occurred during the recent financial crisis (Bernanke (2009a)).

Overall, our paper contributes to both the experimental and financial literature by bringing short-term credit markets into the lab through a continuous-time setup. The robust patterns observed across the whole length of the experiment suggest that this setup can be a good starting point for future experiments on both short-term credit markets and asynchronous coordination games.

References

Anderson, Steven T., Daniel Friedman, and Ryan Oprea, "Preemption Games: Theory and Experiment," *American Economic Review*, 2010, *100* (4), 1778–1803.

Arifovic, Jasmina, Janet Hua Jiang, and Yiping Xu, "Experimental evidence of bank runs as pure coordination failures," *Journal of Economic Dynamics and Control*, 2013.

Baghestanian, Sascha and Baptiste Massenot, "Credit cycles: Experimental evidence," 2016.

Barboni, Giorgia, Tania Treibich et al., "Risk aversion and signalling in single and multiple-bank lending," Technical Report 2013.

Bernanke, Ben S., "Financial regulation and financial stability: a speech at the Federal Deposit Insurance Corporation's Forum on Mortgage Lending for Low and Moderate Income Households, Arlington, Virginia, July 8, 2008," *Speech*, 2008.

_ , "Financial regulation and supervision after the crisis: the role of the Federal Reserve : a speech at the Federal Reserve Bank of Boston's 54th Economic Conference, Chatham, Massachusetts, October 23, 2009," *Speech*, 2009.

_ , "Reflections on a year of crisis: a speech at the Federal Reserve Bank of Kansas City's Annual Economic Symposium, Jackson Hole, Wyoming, August 21, 2009," *Speech*, 2009.

Brown, Martin and Christian Zehnder, "Credit reporting, relationship banking, and loan repayment," *Journal of Money, Credit and Banking*, 2007, *39* (8), 1883–1918.

_ **and** _ , "The emergence of information sharing in credit markets," *Journal of Financial Intermediation*, 2010, *19* (2), 255–278.

_ **, Stefan T Trautmann, and Razvan Vlahu**, "Understanding Bank-Run Contagion," *Management Science*, 2017, *63* (7), 2272–2282.

Brunnermeier, Markus K., "Deciphering the Liquidity and Credit Crunch 2007-2008," *Journal of Economic Perspectives*, 2009, *23* (1), 77–100.

— **and John Morgan**, "Clock games: Theory and experiments," *Games and Economic Behavior*, 2010, *68* (2), 532–550.

— **, Andrew Crockett, Charles Goodhart, Avi Persaud, and Hyun Shin**, *The fundamental principles of financial regulation*, Geneva London: International Center for Monetary and Banking Studies Centre for Economic Policy Research, 2009.

Calford, Evan and Ryan Oprea, "Continuity, Inertia, and Strategic Uncertainty: A Test of the Theory of Continuous Time Games," *Econometrica*, 2017, *85* (3), 915–935.

Cason, Timothy N, Lata Gangadharan, and Pushkar Maitra, "Moral hazard and peer monitoring in a laboratory microfinance experiment," *Journal of Economic Behavior & Organization*, 2012, *82* (1), 192–209.

Chakravarty, Surajeet, Miguel A Fonseca, and Todd R Kaplan, "An experiment on the causes of bank run contagions," *European Economic Review*, 2014, *72*, 39–51.

Cheung, Yin-Wong and Daniel Friedman, "Speculative attacks: A laboratory study in continuous time," *Journal of International Money and Finance*, 2009, *28* (6), 1064–1082.

Christie, Angelina Nikitenko, "Asymmetric information and bank lending: The role of formal and informal institutions (a survey of laboratory research)," in "Experiments in Financial Economics," Emerald Group Publishing Limited, 2013, pp. 5–30.

Diamond, Douglas W. and Philip H. Dybvig, "Bank Runs, Deposit Insurance, and Liquidity," *Journal of Political Economy*, 1983, *91* (3), 401–19.

Dufwenberg, Martin, "Banking on experiments?," *Journal of Economic Studies*, 2015, *42* (6), 943–971.

Farhi, Emmanuel and Jean Tirole, "Collective Moral Hazard, Maturity Mismatch, and Systemic Bailouts," *American Economic Review*, February 2012, *102* (1), 60–93.

Fleming, Thomas R., Judith R. O'Fallon, Peter C. O'Brien, and David P. Harrington, "Modified Kolmogorov-Smirnov Test Procedures with Application to Arbitrarily Right-Censored Data," *Biometrics*, December 1980, *36* (4), 607.

Fréchette, Guillaume R, "Experimental economics across subject populations," *The handbook of experimental economics*, 2016, *2*, 435–480.

Friedman, Daniel and Ryan Oprea, "A Continuous Dilemma," *American Economic Review*, 2012, *102* (1), 337–63.

Garratt, Rod and Todd Keister, "Bank runs as coordination failures: An experimental study," *Journal of Economic Behavior & Organization*, 2009, *71* (2), 300–317.

Gaugler, T., D. Kim, and S. Liao, "Comparing Two Survival Time Distributions: An Investigation of Several Weight Functions for the Weighted Logrank Statistic," *Communications in Statistics - Simulation and Computation*, 2007, *36* (2), 423–435.

Goldstein, Itay and Ady Pauzner, "Demand-Deposit Contracts and the Probability of Bank Runs," *Journal of Finance*, 2005, *60* (3), 1293–1327.

Harrington, David P. and Thomas R. Fleming, "A Class of Rank Test Procedures for Censored Survival Data," *Biometrika*, December 1982, *69* (3), 553.

He, Zhiguo and Wei Xiong, "Dynamic Debt Runs," *Review of Financial Studies*, 2012, *25* (6), 1799–1843.

Heinemann, Frank, "Understanding financial crises: The contribution of experimental economics," *Annals of Economics and Statistics/ANNALES D'ÉCONOMIE ET DE STATISTIQUE*, 2012, pp. 7–29.

Kaplan, Edward L. and Paul Meier, "Nonparametric estimation from incomplete observations," *Journal of the American statistical association*, 1958, *53* (282), 457–481.

Kiss, Hubert Janos, Ismael Rodriguez-Lara, and Alfonso Rosa-García, "On the Effects of Deposit Insurance and Observability on Bank Runs: An Experimental Study," *Journal of Money, Credit and Banking*, 2012, *44* (8), 1651–1665.

_ , _ , and _ , "Do social networks prevent or promote bank runs?," *Journal of Economic Behavior & Organization*, 2014, *101*, 87–99.

Krishnamurthy, Arvind, "How Debt Markets Have Malfunctioned in the Crisis," *Journal of Economic Perspectives*, February 2010, *24* (1), 3–28.

Madies, Philippe, "An Experimental Exploration of Self-Fulfilling Banking Panics: Their Occurrence, Persistence, and Prevention," *The Journal of Business*, 2006, *79* (4), 1831–1866.

Malherbe, Frederic, "Self-Fulfilling Liquidity Dry-Ups," *The Journal of Finance*, April 2014, *69* (2), 947–970.

Oprea, Ryan, Daniel Friedman, and Steven T. Anderson, "Learning to Wait: A Laboratory Investigation," *Review of Economic Studies*, 2009, *76* (3), 1103–1124.

Peto, Richard and Julian Peto, "Asymptotically Efficient Rank Invariant Test Procedures," *Journal of the Royal Statistical Society. Series A (General)*, 1972, *135* (2), 185.

Prentice, R. L., "Linear Rank Tests with Right Censored Data," *Biometrika*, April 1978, *65* (1), 167.

Schotter, Andrew and Tanju Yorulmazer, "On the dynamics and severity of bank runs: An experimental study," *Journal of Financial Intermediation*, 2009, *18* (2), 217–241.

Suciu, Gabriel P, Stanley Lemeshow, and Melvin Moeschberger, "Statistical Tests of the Equality of Survival Curves: Reconsidering the Options," in N. Balakrishnan and C.R. Rao, ed., *Handbook of Statistics*, Vol. Volume 23 of *Advances in Survival Analysis*, Elsevier, 2003, pp. 251–262.

Tasneem, Dina, Jim Engle-Warnick, and Hassan Benchekroun, "An experimental study of a common property renewable resource game in continuous time," *Journal of Economic Behavior & Organization*, 2017, *140*, 91–119.

A Demographic Data

Of the total of 92 subjects that participated in the experiment 29 (31.52%)were female and 63 (68.48%) male. The field of study along with gender are listed in Table 3.

Field of Study	Female	Male	Total
Other	0	1	1
Anthropology	1	0	1
Art	0	1	1
Art History	1	0	1
Biology	7	7	14
Business Administration	2	5	7
Chemistry	1	1	2
Commercial Information Technology	0	4	4
Computer Science	2	4	6
Economic mathematics	0	2	2
Economics	3	14	17
Engineering	1	2	3
Geology	1	2	3
History	0	1	1
Language and Literature Studies	2	2	4
Law	0	1	1
Mathematics	1	3	4
Not set	3	6	9
Physics	0	3	3
Political Science	0	2	2
Psychology	2	1	3
Sociology	2	1	3
Total	29	63	92

Table 3: Gender of participants

B Extra Graphs

The CDF functions of the median choice per group/session are plotted in Figure 8. The curves are less smooth than those of Figure 4, but the same qualitative result is clear.

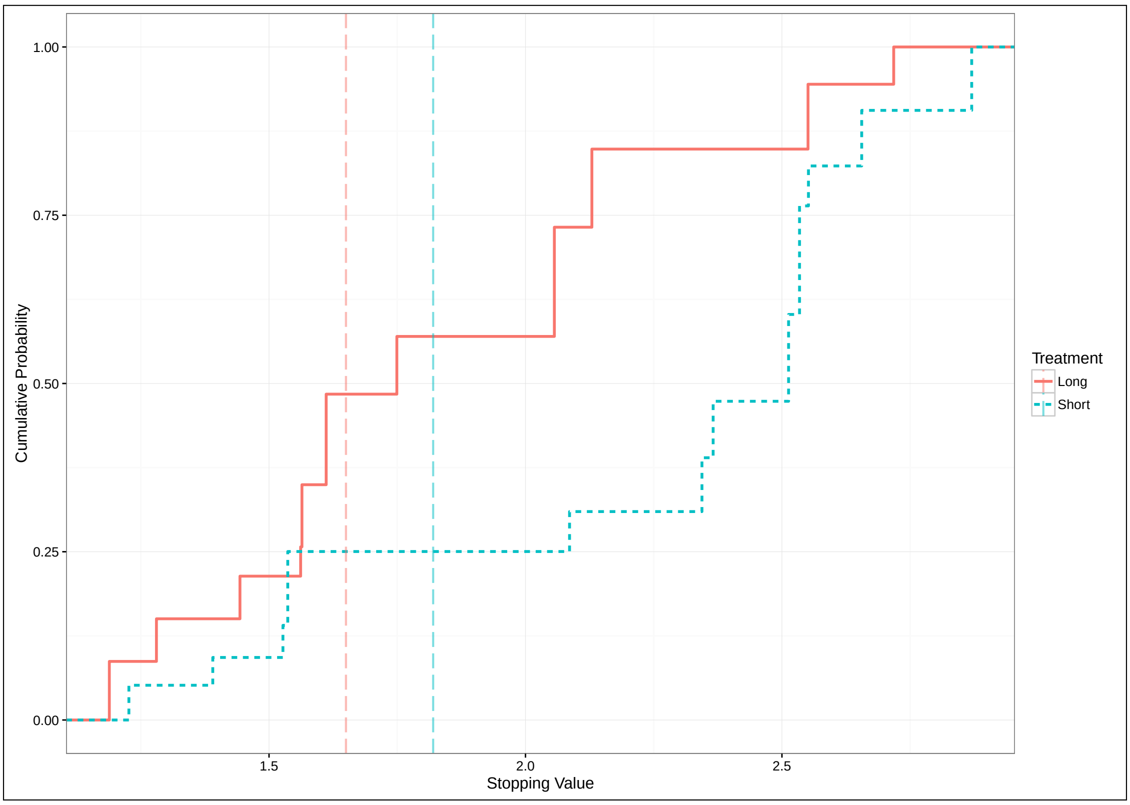

Figure 8: CDF of median stopping values per group

In Figure 9 we present the conditional mean of each group's median decision. Consistent with Figure 4, if a subject decide to stop rolling her credit, then, she does so for higher values in the Short treatment. Additionally, we observe how the patterns are very similar across treatments, this is a result of the collateral following the same process in both treatments.

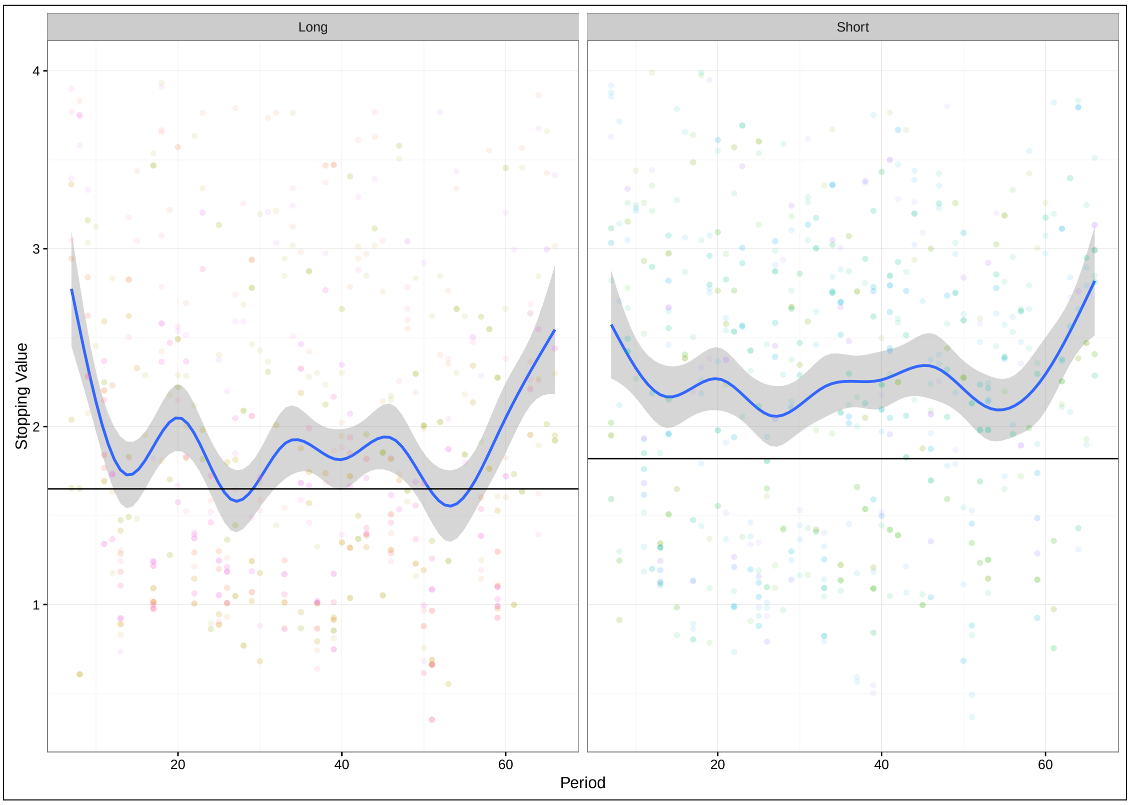

Figure 9: Time series of the conditional mean of each group's median decision (blue line) with the standard error (gray), and actual median stopping value per group (dots).

C Picking the Correct Weight Function

Because the hazard functions cross each other, we need to take a "search and find" approach to choose the best non-parametric comparison method for our analysis. To do so we will need a set of different weight functions to compose our test statistic, and compare the "smoothness" of the resulting p-values for the different possible weights using bootstrapping techniques.

Following Gaugler et al. (2007) notation, we define the logrank statistic comparing the data from both Long and Short treatments as:

$$A_w = \sum_{i=1}^{l} W_i \left[d_i - \frac{n_i D_i}{N_i} \right] \tag{5}$$

Where d_i is the number of subjects that stopped rolling over their credit in the Long treatment at a value of the collateral $t = i$, n_i is the number at risk at $t = i$ in the same group, D_i the *pooled* (both Long and Short treatments) number of stopping decisions *until* $t = i$, and $N = i$ is the number of *pooled* subjects at risk at $t = i$. Finally, W_i is the weight function for the statistic at $t = i$. The weight functions are critical in determining the results of the test, and should be used in accordance with the needs of the researcher. Some examples are the Logrank which uses $W_i = 1$, where all observations have the same weight, the Gehan ($W_i = N_i$), or the Tarone-Ware $\left(W_i = N_i^{1/2} \right)$, both of which are designed to give more emphasis to the regions that contain more observations.

In our case we will study variations of an extremely versatile and well known weight function, the Fleming-Harrington weight function (Harrington and Fleming (1982)) which includes many other weight functions as special cases[24]:

$$W_i = \left[\hat{S}(t_{i-1}) \right]^p \left[1 - \hat{S}(t_{i-1}) \right]^q \tag{6}$$

The Fleming-Harrington weight function for the statistic at $t = i$ is a function of the Kaplan-Meier survivor function estimate at $t = i - 1$, $(\hat{S}(t_{i-1}))$, and two parameters, p and q which are used to give more or less importance to the different areas of study.[25] In particular, when $q = 0$ and $p > 0$ more weight is given to rollover stops for high values of

[24]For example, when $p = 0$ and $q = 0$ the Fleming Harrington weight function turns into the the logrank test ($W_i = 1$).

[25]The K-M survivor function estimate is defined as $\hat{S} = \prod_{t_i \leq t} \left(1 - \frac{b_i}{m_i} \right)$.

the collateral, and when $q > 0$ and $p = 0$ more weight is assigned to stopping decisions for low values of the collateral.

In the following we will study different weight functions as suggested in Gaugler et al. (2007) by modifying the time dependence of the Fleming-Harrington weight function at $t = i$ from $t = i - 1$ to $t = i$, so, from$\hat{S}(t_{i-1})$ to $\hat{S}(t_i)$, and by changing the Kaplan-Meier estimate$\left(\hat{S}(.)\right)$ by the Peto-Peto estimate $\left[\tilde{S}(.)\right]$ [26]. This will leave us with four different weight functions; the original F-H $\left(\hat{W}_{pq}(t_{i-1})\right)$, a modified F-H $\left(\hat{W}_{pq}(t_i)\right)$, the original P-P $\left(\tilde{W}_{pq}(t_{i-1})\right)$Pa and a modified P-P $\left(\tilde{W}_{pq}(t_i)\right)$(Equation 7):

$$Kaplan-Meier = \begin{cases} \hat{W}_{pq}(t_{i-1}) = \left[\hat{S}(t_{i-1})\right]^p \left[1 - \hat{S}(t_{i-1})\right]^q \\ \hat{W}_{pq}(t_i) = \left[\hat{S}(t_i)\right]^p \left[1 - \hat{S}(t_i)\right]^q \end{cases} \quad Peto-Peto \begin{cases} \tilde{W}_{pq}(t_{i-1}) = \left[\tilde{S}(t_{i-1})\right]^p \left[1 - \tilde{S}(t_{i-1})\right]^q \\ \tilde{W}_{pq}(t_i) = \left[\tilde{S}(t_i)\right]^p \left[1 - \tilde{S}(t_i)\right]^q \end{cases} \tag{7}$$

In Figure 10 we present the plots, for different p and q values, for the four weight functions[27]. As we can see the logrank weight function gives the same weight (1) to all observations in the data, while all other weight functions seem to converge at giving a weight of 0.5 to those observations at the lowest values of the collateral. This convergence is due to the heavy right-hand censoring observed in our data. Notice also that for the weight functions that use the survivor estimate evaluated at $t = i - 1$ we see a jump at $t = 0$. This jump could be problematic if we were interested in the differences of our hazard curves for high values of the collateral, yet we are interested in the lower values of the collateral, so our choice should *a priori* favor the cases where $p < 0.5$ and $q > 0.5$ which are not affected by the jump. For a longer discussion on the implication of these weight jumps see Gaugler et al. (2007).

Next we compare the evolution of p-values across the weight functions, for the different values of p and q (Table 5)[28]. In addition we also compare the bootstrapped p-values to the asymptotic p-values (Table 4).

[26] The Peto-Peto as survivor function estimate is defined as $\tilde{S} = \prod_{t_i \le t}\left(1 - \frac{b_i}{m_i+1}\right)$.

[27] Following Gaugler et al. (2007)we have limited the values of p and q to those where $p + q = 1$.

[28] To find the p-values we follow Gaugler et al. (2007) and create a 1000 bootstrap synthetic datasets to then calculate for each of them the test statistic $(A_1^*, ..., A_{1000}^*)$ following Equation 5. Finding the bootstrap p-value as $p* = \sum_{i=1}^{1000} \mathbf{I}\{A_I^* \ge A_{org}\}/1000$ where A_{org} is the value of the test statistic calculated from the original data set.

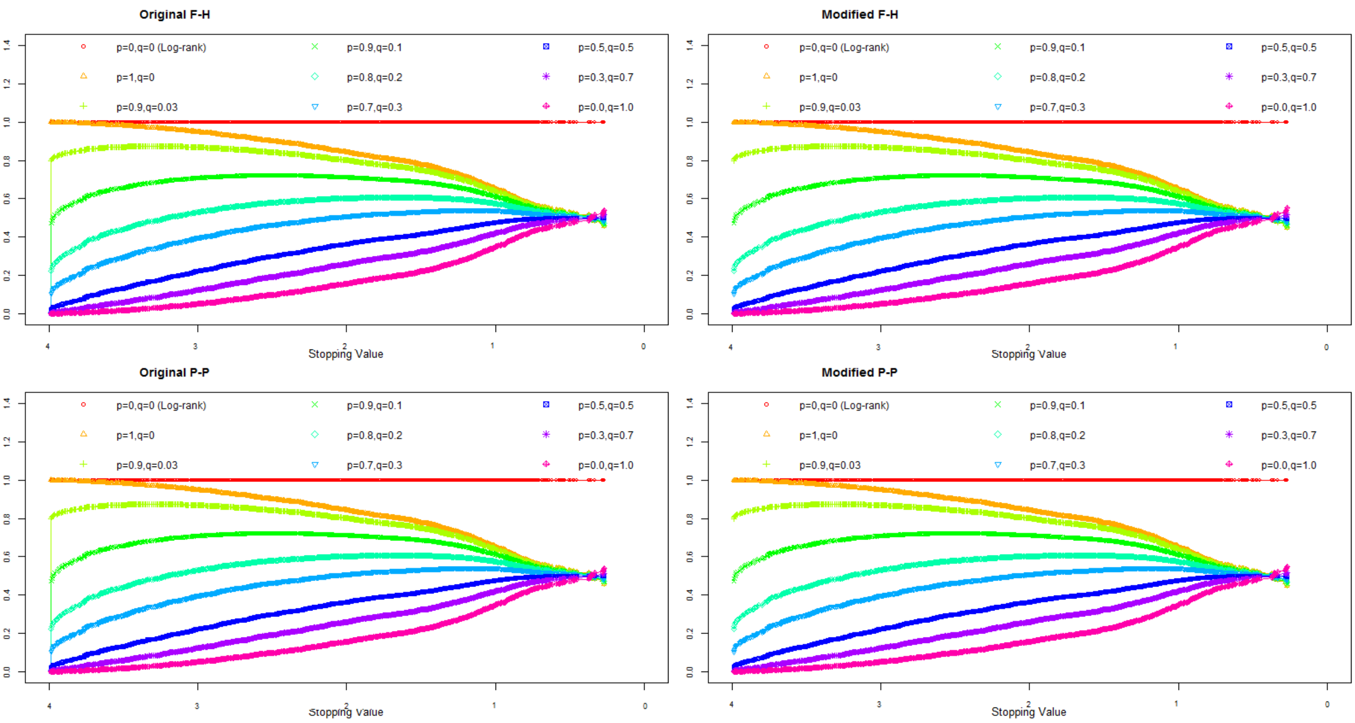

Figure 10: Four different weight functions

As we can see, the bootstrapped p-values are similar to those coming from the asymptotic theory. In both cases, the results show that we cannot reject the null hypothesis of equality between both survivor curves when we place all the weight on the early stopping decisions, but that once we move away from $p = 1.00$ and $q = 0.00$, there is a sharp drop in p-values with significant differences for all weight functions where $p \leq 0.9$. This abrupt drop in p-values is consistent with Figure 6, where the divergence between both hazard

Table 4: Asymptotic p-values

p	q	$\hat{W}_{pq}(t_{i-1})$	$\hat{W}_{pq}(t_i)$	$\tilde{W}_{pq}(t_{i-1})$	$\tilde{W}_{pq}(t_i)$
1.00	*0.00*	0.244	0.245	0.244	0.245
0.97	*0.03*	0.140	0.159	0.139	0.158
0.90	*0.10*	0.038	0.043	0.038	0.043
0.80	*0.20*	0.003	0.003	0.003	0.003
0.70	*0.30*	0.000	0.000	0.000	0.000
0.50	*0.50*	0.000	0.000	0.000	0.000
0.30	*0.70*	0.000	0.000	0.000	0.000
0.00	*1.00*	0.000	0.000	0.000	0.000
0	*0*	0.013	0.013	0.013	0.013

Table 5: Bootstrapped p-values

p	q	$\hat{W}_{pq}(t_{i-1})$	$\hat{W}_{pq}(t_i)$	$\tilde{W}_{pq}(t_{i-1})$	$\tilde{W}_{pq}(t_i)$
1.00	*0.00*	0.246	0.227	0.237	0.259
0.97	*0.03*	0.159	0.139	0.133	0.170
0.90	*0.10*	0.049	0.042	0.045	0.050
0.80	*0.20*	0.003	0.007	0.006	0.003
0.70	*0.30*	0.000	0.000	0.000	0.000
0.50	*0.50*	0.000	0.000	0.000	0.000
0.30	*0.70*	0.000	0.000	0.000	0.000
0.00	*1.00*	0.000	0.000	0.000	0.000
0	*0*	0.016	0.014	0.017	0.016

functions is clearly higher for the lower values of the collateral. Therefore, not only are the bootstrapped p-values of all weight functions aligned with their asymptotic counterparts, but the results match a graphical inspection of the data.

Like in Gaugler et al. (2007), the jump in p-values is much smoother in both $\hat{W}_{pq}(t_i)$ and $\tilde{W}_{pq}(t_i)$ than in the cases where the weight function is based on the survivor estimate at t_{i-1}. And between the two, the best choice for is the Peto-Peto weight function with no time lag ($W_{pq}(t_i)$), as it has the least variation in p-values across all the tested weight combinations. This turns out to be the same conclusion that Gaugler et al. (2007) reach in their own analysis of all the above weight functions.

- Result: Like in Gaugler et al. (2007) the weight function that seems most appropriate for our test if the modified Peto-Peto: $\tilde{W}_{pq}(t_i) = \left[\tilde{S}(t_i)\right]^p \left[1 - \tilde{S}(t_i)\right]^q$.

D Instructions

Timing of the Experimentt:

The session we will be running today has 60 rounds. At the beginning of the session you will be grouped with 3 other subjects with whom you will play all 60 rounds of the session.

The time units of the round are "ticks" (1/5 of a second). Each round has a probability of 1/150 per tick of maturing; this means that on average each round will last 30 seconds.

The Common Project:

In each round, everyone in your group will start by investing 1 florin (lab currency) into a common project. Every tick the value of the common project will change. To be precise:

- The value of the common project will go up with probability: 0.5001, and down with probability: 0.4999.
- The change in value (whether up or down) will always be 7% of the current value of the investment.

You will be able to track the value of the firm on your screen:

[Image on projector]

Your Decision:

In each round you will make only **ONE** decision:

- To stay in the common project
- To exit the common project

How to exit a project: To exit the common project you will need to slide (not click) your mouse over the counter at the bottom of your screen and connect the numbers 3, 2, and 1

[Image on projector]

Once you have done so a green line will appear on your screen. This green line marks your "**exit request**" and you will exit at the next "**exit gate**" after your exit request.

Exit gates are individual (so no two players share the same exit gate), and happen every 8 seconds. To be more precise:

- In each round, every member of a group is assigned a first "exit gate" within the first 8 seconds
- After that, his next exit opportunities will happen every 8 seconds.
- Example: imagine your first exit opportunity is in second 2 of the round, then your next exit opportunity will be in second 10, then 18, then 26 etc.

[Image on projector]

To stay in the project you do not have to do anything.

Overview:

1. In this experiment you are grouped with three other subjects across 60 rounds.
2. In each round you all start with an investment of 1 florin in the common project
3. Each round you are asked to make one decision: whether or not to stay invested in the common project
4. To exit you need to swipe your mouse over the 3,2,1 countdown area.
5. This swiping will record an exit request and you will exit at your next exit gate
6. To stay you do not need to do anything

Payoffs:

Your payoff in each round will come from two different sources:

- Constant Return
- Original investment return

How much you make from each income source will depend on your decision to stay or to exit, and on the staying or leaving decisions of the other investors in your group.

Constant Return: For every "tick" that you keep your investment in the project, you will get a constant return. This constant return is of 0.004 florins per tick. This means that if you keep your investment for 30 seconds you will get 0.6 florins from the constant return (so a 60% return for every 30 seconds).

Original investment of 1 florin: Of the original investment of 1 florin that you made at the beginning of the round you can get back either the original florin you invested, or a part of the florin you invested, but never more.

This payoff will depend on:

1. Your decision to stay or to exit
2. The decisions of the other investors in your group
3. When and how the round ends.

The round can end in three different ways:

1. You Exit the project: if, at some point, you decide to exit the project, and are able to do so, you will get your 1 florin back independently of the value of the common project. On the other hand, you will stop getting paid the constant return per tick for the rest of the round.
2. Premature end of the project: if 2 investors in your group exit the project, then the project will continue running for 2 extra seconds before it "ends early" and pays all of the remaining investors a "staying value". How much the staying value pays back will depend on where the jagged yellow line is at the moment of the premature ending: a) If the jagged yellow line is above 1, then you will be paid 1 florin. b) If the jagged yellow line is below 1, then you will be paid the value of the line at that point.
3. Maturation of the project: as mentioned, the common project has a probability of 1/150 per tick of maturing. If the common project matures before an early stop

happens, then all investors will be paid depending on the value of the common project (green jagged line): a) If the jagged green line is 1 or greater than 1, then all players that are still invested get their 1 florin back b) If the value of the common project is below 1, then all players that are still invested will get back the value of the common project at that point.

You can track both the value of the project and the premature ending value of the project on your screen.

[Image on projector]

Overview of the payoffs:

1. Your payoffs come from two different sources: a. Constant payoff b. Individual end of the round

2. The constant payoff gives you 0.004 florins per tick as long as you are invested and the round has not finished (there has not been a premature ending or a maturation of the project)

3. Individual end of projects has 3 different ways of taking place: a.

- You withdraw your investment and get back your entire 1 florin independent of the value of the common project

- The project has a premature ending, in which case those investors that are still in the project get back 1 florin if the yellow jagged line is above 1, or the value of the jagged line if it is below the value of 1

- The project matures, at which point all those still invested get back 1 florin if the green line was above 1, the value of the green line if it was below 1

Important things to notice:

All rounds will continue ticking until the project's maturation, so even if there are premature ending, you will not be given this information until the end of the round. You will also not be told when other investors are leaving the common project nor will you be told where your exit gates are. The information that you will see while the round is ticking will be:

- Value of the project
- Staying value
- Past exit requests by all investors in your group (upper right corner of screen)

[Image on projector]

Once the project has matured, then a screen will appear showing the whole unraveling of the round which includes:

- The exit requests made by all players (green lines)
- The actual exits at each individual exit gate (yellow lines)
- You will also be informed about your exit request and your allowed exit tick.
- Finally, if there was an premature ending it will be shown as a red line.

[Image on projector]

In summary:

Your goal each round is to decide whether you leave or not the project balancing the advantages and disadvantages of staying invested, the probability of a natural end and the behavior of other investors.

But not all rounds are paid. Not all rounds will count for your final payoffs. Although you will see how much you made at the end of each round, 10 of the 60 rounds will count towards your final payoffs. These 10 rounds are randomly chosen by the computer.

Practice: Before the session properly begins, we will have 6 practice rounds so that you get used to the mechanics of the session, so you should practice exiting. These rounds will be shorter than the rounds during the experiment.

While the instructions are somewhat long and complex, it is very important that you understand how the game works. You don't need to really understand all of the probabilities and numbers that we give you, as you can learn from experience, but you should make sure that you understand the mechanics of the game.

FAQ:

1) Is there a pattern in the change of value of the common project? No, we really tried to make it random. No matter what is the history of values that the common project took the probabilities of going up or down on value are always the same.

2) If values over the threshold of 1 always pay me back 1 Florin, why do you show them to me? We show you these values because we think you might be interested in knowing how far away you are from the 1 florin threshold.

Please feel free to ask as many questions as necessary to make sure that you have a full understanding of the instructions. To ask a question, just raise your hand to call my attention.