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Coordination in Market and Bank Run Experiments

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Universiteit van Amsterdam

Coordination in Market and Bank Run Experiments

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Coordination in Market and Bank Run Experiments

ACADEMISCH PROEFSCHRIFT

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Contents

CHAPTER 1

Introduction

Economics is a complicated science. We, as its practitioners, often try to describe, understand, and predict phenomena in large systems of interacting entities. This bears some similarity to the physical sciences, in which there is also an interest in understanding how the macroscopic properties of a system follow from the interactions of its constituents. However, unlike the mindless particles in physical systems, the entities in economic systems are thinking. In particular, their actions may depend on what they believe that others are going to do and how they expect the system to evolve. It is for this reason that beliefs and expectations play an important role in economics.

There is no definitive model for how beliefs and expectations form. One possibility is that they are based on observations of the same quantity at earlier points in time. An early example of that is the naive expectations in the cobweb model, introduced in papers by Schultz (1930), Tinbergen (1930), and Ricci (1930). Here the agents (producers) expect that the future price of the commodity they produce will be equal to the last price they observed (at least in expectation). In the years after other variants have been proposed, such as trend following or trend reversing expectations (Goodwin, 1947) and adaptive expectations (Nerlove, 1958).

The myriad of possibilities leads to a problem. Different assumptions regarding the expectations lead to different predictions about the dynamics of the system. Which assumptions should one make? To solve (or circumvent) this problem economists often choose the one expectation or belief that is special: the one that will turn out to be correct (also called rational expectations). In other words, we impose consistency between expectations and outcomes. Individuals may have difficulty forming rational expectations as it requires detailed information about the economic system and correct predictions about the actions of all the other people involved. However, Muth (1961) argues that using rational expectations in a model does produce the correct results, as people's expectations should be distributed around the rational one.

Muth's rational expectation hypothesis became quite influential in the decades following its introduction. Despite its successes, it also became clear that there are some phenomena that are difficult to explain with rational expectations. One of these is the occurrence of bubbles and crashes in asset markets. The rational expectation hypothesis can also not help us to determine which expectations to use when multiple rational expectations equilibria are present. This is for example the case in the banking sector, where banks typically only survive when people expect them to survive. When this expectation reverses, depositors rush to get their money out, resulting in a bankruptcy of the bank. Both situations are equilibria, driven by and consistent with expectations, but the rational expectations hypothesis cannot predict which one of the two will prevail. Finally, because the rational expectations hypothesis, in the sense of Muth, is not concerned with individual expectations, one may wonder how expectations within the population evolve. For example, can people learn from their mistakes, and will the distribution of expectations narrow as a result?

When the rational benchmark fails or fails to make a unique prediction, we are often back in a situation with numerous possible modeling assumptions that could all solve the problem. Under these circumstances laboratory experiments can be a great help. For example, our understanding of bubbles and crashes has benefitted considerably from the asset market experiments pioneered by Smith et al. (1988) and the learning-to-forecast experiments following Hommes et al. (2005). And since the early 2000s there is also a growing interest in experimental bank run studies, aimed at determining which circumstances lead to panic withdrawals from a bank (Kiss et al., 2022a). In this thesis I present three experiments in which the outcomes are strongly driven by (non-rational) expectations.

The central question in Chapter 2 is whether futures markets have a stabilizing or destabilizing effect on commodity prices. In theories with rational expectations futures markets always have a stabilizing influence on commodity prices. However, in the policy debate this is a matter of great dispute and for some commodities futures markets have been banned as a result. The empirical evidence is not fully conclusive either. We try to resolve this question by eliciting expectations in a learning-to-forecast experiment in which a futures market and a spot market are coupled. The strength of the coupling depends on the parameters in the model. It increases with the number of speculators on the futures market and decreases with storage costs and speculator risk aversion. We find that the spot price volatility changes non-monotonically with the strength of the coupling, resulting in a stabilizing effect on spot prices for weakly coupled markets and a destabilizing effect when the coupling with the futures market is strong.

In Chapter 3 I study the effect of the deposit decision on subsequent panic withdrawals from banks. Most of the literature focusses exclusively on withdrawal decisions. However, being a depositor in a bank is a choice. The depositors could also have chosen to keep their money at home or deposit it in another bank. To find out how this deposit choice affects withdrawal decisions, I run a bank run experiment with two treatments. Participants in the choice treatment first have to choose whether to receive an endowment in a 'risky' bank paying a high interest rate or a 'safer', lower-interest rate bank. Subsequently they have to decide whether they withdraw their money or not. Those in the baseline treatment cannot choose a bank and only make a withdrawal decision. I find that, despite a lower interest rate, 'safer' banks consistently attract almost half of the depositors in the choice treatment. Offering the deposit decision strongly reduces withdrawals in the riskier banks, but not in safer ones.

Chapter 4 builds on the result in Chapter 3 that the participants in the bank choice experiment do not coordinate on a Nash equilibrium. As a result, those who choose to deposit in the safer bank earn (considerably) less than they could have earned. The aim in this chapter is to find out whether these depositors can learn to increase their earnings by depositing in the risky bank, whether the risky bank will remain solvent after the influx of new depositors, and how the dynamics depend on the relative riskiness of the banks and the information environment. We find that the participants learn to coordinate on the risky bank without withdrawing (a Nash equilibrium) under low and medium risk, but efficient coordination fails under high risk, irrespective of the information environment. Simulations with an individual evolutionary algorithm show a similar picture, but only if we assume that the agents are very sophisticated in updating their beliefs.

CHAPTER 2

The effect of futures markets on the stability of commodity prices[1]

Do futures markets have a stabilizing or destabilizing effect on commodity prices? The empirical evidence is inconclusive. We try to resolve this question by means of a learning-to-forecast experiment in which a futures market and a spot market are coupled. The strength of the coupling depends positively on the number of speculators on the futures market and negatively on storage costs and speculator risk aversion. We find that the spot price volatility changes non-monotonically with the strength of the coupling, resulting in a stabilizing effect on spot prices for weakly coupled markets and a destabilizing effect when the coupling with the futures market is strong.

[1]Adapted from: de Jong, J., Sonnemans, J., and Tuinstra, J. (2022). The effect of futures markets on the stability of commodity prices. Journal of Economic Behavior & Organization, 198, 176-211.

> Speculators may do no harm as bubbles on a steady stream of enterprise. But the position is serious when enterprise becomes the bubble on a whirlpool of speculation. When the capital development of a country becomes a by-product of the activities of a casino, the job is likely to be ill-done.
>
> — John Maynard Keynes, The General Theory of Employment, Interest and Money (1936)

2.1 Introduction

Much of the theoretical work on futures markets suggests that they have a stabilizing effect on commodity prices (Friedman, 1953). Yet, in the policy debate there continue to be calls for tighter regulations or even bans on all commodity future trading based on the argument that speculation in the futures market is a source of instability for commodity prices (Kennedy, 2012, April 11). The matter here may not simply be one of who is right. As was already acknowledged by Kaldor (1939) and many authors afterwards, there may be some merit to both claims in the sense that both a stabilizing and a destabilizing effect exist. The question is whether we can identify one effect that will always dominate.

The, at some times, fierce debate has inspired a large body of empirical work on the effect of futures markets on commodity price stability. Worth noting here are the studies using the introduction (or abolishment) of futures markets, such as the ones for onions (Working, 1960; Gray, 1963), pork bellies and beef (Powers, 1970), live cattle (Taylor and Leuthold, 1974), wheat (Netz, 1995), and potatoes (Morgan, 1999). In almost all cases the authors conclude that in the years following the introduction (abolishment) of a futures market, the volatility in the commodity spot prices was lower (higher) than in the years before. These results suggest that a stabilizing effect of futures markets does exist and can be dominant, at least in a certain period following a futures market's introduction. However, there is convincing empirical evidence of a destabilizing effect as well. Roll (1984) argues that a large part of the volatility in the prices of orange juice futures cannot be explained by any changes in real economic variables such as the weather or changes in demand. Because the spot and futures prices of a commodity are typically linked, we expect this excess volatility to spill over into the spot market. One indication that this is happening is provided by Pindyck and Rotemberg (1990) who find a stronger comovement in commodity spot prices than can be explained by macroeconomic variables.

More recently the question of the impact of future markets on commodity price stability again received a lot of attention. Masters and White (2008) put forward the hypothesis that the advent of commodity index investing was responsible for the surge in commodity prices between 2002 and 2008. Although most authors of empirical studies agree that the surge itself was due to other factors, they arrive at different conclusions regarding the effect of the 'financialization' of commodity markets on price volatility. Du et al. (2011), McPhail et al. (2012), and Algieri (2016) claim that it increased the volatility of commodity prices, while Büyükşahin and Harris (2011), Bohl and Stephan (2013), and Brunetti et al. (2016) do not find evidence of this.

There has been some effort to include destabilizing effects of futures markets in theoretical models. Several authors look at situations of asymmetric information, in which spot market participants take decisions that depend on the futures price. In this case noise or biases injected by speculators on the futures market can adversely affect spot price stability (Stein, 1987; Sockin and Xiong, 2015; Goldstein and Yang, 2021). When there is no information asymmetry, futures markets can still affect spot prices through the risk or storage channels (Cheng and Xiong, 2014). An example of the risk channel is presented by Newbery (1987), who argues that futures markets can stimulate risk taking by producers, creating stronger fluctuations in supply and thus increased price volatility. If the storage channel is important, shocks to inventory demand (Kawai, 1983) or growth shocks to the economy, as in Dvir and Rogoff (2009), could cause extra volatility in the spot market. However, these latter models do not address the main concern in the policy debate, which is that speculation on the futures markets itself can be a source of instability. To faithfully model destabilizing speculation in production economies without asymmetric information has proven notoriously difficult with rational expectations.[2] At the same time, any other choice of expectations requires a careful justification, since there are many ways to be irrational (Sims, 1980).

In this chapter we explore how futures markets affect spot prices through the storage channel when all agents have the same information, but expectations are not necessarily rational. Using a stylized model of coupled commodity spot and futures markets, we first show how naive or rational expectations lead to a stabilizing effect of the futures market on spot prices, while for expectations with a trend-following component the effect can also be destabilizing. Next we look at what expectations people actually form under these circumstances using a learning-to-forecast experiment. The participants in this experiment are told that they act as 'advisors' to the agents in the model and are asked to forecast spot prices based on information about past prices. These forecasts are then used in the model to generate a new set of prices on the spot and futures markets upon which the cycle repeats. Note that this chapter is the first that uses a laboratory experiment to

[2] In a model without lagged production it is possible for speculators to destabilize spot prices without information asymmetry, as shown by Hart and Kreps (1986). This may be applicable to shorter timescales, on which producers cannot react to changes in demand. We only consider timescales on which production does play a role.

investigate the storage channel.

We gain some important insights with this approach. Our main result is that the volatility of the spot prices changes non-monotonically with the parameters in the model. As a consequence futures markets do not always have a stabilizing effect. Neither will they always be destabilizing. When the spot and futures markets are only weakly coupled, for example because it is very costly to store the commodity, there are few speculators, or these speculators are very risk-averse, the stabilizing effect of futures markets dominates and spot price stability will increase with increasing coupling strength. However, as the coupling strength becomes stronger this trend reverses and eventually the net effect of the futures market becomes a destabilizing one. In our experimental treatment with the strongest coupling we even observe commodity price bubbles and crashes. None of these markets appear to stabilize towards the end of the experiment.

To understand this result we have to look at the individual decisions in the experiment. When the coupling strength is weak the price dynamics is dominated by negative expectations feedback: the higher the expectations of the price in the next period, the lower the price will be. This is due to the producers in the model, who will increase production when expecting higher prices. This increases supply and subsequently lowers prices. It turns out that under those circumstances the predictions of the participants stay very close to the fundamental price. This results in very stable price dynamics where the only deviations from the fundamental price come from small external demand shocks. Because futures markets help to smooth these external shocks, the price volatility decreases with increased strength of coupling between the spot and futures markets.

When the coupling strength is increased further, for example due to an increasing number of speculators on the futures market, the influence of the negative feedback from expectations diminishes because excess production by producers is more easily absorbed in the inventories. Instead, the expectations of the speculators on the futures market become more important. Unlike the producers' expectations, the expectations of the speculators have a positive impact on prices. In first instance it will affect the futures prices, which will be raised if the speculators adjust their expectations upwards. However, higher futures prices mean that buying the product in the next period becomes more expensive. This will induce inventory holders to buy more of the product on the spot market in the current period and increase the amounts they have in storage. The end result is that higher speculator expectations also raise prices on the spot market, a form of positive expectations feedback. When the positive feedback strongly dominates, the participants in the experiment do not coordinate their expectations on the fundamental price. Instead, their expectations can be best described as trend-following and it results in strongly fluctuating spot prices. This tendency to extrapolate past returns has also been found in investor surveys (Greenwood and Shleifer, 2014; Amromin and Sharpe, 2014) and gives rise to asset market bubbles when incorporated into (standard) models (Adam et al., 2017; Barberis et al., 2018).

Our results for the experimental markets with the weakest and strongest coupling are in line with previous results in the learning-to-forecast literature. Hommes et al. (2007) perform an experimental test of the cobweb theorem, in which the feedback from expectations to prices is purely negative. They find that many participants are able to learn the fundamental price and that their expectations can be classified as (close to) rational. On the other side of the spectrum are a number of asset market experiments in which the expectations feedback is purely positive. Hommes et al. (2005, 2008) observe frequent bubbles and crashes in experimental markets under those circumstances. The positive feedback does need to be stronger though than about 2/3 in order to observe permanently unstable prices (Sonnemans and Tuinstra, 2010; Bao and Hommes, 2019).[3] The work by Heemeijer et al. (2009) confirms that the striking difference in results of the different learning-to-forecast experiments is indeed due to the different direction of expectations feedback.

We are not the first to employ the laboratory experiment as a tool to study the effect of futures markets as there is a small literature with experiments in which futures markets are introduced next to asset markets (without production). Forsythe et al. (1984, 1982) and Friedman et al. (1984) use a design in which participants have private information about how much they value an asset. The assets in these experiments live for two or three periods and can be traded in each period through a continuous double auction. Typically, a futures market for the asset in the last period of its life significantly increases the speed at which the participants converge to coordination on the rational expectations equilibrium. The results are more mixed when futures markets are introduced in the asset market experiments in the style of Smith et al. (1988). Porter and Smith (1995) introduce a market for futures that mature in period 8 out of 15 and conclude that the bubbles are reduced compared to the treatment without a futures market. However, in a replication with digital options instead of futures contracts the effect is not found (Palan, 2010). Noussair and Tucker (2006) open futures markets for each period before the spot market opens. This forces the participants to consider future prices of the commodity before trading and the authors find that this eliminates bubbles completely. Finally, Noussair et al. (2016), in an experiment with futures that mature in the final

[3] This means that the deviation of the realized price from the fundamental price is two-thirds of the deviation of the average expectation from the fundamental price.

period, find considerable overpricing in the futures market itself. On average participants with higher CRT scores make profits in these markets, at the cost of participants with lower CRT scores. There thus appears to be evidence for a stabilizing effect in some of these experiments. However, when a stabilizing effect was found, it was based on the information channel and not related to storage as in our experiment.

The rest of this chapter is organized as follows. In the next section (Section 2.2) we introduce the model. This is followed by the experimental design in Section 2.3, the results of the experiment in Section 2.4, and the conclusion in Section 2.5.

2.2 Model of coupled spot-futures markets

The model used in this chapter shares its essence with those of Muth (1961) and Sarris (1984), who also modeled the effect of speculation on the price of a storable commodity. It features four types of agents: producers, consumers, speculators, and inventory holders. The purpose behind this is not to model four different types of people, but to model four different types of roles. Combining some of these roles in a single decision maker, for example a producer who also keeps inventories or an inventory holder who also chooses to speculate, would not alter the analysis below. The separation here is for analytical convenience only. Each period the agents in the model interact with each other on a spot and a futures market. They take decisions that maximize their expected (risk-adjusted) profits, given the information available and, in case of the producers and speculators, given their expectations about prices in the future.

2.2.1 The spot market

The main actors on the spot market are producers and consumers. There are K producers and they all need one period to produce the commodity. Therefore an individual producer needs to decide one period in advance how much to produce, before knowing the price she will get for her product. She chooses optimally, maximizing expected profit given her expectation of next period's price $p^{e,p}_{k,t}$ and some non-linear cost function, resulting in an S-shaped individual supply curve:

$$S_{k,t}\left(p^{e,p}_{k,t}\right) = c\left(1+\tanh\left(\lambda\left(p^{e,p}_{k,t}-d\right)\right)\right), \qquad c, d, \lambda > 0. \tag{2.1}$$

The parameter λ, which is linked to the steepness of the supply curve, can be tuned to have either a locally stable fundamental price or a locally stable two-cycle under naive expectations (Hommes, 1994). There are two reasons to choose a supply curve of this form. First of all, it ensures that supply is bounded, which is a realistic feature for short-term production decisions (see Hommes (1994) for a more extensive justification). Second, when combined with a downward sloping demand curve, the S-shaped supply curve can give rise to a stable two-cycle in which prices alternate between high and low indefinitely under naive or adaptive expectations. It is worthwhile to allow for this possibility in the experiment.

The combined supply of the producers meets a consumer demand that linearly decreases with price p_t:

$$D_t\left(p_t\right) = a - bp_t + \epsilon_t, \qquad a, b > 0, \qquad \epsilon_t \sim \mathcal{N}\left(0, \sigma_\epsilon^2\right). \tag{2.2}$$

The ϵ_t represent small, independent demand shocks. [4] Except for being a realistic feature of commodity markets, the shocks are a crucial component of the model. The shocks provide a basic level of volatility, without which there would be nothing to stabilize. We need them to discern a possibly stabilizing effect of futures markets.

2.2.2 The futures market

The futures market features H speculators speculating on the spot price of the commodity in the next period by buying and selling futures. At the moment they trade, the current period's spot price is not yet known and therefore their decisions are based on two-period ahead forecasts by their advisors. In fact, the current period's spot price will depend on the speculators' decisions.

A speculator's only concern is her next period wealth $W_{h,t+1}$, which depends on prices and the quantity $z_{h,t}$ of the product that her position in futures represents:

$$\mathrm{E}_{ht}\left[W_{h,t+1}\right] = W_{h,t} + \left(p^{e,s}_{h,t+1} - p^f_{t+1}\right) z_{h,t}. \tag{2.3}$$

Here $z_{h,t}$ may be positive or negative, depending on whether the speculator's position is long or short, respectively. In Eq. (2.3) $p^{e,s}_{h,t+1}$ is the speculator's prediction of next period's spot price and p^f_{t+1} is the price in the futures contract. Note that this is the current futures price, and known with certainty to the speculators at the moment of trade, but it is denoted with the subscript $t+1$ to emphasize that it is the price the speculator agrees to pay or be paid in the next period.

One of the challenges in trading commodity futures is that commodity prices may be

[4] In principle it would have also been possible to independently add aggregate supply shocks. However, in this case having a single or multiple independent shocks in one period does not change the price dynamics.

excessively volatile and speculators must take this risk into account. We assume that they will do this by mean-variance maximization of their next period wealth $W_{h,t+1}$:

$$\max_{z_{h,t}} \left\{ \mathrm{E}_{ht}\left[W_{h,t+1}\right] - \frac{\phi}{2}\mathrm{Var}_{ht}\left[W_{h,t+1}\right] \right\}$$
$$= \max_{z_{h,t}} \left\{ W_{h,t} + \left(p^{e,s}_{h,t+1} - p^{f}_{t+1}\right) z_{h,t} - \frac{\phi}{2} z^2_{h,t} \mathrm{Var}_{ht}\left[p_{t+1}\right] \right\}. \quad (2.4)$$

Here ϕ is the coefficient of absolute risk aversion.[5] As in the asset market models by Brock and Hommes (1998) and Hommes et al. (2005, 2008), we make the additional assumption that the speculators' perception of the price volatility remains constant:

$$\mathrm{Var}_{ht}\left[p_{t+1}\right] = \sigma^2. \quad (2.5)$$

One way to interpret this assumption is that the speculators have a good sense of the volatility they should expect because they know how the prices of the commodity varied historically. This leaves them with little reason to update as long as the parameters of the system do not change.

The position that speculator h takes, follows from carrying out the maximization in Eq. (2.4):

$$z_{h,t} = \frac{1}{\phi\sigma^2}\left(p^{e,s}_{h,t+1} - p^{f}_{t+1}\right). \quad (2.6)$$

Total demand z_t by all speculators combined is then:

$$z_t = \frac{H}{\phi\sigma^2}\left(\bar{p}^{e,s}_{t+1} - p^{f}_{t+1}\right), \quad (2.7)$$

with $\bar{p}^{e,s}_{t+1}$ the speculators' average prediction of the next period's spot price. The result in Eq. (2.7) is intuitive. The speculators' aggregate demand for futures increases with the difference between their average expectation of the next period's price and the futures price. This difference is the risk premium responsible for the expected profit of the speculators. Also, the absolute value of z increases with the number of speculators active in the market and decreases with increased risk aversion (higher ϕ) and perceived volatility (higher σ^2).

On an isolated futures market the speculators can only trade with each other ($z_t = 0$). As a result, the futures price is exactly equal to the speculators' average expectation

[5] It can be shown that when returns are normally distributed this mean-variance maximization is exactly the one performed by rational agents possessing a constant absolute risk aversion (CARA) utility function (e.g. Sargent (1987)).

of the next period's spot price and the risk premium vanishes. Without the prospect of profits for speculators, it is questionable whether a futures market can continue to operate. Some form of coupling with the corresponding spot market is therefore crucial for a futures market.

2.2.3 Market coupling by inventory holders

For many market participants keeping inventories is an essential part of their operations, for example because they sell out of inventory or in order to guarantee continuous operation of a production process. In the absence of speculation inventory holders will balance this convenience yield with interest and storage costs to find the optimal working inventory. However, the availability of futures contracts invites inventory holders to engage in arbitrage. When the futures price is high compared to the spot price, it is profitable to take a short position on the futures market and at the same time buy some of the commodity on the spot market to store it for one period. In the reverse situation, inventory holders can combine selling some of their inventory on the spot market with a long position on the futures market. Although keeping a lower than optimal inventory costs them in terms of convenience yield, it guarantees them a restock in the next period at a very favorable price. Note that for this to be pure arbitrage, the amount bought or sold on the spot market must exactly match the position taken in the futures market.

In practice the costs of keeping inventories are often (partially) determined by supply and demand on a market for storage. To model such a market in detail is beyond the scope of this chapter. Therefore, as in Sarris (1984), we introduce a single representative inventory holder, whose costs increase quadratically for any deviation from optimal working inventories. In case of a positive deviation this is due to rising interest and storage costs (including possible loss of quality of the commodity under storage), while for negative deviations the increase stems from a reduction of the convenience yield. We write the inventory holder's profit from arbitrage as:

$$\pi_t = \left(p^f_{t+1} - p_t\right) I_t - \frac{\gamma}{2} I_t^2, \tag{2.8}$$

where I_t is the aggregate deviation from optimal inventories and γ is a cost parameter which is higher when the costs associated with inventory deviation are higher. Maximization of this profit yields the total inventory deviation in period t:

$$I_t = \frac{p^f_{t+1} - p_t}{\gamma}. \tag{2.9}$$

The inventory deviation I_t (which may be negative as long as total inventories are positive) is the quantity of the commodity that the inventory holders demand on the spot market and, because they engage in pure arbitrage, supply on the futures market. Regardless of whether this supply is positive (short position) or negative (long position), the speculators will automatically take the other side of the market. Therefore

$$z_t = I_t. \tag{2.10}$$

Combining Eqs. (2.7), (2.9), and (2.10) leads to the following relation between spot prices, futures prices, and the speculators' expectations:

$$p^f_{t+1} = \frac{p_t + \frac{\gamma H}{\phi\sigma^2}\bar{p}^{e,s}_{t+1}}{1 + \frac{\gamma H}{\phi\sigma^2}}. \tag{2.11}$$

Using this result in Eq. (2.9) the inventory deviation becomes:

$$I_t = \frac{\bar{p}^{e,s}_{t+1} - p_t}{\frac{\phi\sigma^2}{H} + \gamma} = A\left(\bar{p}^{e,s}_{t+1} - p_t\right), \tag{2.12}$$

where

$$A = \frac{1}{\frac{\phi\sigma^2}{H} + \gamma}. \tag{2.13}$$

In the end the expression for the inventory deviation takes a simple form: it changes linearly with the difference between the speculators' expected price for the next period and the current period spot price. Muth (1961) and Sarris (1984) arrive at a similar expression for the inventory deviation under speculative storage. Note that all model parameters related to the coupling between the spot and futures markets combine into one parameter: A. The size of A determines to what extent inventories respond to differences between expectations of prices in the next period and current spot prices and can therefore be interpreted as the strength of the coupling between the two markets. As expected, the coupling strength increases when storage costs go down (lower γ). However, increased speculative demand due to a larger number of speculators or decreased risk aversion can also strengthen the coupling. [6] Financialization is therefore one of the processes that lead

[6]Note that A can also be affected by the volatility of the spot prices via σ^2. If a change in A changes the volatility of spot prices and speculators correctly update σ^2 to reflect the new situation, then any attempt to change the coupling strength by changing one of the parameters ϕ, γ, or H will be either amplified or dampened by the accompanying change in σ^2 (the direction of the change will always stay the same). This is not a concern for our experiment, which is run for fixed values of A. However, in cases where one wants to investigate the dynamic response to a change in one of the parameters, it does need to be taken into account.

to an increase in A in this model.

The actions of the inventory holders affect the situation on the spot market. A change in inventories generates extra demand or supply, pushing spot prices up and down, respectively. The market clearing condition for the spot market becomes:

$$\sum_{k=1}^{K} S_{k,t}\left(p_{k,t}^{e,p}\right) + I_{t-1}\left(\bar{p}_t^{e,s}, p_{t-1}\right) = D_t\left(p_t\right) + I_t\left(\bar{p}_{t+1}^{e,s}, p_t\right).$$

Using Eqs. (2.1), (2.2), and (2.9) in the market clearing condition and solving for the spot price yields the price equation:

$$p_t = \frac{a - cK - c\sum_{k=1}^{K} \tanh\left(\lambda\left(p_{k,t}^{e,p} - d\right)\right) + A\bar{p}_{t+1}^{e,s} - I_{t-1}\left(\bar{p}_t^{e,s}, p_{t-1}\right)}{A+b} + \frac{\epsilon_t}{A+b}. \tag{2.14}$$

The structure of the equation above reveals the properties of the system. As one would expect, p_t decreases when the producers expect higher prices (negative feedback) and increases when the speculators expect higher prices (positive feedback).[7] The positive feedback is moderated by the coupling strength A and can vary from being absent ($A = 0$) to completely dominating ($A \to \infty$). The system also contains a state variable in the form of the previous period inventory deviation $I_{t-1}\left(\bar{p}_t^{e,s}, p_{t-1}\right)$. Naturally, if a large inventory has been build up, this has a negative effect on spot prices and vice versa for a large shortage. Finally, the coupling between the markets weakens the effect of the extrinsic demand shocks on the spot price. This is the stabilizing effect of futures markets.

2.2.4 Limit cases

The limiting cases $A = 0$ and $A \to \infty$ of this model deserve some extra attention. For $A = 0$ the price equation reduces to the one for an isolated spot market:

$$\lim_{A \downarrow 0} p_t = \frac{a - cK - c\sum_{k=1}^{K} \tanh\left(\lambda\left(p_{k,t}^{e,p} - d\right)\right)}{b} + \frac{\epsilon_t}{b}. \tag{2.15}$$

Without a coupling to the futures market, there is no role for inventories and no positive feedback from expectations. Also, other than the coupled system, the isolated spot market features a unique[8] rational expectations equilibrium (REE), in which the producers'

[7]Note that, where the demand of each speculator is linear in its prediction and therefore the spot market price only depends on the speculators' expectations through the average prediction of the speculators, each producer's supply is a nonlinear function of his prediction, and therefore each producer's prediction enters separately in Eq. 2.14.

[8]This is due to the fact that a strictly increasing (supply) function and strictly decreasing (demand) function intersect exactly once.

expectations are equal to the expected value of p_t. Unfortunately the REE price p^* cannot be written in closed form. However, despite this, participants in the cobweb experiment by Hommes et al. (2007), which essentially uses Eq. (2.15) as the underlying equation, manage to find the REE price and coordinate on it.

When $A \to \infty$ the spot prices are fully determined by the expectations of the speculators:

$$\lim_{A\to\infty} p_t = \bar{p}_{t+1}^{e,s} - \bar{p}_t^{e,s} + p_{t-1}. \tag{2.16}$$

In this limit case there is no negative feedback from producers' expectations and no effect of extrinsic demand shocks on prices. The structure of the equation is such that the change in the spot price exactly equals the change in the expectation for the *next* period spot price by the speculators. An important consequence of this is that if speculators adopt trend-following expectations, price bubbles can continue to grow forever.

2.2.5 Simulations

To gain further insight, we look at the price dynamics that the model produces with a few commonly used types of expectations:

$$\text{Rational:} \quad \bar{p}_{k,t}^{e,p} = \mathrm{E}_{\mathrm{t}-1}\left[p_t\right], \qquad \bar{p}_{k,t}^{e,s} = \mathrm{E}_{\mathrm{t}-2}\left[p_t\right] \tag{2.17}$$

$$\text{Naive:} \quad p_{k,t}^{e,p} = p_{t-1}, \qquad p_{k,t}^{e,s} = p_{t-2} \tag{2.18}$$

$$\text{Trend-following:} \quad p_{k,t}^{e,p} = p_{t-1} + \alpha\left(p_{t-1} - p_{t-2}\right), \quad p_{k,t}^{e,s} = p_{t-2} + 2\alpha\left(p_{t-2} - p_{t-3}\right). \tag{2.19}$$

The parameter α for the trend-following expectations can be any positive number. We follow Anufriev and Hommes (2012a,b) and consider a weak trend rule (WTR) with $\alpha = 0.4$ and a strong trend rule (STR) with $\alpha = 1.3$. In Appendix 2.B we show that not only naive and trend-following expectations, but also rational expectations are fully determined by the history of prices. This makes it possible to conveniently simulate time series of spot prices using Eq. (2.14) and investigate how stable prices are for different parameter choices and types of expectations. We present a brief description of the simulations and a summary of the results here and refer the interested reader to Appendix 2.B for the details and the results of an accompanying stability analysis.

A few parameters in our simulations are fixed. The number of producers and speculators is always 4 ($K = H = 4$) and we use supply/demand parameter values at $a = 12$, $b = 1$, $c = 1.5$, and $d = 6$. Also, each time series is 10000 periods long. As a measure of price instability we take the variance of the prices in the time series relative to the

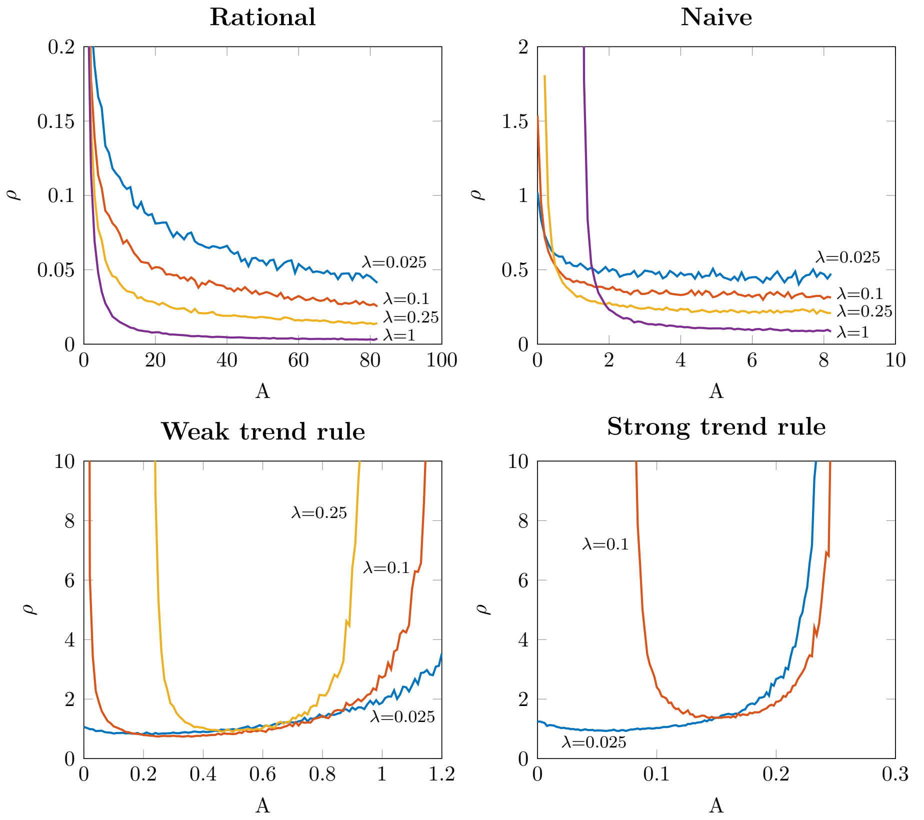


Figure 2.1: Variance of simulated spot prices relative to the variance of the external noise process for four different expectations rules.

variance of the demand shocks σ_ϵ^2:

$$\rho = \frac{\mathrm{Var}\,(p_t)}{\sigma_\epsilon^2}. \tag{2.20}$$

Figure 2.1 summarizes the results of our simulations. It shows for each expectations rule how ρ changes with the coupling strength A. For rational and naive expectations the spot price variance decreases as the coupling becomes stronger, which means that the futures market always has a stabilizing effect for these types of expectations. However, with trend-following expectations a higher coupling strength does not always lead to a decrease in price variance. Here we typically see a U-shaped curve, meaning that the futures market has a stabilizing influence when the spot and futures markets are weakly coupled, but that its influence becomes destabilizing as the strength of the coupling increases beyond a certain point. Together the simulations show that whether futures markets have a stabilizing or destabilizing effect depends on how people form expectations. However, earlier experimental studies have shown that there is not one way in which people form price expectations from a history of prices, it depends on the environment and is particularly sensitive to the feedback structure Bao et al. (2021). To learn how people form expectations in an environment with coupled spot and futures markets and see the effect of these particular expectations on spot price stability, we can use a learning-to-forecast experiment.

2.3 Experimental design

In our experimental design we stay close to the model outlined in the previous section. The participants are told that they will take up the role of advisor to either a producer or a speculator. Their task is to provide price forecasts, one period ahead if working for a producer or two periods ahead if working for a speculator. The more accurate their prediction is, the more points they earn. The participants learn about their exact role (i.e. working for a producer or a speculator) just before the start of the actual experiment.

Each instance of coupled experimental spot and futures markets consists of four advisors to producers and four advisors to speculators (the exact numbers are not known to the participants). Each advisor is coupled to exactly one producer or speculator and each producer or speculator is coupled to exactly one advisor. Producers and speculators take the predictions of their advisors as their expectations without modification. Their decisions, and the decisions of the other agents in the model, are completely automated and optimal according to the model specification. When all participants in a session have submitted their forecasts, the computer calculates the spot price in the next period according to Eq. (2.14) and updates the participants' screens with the new price. The experimental markets always last 50 periods.

To help the participants in making their forecasts, they are provided with a history of all spot prices up to the current period as well as their previous predictions. They get this information both in graph and in table form (see Fig. 2.2 for a screenshot of the interface). At the start of the experiment, when no past prices are available, the participants receive a hint that the spot price will most likely be between 8 and 50 in the first period (the full range of spot prices is from 0 to 1000). Also, in the instructions we include a qualitative description of the economy, emphasizing the role of producers and speculators and the negative and positive feedback from expectations (see Appendix 3.B). Participants can only proceed to the experiment after answering a few questions

Figure 2.2: Screenshot of the interface. Past spot prices and the individual's own past predictions are available both in graph and in table form. In the lower left corner the participants are reminded of their task (one-period-ahead or two-period-ahead prediction), their earnings up to that point, and the current period.

about these concepts correctly. The exact equations of the model are not shared with the participants, nor are they given the commodity's fundamental price.

During the experiment the participants can only see spot prices and the reason for this is twofold. First of all, we want to eliminate the possibility that participants confuse the spot and futures price information and accidentally forecast futures prices instead of spot prices. Second, showing several different types of information would make it much more difficult to reconstruct how individual participants form expectations and thus to interpret the results. Of all the information we could show, we consider the history of spot prices the most useful, as this is the price that we ask participants to forecast. A look at Eq. (2.14) reveals that also for individual participants it is most useful to think in terms of spot prices as it is the collection of all spot price forecasts that largely determines what the spot price will be in the next period. The current deviation of inventories from its optimum, I, is the only other information that plays a role in formation of the price that participants are trying to forecast. If not available, its sign can be deduced from the history of absolute inventories or from the futures price via Eq. (2.12). We think that a variation of this experiment with extra information is an interesting direction for future research.

Payment of the participants is based entirely on the accuracy of their predictions, using the function:

$$earnings_t = \max\left\{1300 - \frac{1300}{25} error_t^2, 0\right\}, \tag{2.21}$$

where the error is the absolute difference between the realized and predicted prices in period t. At the end of the experiment, the total earnings in points are converted into euros, at a rate 1 euro for 2000 points.

The parameters of the model are chosen such that the fundamental price in the experiment is not a round number, in this case $p^* = 20.7$. This is achieved by taking $a = 41.4$, $b = 1$, $c = 5.175$, and $d = 20.7$. The slope parameter in the individual supply functions is $\lambda = 0.0725$, just large enough to make the price dynamics of an isolated spot market unstable under naive expectations.[9] For the levels of optimal inventories we take high values, such that it is unlikely that the inventories ever reach zero during the experiment. Finally, we set $\sigma_\epsilon = 1.5$ as the standard deviation of the independent demand shocks. We have four treatments, each corresponding to a different strength of coupling between the spot and futures markets: almost isolated markets ($A = 0.01$), weakly coupled markets ($A = 0.5$), strongly coupled markets ($A = 10$), and very strongly coupled markets ($A = 30$).

The main question is whether futures markets always have a stabilizing effect on spot prices or whether they can also be a destabilizing force. To that end we will compare the standard deviations of the spot prices in the different treatments. For each pair of treatments, the null hypothesis is that the standard deviations of the spot prices are the same in each treatment. The alternative hypothesis is that they are not. In the case that we find significant differences, we are particularly interested to know whether the stability changes monotonically with coupling strength A or not as this is where our simulations with different types of expectations differ the most. Naive and rational expectations lead to a monotonic decrease of price fluctuations with A, while in the case of trend-following expectations the volatility first decreases and then increases for larger values of A (a U-shape).

Our experiment was programmed in oTree (Chen et al., 2016) and run at the CREED laboratory of the University of Amsterdam in May and June 2018. 256 people participated, the majority being undergraduate students in Economics and Business Economics

[9] The eigenvalue of the system with isolated spot and futures markets under naive expectations is equal to 1.50075 (see Appendix 2.B)

Table 2.1: Standard deviations of spot prices

	All periods				Last 25 periods			
	$A = 0.01$	$A = 0.5$	$A = 10$	$A = 30$	$A = 0.01$	$A = 0.5$	$A = 10$	$A = 30$
Group 1	3.11	1.10	9.15	6.20	1.65	1.03	4.39	4.16
Group 2	2.01	1.08	10.57	3.15	1.40	0.78	9.85	2.07
Group 3	2.14	1.52	33.38	40.98	1.71	1.52	2.40	48.18
Group 4	2.45	1.30	17.93	223.68	1.77	1.10	5.45	216.94
Group 5	2.23	1.25	4.77	23.16	1.54	0.95	0.82	27.38
Group 6	2.35	1.51	1.00	2.95	1.69	1.37	0.56	3.17
Group 7	2.19	1.39	4.05	12.48	1.60	1.40	1.98	13.14
Group 8	3.02	1.53	1.64	75.03	1.77	1.18	0.63	90.26
Mean	2.44	1.34	10.31	48.45	1.64	1.17	3.26	50.66

at the University of Amsterdam (58%), and most others were either enrolled in another social science program (18%), or studied law (11%). 44% of the participants was male and the average age was 21.8 years. Sessions lasted approximately 1.5 hours during which the participants earned on average €28.78.

2.4 Results

Figure 2.3(a) shows semi-log plots of the spot prices in each period for the treatment in which the coupling between the spot and futures markets is negligible ($A = 0.01$)[10]. The results are in line with earlier learning-to-forecast experiments with isolated spot markets by Hommes et al. (2007) and Heemeijer et al. (2009). In each experimental spot market we find prices fluctuating around the fundamental value of 20.7. The first 5 to 10 periods are characterized by larger deviations as in this stage the participants are still learning the fundamental price (see the analysis by Heemeijer et al. (2009) and the enlarged plots including individual forecasts in Appendix 2.D). Afterwards the price fluctuations stay at a similar level. This level lies, considering that the average standard deviation of prices in the last 25 periods is 1.64 (Table 2.1, 6th column), only slightly above the level of the external noise process ($\sigma_\epsilon = 1.5$).

Compared to the almost-isolated markets, the treatment with weak coupling ($A = 0.5$) changes the situation in two ways. On the one hand increased flexibility of inventories

[10] With some additional assumptions we could also plot futures prices for all markets. These are shown in Appendix 2.C

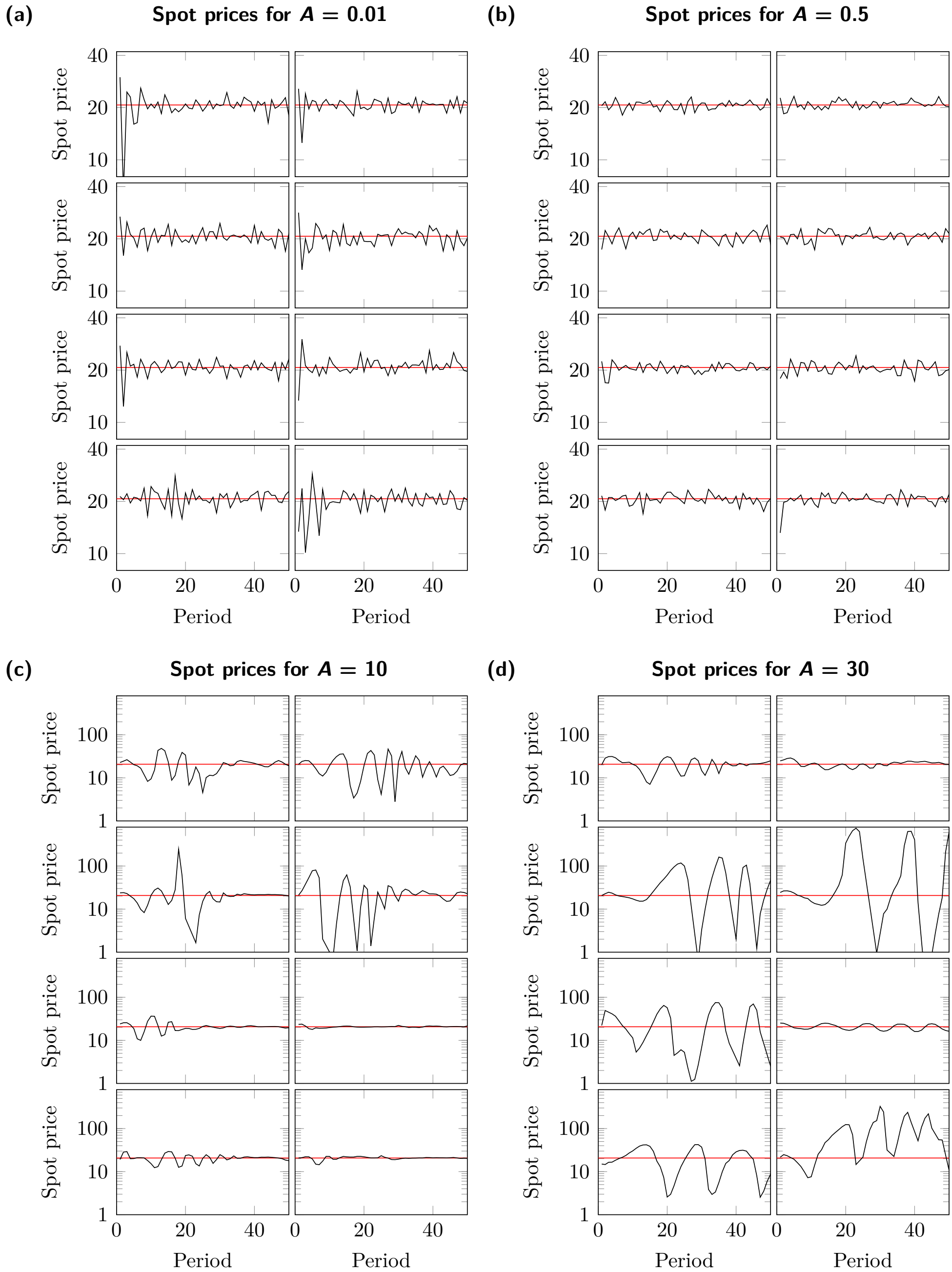


Figure 2.3: Semi-log plots of prices in different experimental spot markets. There are four treatments, differing only in the strength of the coupling between the spot and futures markets: $A = 0.01$ (a), $A = 0.5$ (b), $A = 10$ (c), $A = 30$ (d). The graphs in the lower two subfigures have larger scales than the graphs in the upper two subfigures.

effectively reduces the external demand shocks by a factor of 1.5. On the other hand, through the market coupling the spot prices become subject to positive expectations feedback, which may make it harder for the participants to find the fundamental price and coordinate their expectations on it. Fig. 2.3(b) shows that at coupling strength $A = 0.5$ there is no sign of the latter. As in the almost-isolated treatment the spot prices fluctuate around the fundamental value at a slightly higher level than that caused by the external demand shocks (1.17 instead of 1.00, see Table 2.1, 7th column). However, because the external demand shocks are now effectively smaller, prices are on average considerably more stable in this treatment.

When the coupling strength is further increased to $A = 10$, spot prices follow a very different pattern (see Fig. 2.3(c)). Instead of seemingly random fluctuations, they move in multi-period cycles around the fundamental value. The amplitudes of these cycles differ in different experimental spot markets, but they are in general much larger than those of the fluctuations in the first two treatments (note the change in scale). Compared to the cycles that have been observed in learning-to-forecast experiments with asset markets, the price dynamics in this treatment stands out in two ways. First of all, the length of the cycles is not stable, but seems to decrease. Second, the amplitude of the cycles decreases over time. As a result the participants eventually learn the fundamental price (after about 30 to 40 periods) and start to coordinate their expectations on it. A learning time of 30 to 40 periods is quite remarkable for a learning-to-forecast experiment, in which participants usually learn to forecast the fundamental price within the first 10 periods or not at all.

Figure 2.3(d) shows the spot prices in experimental markets with the strongest coupling: $A = 30$. In this treatment the spot prices are almost completely determined by the speculators on the futures market. The observed dynamics varies. In some markets the spot prices move in multi-period cycles around the fundamental value until the end the experiment, while some other markets are characterized by large bubbles and crashes. One feature that distinguishes these markets from the experimental markets in the treatment with $A = 10$ is that in none of the markets spot prices stabilize during the experiment. Even in the first market, where prices seemed to have stabilized after 40 periods, a new cycle or bubble is forming in the last few periods. In many aspects the observed price dynamics is similar to that in learning-to-forecast experiments with asset markets (Hommes et al., 2008; Heemeijer et al., 2009). Note that for the participants, who are being paid based on the accuracy of their predictions, this is very unfavorable. Considering that we observe a few attempts at market manipulation in this strongest coupling treatment, some participants are also aware of this. However, despite the incentive the participants are not able to coordinate on another prediction strategy.

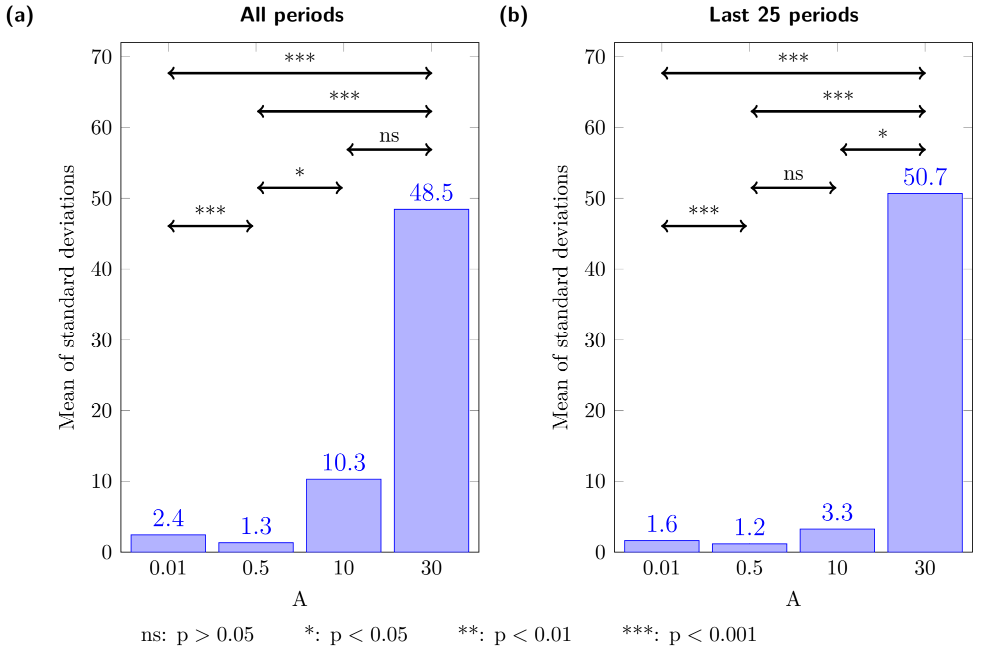


Figure 2.4: Bar plots showing for each treatment the mean of the standard deviations of spot prices in all periods (a) or the last 25 periods (b). In each plot we also indicated between which pairs of treatments the difference in standard deviation is significant (Mann-Whitney U-test, two-sided).

To assess the effect of the futures market on the stability of spot prices, we calculated the standard deviation of the prices in each experimental spot market. The results for all 32 spot markets, 8 per treatment, are presented in Table 2.1 and the mean standard deviations for each treatment are also plotted in Fig. 2.4. Note that the mean standard deviation changes non-monotonically with the coupling strength: between $A = 0.01$ and $A = 0.5$ it decreases but then it increases between $A = 0.5$ and $A = 10$ and between $A = 10$ and $A = 30$. We used the Mann-Whitney U-test (two-sided) to determine between which of these treatment pairs the difference with respect to the spot price standard deviation is significant. The results of these tests are also depicted in Fig. 2.4. Because both the decrease of the standard deviation between $A = 0.01$ and $A = 0.5$ and the increase between $A = 0.5$ and $A = 10$ are statistically significant (with $p < 0.001$ and $p = 0.010$, respectively), we conclude that there is a U-shaped dependence of the spot price volatility on the strength of the coupling between spot and futures markets. Moreover, the overall increase in spot price standard deviation between $A = 0.01$ and $A = 30$ is also significant ($p < 0.001$). This suggests that futures markets have a stabilizing effect on spot prices when they are weakly coupled to the spot markets and that they have a destabilizing effect when the coupling strength increases beyond a certain point.

It is not obvious that the outcome of the analysis above remains unchanged when learning effects are taken into account. We noted before that in treatments with low values of A participants learn the fundamental price in the first 5 to 10 periods, resulting in a lower spot price volatility afterwards. Judging from Fig. 2.3 this effect might be stronger for $A = 0.01$ than for $A = 0.5$, which makes it necessary to check whether the outcome changes when we exclude the beginning of the experiment. Another potential problem arises because of learning in the strong coupling treatment ($A = 10$). Towards the end of the experiment prices are quite stable in every $A = 10$ spot market. It is likely that for the last periods the prices in those markets do not fluctuate significantly more than in the $A = 0.5$ markets. To still get a significant U-shape, the increase in mean standard deviation between $A = 10$ and $A = 30$ will need to be significant for those periods. In the end, we address both problems by performing the same analysis on only the last 25 periods. Fig. 2.4(b) shows for each treatment the mean standard deviation of the last 25 prices in each spot market. Also here we find that the dependence of mean standard deviation on the coupling strength is U-shaped. The decrease from $A = 0.01$ to $A = 0.5$ is still significant ($p < 0.001$). As expected this is not the case anymore for the increase between $A = 0.5$ and $A = 10$. However, now the increase between $A = 10$ and $A = 30$ is significant ($p = 0.021$). Therefore we arrive at the same conclusion: the dependence of the spot price volatility on the coupling strength is not monotonic, but U-shaped.

The origin of the left, downward-sloping part of the U-curve is clear. It is driven by increased flexibility of inventories, which mitigates the effect of external shocks in supply and demand on the spot price. How this trend is broken, cannot be explained well with the analysis done so far. Simulations with very simple forecasting rules (Appendix 2.B) reveal that the use of a trend-following heuristic by participants can lead to a U-shape. However, this heuristic also causes extreme spot price fluctuations in almost isolated spot markets, which contradicts our observations in treatment $A = 0.01$. One possibility, that would reconcile the use of simple heuristics with our observations, is that participants use different heuristics in different treatments.

Heemeijer et al. (2009) analyze the individual forecasting strategies of participants in LtF-experiments with both positive and negative expectations feedback markets. They find that in their experiments more than half of the participants use a prediction strategy

Table 2.2: Significance and mean values of trend-following parameters in individual forecast analysis. The percentage expresses the fraction of participants for whose predictions the trend-following parameter is significant. The line below shows the mean trend-following parameter (averaged only over those cases in which the parameter was significant).

	Producers				Speculators			
	0.01	0.5	10	30	0.01	0.5	10	30
Significant trend parameter	28%	34%	69%	88%	28%	13%	59%	75%
Mean value	-0.07	0.21	0.54	0.63	0.02	0.16	0.74	0.80

equivalent to a heuristic of the form:

$$p_t^e = \alpha_1 p_{t-1} + \alpha_2 p_{t-1}^e + (1 - \alpha_1 - \alpha_2)\, p^* + \beta\,(p_{t-1} - p_{t-2})\,. \tag{2.22}$$

According to this equation participants' expectations are a weighted average of the last spot price p_{t-1}, the last prediction p_{t-1}^e, and the fundamental price p^* complemented by a trend term with coefficient β. Interestingly, these are also the four elements most often mentioned by our participants when asked about their strategy in the questionnaire at the end of the experiment. Therefore, we estimated Eq. (2.22) for all forecasts of advisors to producers in our experiment and a similar one (with p_{t+1}^e and p_t^e instead of p_t^e and p_{t-1}^e, respectively) for forecasts of advisors to speculators. In case any of the p-values were above 0.05, the parameter with the highest p-value was removed and the equation was then estimated again. This was repeated until all remaining parameters were significant at the 5% level. The first 10 periods, which we consider as a learning phase, and predictions of 0 or 1000, which form the boundaries of the acceptable price range, are not included in the estimation. The estimation results for each individual participant are provided in Appendix 2.E.

Table 2.2 shows for each treatment the fraction of participants for whose predictions the trend-following parameter β is significant, as well as the mean value. For the almost-isolated markets ($A = 0.01$) we observe only a limited number of strategies with significant trend-following (28%). Moreover, because there are also some cases for which the parameter is negative, the mean value of the parameter is almost 0. It therefore seems that in this treatment trend-following behavior does not play a role in the price dynamics. For $A = 0.5$ the fraction of participants that demonstrably uses trend-following is also small. By contrast, in treatments with strong market coupling ($A = 10$ and $A = 30$) more than half the participants have trend-following parameters significantly different from 0 (more than 75% for $A = 30$) and the mean value of the parameter ranges from 0.54 for producers in $A = 10$ to 0.80 for speculators in $A = 30$. Clearly, in these markets trend-following does play a role in forecasting spot prices and increasingly so when the coupling strength increases. This offers an explanation for the high volatility of spot prices in strongly coupled markets.

2.5 Conclusion

The effect of futures markets on the stability of commodity spot prices remains a topic that attracts much discussion. In most theoretical work authors assume that agents have rational expectations. Although this choice has many merits, we know from experiments that the expectations that people form are not always in line with the rational expectations hypothesis. We explored how a futures market affects spot price stability under different types of expectations in a stylized model of coupled spot and futures markets. The model features two types of agents whose expectations are important: producers and speculators. The producers produce more if they expect higher prices, which leads to lower market prices in the next period (negative expectations feedback). By contrast, when the speculators on the futures market expect prices to rise, higher futures prices lead to more of the commodity being stored, increasing the prices in the spot market (positive expectations feedback). A central role is played by the coupling between the spot and the futures market, which is based on storage. The stronger this coupling, the larger is the influence of the futures market on spot prices. A very strong coupling arises when storage is cheap and speculators are numerous and relatively risk tolerant.

In simulations with different types of expectations we find that with rational and naive expectations futures markets have a stabilizing influence on spot prices and that the variance of spot prices decreases as the coupling becomes stronger. However, when expectations contain a trend-following component the effect of the futures market is U-shaped: it is stabilizing for weak or moderate coupling, but destabilizing when spot and futures markets are strongly coupled. To determine what expectations people actually form under these circumstances and how this influences price stability, we used a learning-to-forecast experiment. In the experiment we let half of the participants forecast prices for producers, while the other half provided forecasts for the speculators. The experimental results show a U-shaped relationship between the coupling strength A and spot price volatility. Experimental markets with weak coupling ($A = 0.5$) exhibit significantly smaller spot price fluctuations than almost isolated markets ($A = 0.01$). However, when the coupling strength is increased further to $A = 10$ or $A = 30$, prices deviate from their fundamental value considerably more. An analysis of individual forecasting strategies reveals a considerable amount of trend-following in the treatments with strongly coupled markets.

Our findings suggest that there is not one answer to the question whether futures markets work to stabilize or destabilize commodity spot prices. The answer depends on the circumstances, in particular on how strongly the spot and futures markets are coupled. In our setup, weakly coupled spot and futures markets show lower volatility of spot prices than an isolated spot market, while in the case of a strong coupling the net effect of the futures market is clearly a destabilizing one. Because the dependence of the volatility on the coupling strength is U-shaped, also the response of the volatility to an increase in the coupling strength is ambiguous. Therefore a process like financialization, which in our model could be characterized by an increase in A, may reduce the volatility of spot prices for some commodities, but increase it for commodities for which the futures and spot markets are more strongly coupled.

The model, that we introduced in Section 2.2, was kept relatively simple and stylized. This benefitted the analysis and was particularly important for the experiment as it allowed us to clearly explain the relationship between the expectations of producers and speculators and the next-period spot price in the instructions. However, to achieve this simplicity we had to omit a few elements that are often relevant in real markets. One of these is an information channel through which futures prices can influence expectations of spot market participants. This channel is particularly important when speculators on the futures market possess private information that is also relevant for spot market participants. In that case the futures price can convey (some of) this information and affect trades on the spot market, as in the experiments of Forsythe et al. (1984, 1982) and Friedman et al. (1984). It is possible to extend our model with such a feature as well, by giving the speculators private information about future shocks. We think that this would have a stabilizing effect when the coupling between the markets is weak or moderate as producers can use the futures price to better estimate demand in the next period. In situations with strongly coupled spot and futures markets the demand shocks do not have a meaningful impact on spot prices, leaving little room for this channel to affect price stability there.

Another important element that we did not incorporate in our model is a fully dynamic environment. Although there are some demand shocks and a state variable in the form of the inventory deviation, most of the parameters in the model are fixed. We needed this to investigate the effects of futures markets as a function of A. In general, when the economy is subject to a shock that changes the equilibrium values, agents will need some time to learn about their new environment. The economy will then go through an adjustment period in which price fluctuations may be higher (see Bao et al. (2012)). In our model a dynamic environment would also make A endogenous, as speculators will likely adjust their expectation of spot price variance σ^2 when they observe that prices have become more or less volatile. Note that this creates another expectations feedback loop in the economy, because a change in σ^2 triggers a change in A, which in turn affects the actual volatility of prices in the spot market. This feedback is positive when the volatility decreases with A (as we found for weakly coupled markets) and negative when it increases with A (as we found for strongly coupled markets). The latter may lead to a situation in which the economy alternately goes through phases with higher and lower volatility. A complete analysis of a dynamic version of the model is left for future research.

Appendix 2.A Instructions to participants

2.A.1 General instructions

General information

In this experiment your task is to predict prices. The better your predictions, the more you will earn. Below you will find some general information about how the prices are formed. Carefully read this information. It will be followed by some questions to check your understanding of the experiment.

The market

We will focus on a single product for which there are several producers. Each period the producers sell everything they produced on a centralized market. The price they receive depends on the total production in that period (supply) and how much the customers want to buy (demand). The customers buy more if the price is lower. As a consequence, market prices will generally be lower in periods with a large production than in periods with a small production.

The producers

A producer sets production in order to maximize profit. His optimal decision depends on the price he will receive for his product. The higher this price, the more he should produce. A complicating factor for the producer is that it takes one period to produce the product. This means that he will need to decide how much to produce **one period in advance**, before he knows the price he will get. His solution is to get an estimate of the price in the next period and base his production decision on this estimate instead. All producers use this method. Note that this means that if on average producers expect higher prices in the next period, total production will be larger. Consequently, the realized prices will then be lower.

The speculators

A speculator specializes in predicting the market price **two periods in advance** as accurately as possible. If his prediction is correct, the speculator can make money. To see how this is possible, consider the following example. Suppose that at the end of period 3, after the market has closed, the speculator expects that the price of sugar in period 5 will be 4 cents per kg. When the market opens in the next period (period 4), he notices that he can buy sugar for 1 cent per kg. He buys a big amount and stores it for one period at a cost of 1 cent per kg. If in period 5 the sugar is indeed worth 4 cents per kg, the speculator made the following profit: 4 (selling price) - 1 (buying price) - 1 (storage costs) = 2 cents per kg.

Also in situations that prices are falling a speculator can make money. This is illustrated in the example below. At the end of period 15 the speculator expects that the price of sugar in period 17 will be 7 cents per kg. In period 16 he notices that people have to pay at least 9 cents for a kg of sugar. He then approaches one of the buyers and proposes to deliver 30 kg of sugar to him in the **next period** for 8 cents per kg. For the buyer, receiving his order in the next period is not as good as getting it immediately. He may get low on inventories in that period, which can for example frustrate the production process (if the buyer is a manufacturer) or disappoint customers (if the buyer is a shop owner). However, he may still agree because he gets the sugar for a lower price. If he agrees to the deal and the speculator was right with his prediction, the speculator buys 30 kg of sugar for 7 cents per kg on the market in period 17 and delivers it to the buyer for 8 cents per kg. This gives the speculator a profit of 1 cent per kg.

It is important to realize that the activities of speculators have real consequences for market prices. If on average the speculators expect prices to rise in period 5 (as in the first example), prices will already increase in period 4 because of higher demand for the product. And when they expect prices to fall in period 17, prices in period 16 will already be lower than they otherwise would be because people postpone buying the product. To summarize, on average higher expectations of speculators for the price in two periods raises prices in the next period and on average lower expectations of speculators lowers prices in the next period.

Role of the participants

The participants in this experiment will work as **financial advisors** for the producers and the speculators. These employers will base their expectations for 100% on the advice that they receive. Each producer and each speculator is advised by exactly one advisor and also each advisor works for one employer only (either a producer or a speculator). Those who advise a producer are asked to predict the price **one period ahead** and those who advise a speculator are asked to predict the price **two periods ahead**.

2.A.2 Extra instructions specific to advisors to producers

Your role

You will work as a financial advisor to a **producer**. This means your task is to predict the price of the product **one period ahead**. You will do this for 50 subsequent time periods. Your earnings during the experiment depend upon your forecasting accuracy. The smaller your forecasting errors in each period, the higher your total earnings.

Your task

The experiment starts with period 0. Below you can see a screen shot in which all the important elements are marked. The starting situation is such that in the first period the price will likely be between 8 and 50. You will start by giving a prediction for the price in period 1. After all participants have given their first prediction, the price for the first period will be revealed and, based on the forecasting error of your prediction, your earnings in the first period will be given.

Earnings

The earnings shown on the computer screen will be in points. If your prediction is p_t^e and the price turns out to be p_t in period t your earnings are determined by the following equation:

$$earnings_t = \max\left\{1300 - \frac{1300}{25}\left(p_t^e - p_t\right)^2, 0\right\}.$$

The maximum possible points you can earn for each period (if you make no prediction error) is 1300, and the larger your prediction error is, the fewer points you earn. You will earn 0 points if your prediction error is larger than 5. The earnings table on your desk shows the number of points you earn for different prediction errors. At the end of the experiment, your total earnings in points will be converted into euros, at an exchange rate of 1 euro for 2000 points. In addition you will receive 7 euros for participating in the experiment.

2.A.3 Extra instructions specific to advisors to speculators

Your role
You will work as a financial advisor to a **speculator**. This means your task is to predict the price of the product **two periods ahead**. You will do this for 50 subsequent time periods. Your earnings during the experiment depend upon your forecasting accuracy. The smaller your forecasting errors in each period, the higher your total earnings.

Your task
The experiment starts with period 0. Below you can see a screen shot in which all the important elements are marked. The starting situation is such that in the first period the price will likely be between 8 and 50. You will start by giving a prediction for the price in period 2. After all participants have given their first prediction, the market price for the first period will be revealed. At that point you are asked to give your prediction for the price of the product in the third period. After all participants have given their predictions again, the spot price in the second period will be revealed and, based on your forecasting error of the first prediction, your earnings for period 2 will be given.

Earnings
The earnings shown on the computer screen will be in points. If your prediction is p_t^e and the price turns out to be p_t in period t your earnings are determined by the following equation:

$$earnings_t = \max\left\{1300 - \frac{1300}{25}\left(p_t^e - p_t\right)^2, 0\right\}.$$

The maximum possible points you can earn for each period (if you make no prediction error) is 1300, and the larger your prediction error is, the fewer points you earn. You will earn 0 points if your prediction error is larger than 5. The earnings table on your desk shows the number of points you earn for different prediction errors. At the end of the experiment, your total earnings in points will be converted into euros, at an exchange rate of 1 euro for 2000 points. In addition you will receive 7 euros for participating in the experiment.

Appendix 2.B Simulations of price dynamics with forecasting heuristics

2.B.1 Introduction

The price dynamics resulting from the model with futures market critically depends on the agents' forecasting strategies. On the one hand the proper use of storage has the potential to lower price volatility in the presence of uncertainty in supply or demand. This is for example the case if inventories adjust upwards in times of low demand/high production and downwards in times of high demand/low production. On the other hand, the presence of a futures market and storage arbitrage also creates a positive feedback mechanism: the expectation of higher spot prices in the next period by speculators will increase spot prices in the current period. This positive expectations feedback can potentially create extreme price fluctuations (Heemeijer et al., 2009). Forecasting strategies may trigger predominantly the first or the second effect, resulting in, respectively, lower and higher volatility compared to a model without futures market. In this appendix the consequences of two boundedly rational strategies are outlined and compared with the price dynamics under rational expectations.

2.B.2 Naive expectations

One example in which the first, price stabilizing, effect will dominate is the case when both the producers and the speculators use a naive forecasting strategy. Note that this means that the producers use the current period's price as their forecast, while the speculators will use the previous period's price. As in a pure cobweb model, a high (low) price will lead naive producers to produce more (less) next period than consumers will wish to purchase at the fundamental price. This behavior drives prices to swing from one side of the fundamental value to the other, either with a decreasing amplitude or an increasing amplitude. If the speculative influence is small (small A), for example because of high storage costs or strongly risk averse speculators, these producer driven price swings dominate and the two-period-ahead predictions of the speculators will be quite accurate. As a result, the futures price will be low in a period with a high commodity spot price, and vice versa. Inventory holders will respond by increasing inventories when prices are low and selling from inventory when prices are high. This increases the stability of the system and lowers price volatility.

If speculative influence is large (large A), low storage costs and low risk premia will drive the current spot price towards the futures price. Again the predictions of naive speculators will be approximately correct, but this time it is 'by construction', because prices will change only slowly. The drivers of the price change in this case will be the producers. Their naive predictions will also be approximately correct, causing high production and considerable inventory build-up when prices are high. The small cost increase associated with the larger inventories brings the price down a bit. When eventually the price reaches the fundamental price p^* a considerable amount of the product will be in storage. The price will keep going down until all excess inventory is sold and then the process reverses. One would thus expect this regime to be characterized by slow oscillations around the fundamental price. Still, the overall price volatility decreases compared to the pure cobweb model.

Formally, the naive forecasting strategy for this model is given by:

$$p_{k,t}^{e,p} = p_{t-1}, \qquad p_{k,t}^{e,s} = p_{t-2}.$$

Substituting these in Eq. (2.14) immediately gives the equation for the price dynamics:

$$p_t = \frac{a - Kc - Kc \tanh\left(\lambda\left(p_{t-1} - d\right)\right) + A\left(2p_{t-1} - p_{t-2}\right)}{A + b} + \frac{\epsilon_t}{A + b}. \tag{2.23}$$

Thus in each period the price is established based on the last two prices plus a stochastic term. The non-stochastic part bears some resemblance to the case of linear backward-looking expectations with two lags treated in Hommes (1998) and we will employ the same technique used there to determine the stability conditions of the steady state at the fundamental price p^*.

Let $p_{t-2} = x_{t-1}$ and $p_{t-1} = y_{t-1}$, such that the non-stochastic part of Eq. (2.23) can be written:

$$\begin{aligned} x_t &= y_{t-1}, \\ y_t &= \frac{a - Kc - Kc \tanh\left(\lambda\left(y_{t-1} - d\right)\right) + A\left(2y_{t-1} - x_{t-1}\right)}{A + b}. \end{aligned}$$

Then $F_{\lambda,A}(x, y)$ maps x and y to their values in the next period:

$$F_{\lambda,A}(x, y) = \left(y, \frac{a - Kc - Kc \tanh\left(\lambda\left(y - d\right)\right) + A\left(2y - x\right)}{A + b}\right). \tag{2.24}$$

The stability conditions depend on the eigenvalues of the Jacobian of the map $F_{\lambda,A}(x, y)$

at the steady state price:

$$JF_{\lambda,A}\left(p^*,p^*\right)=\begin{pmatrix}0 & 1\\ -\frac{A}{A+b} & -\frac{Kc\lambda}{(A+b)\cosh^2(\lambda(p^*-d))}+\frac{2A}{A+b}\end{pmatrix}=\begin{pmatrix}0 & 1\\ -\frac{A}{A+b} & \frac{-B+2A}{A+b}\end{pmatrix}, \tag{2.25}$$

where B is defined as the slope of the supply curve at the fundamental price:

$$B=-\frac{Kc\lambda}{\cosh^2\left(\lambda\left(p^*-d\right)\right)}. \tag{2.26}$$

Only if the absolute values of both eigenvalues are smaller than one, the steady state is stable.

Solving the characteristic equation

$$\xi^2+\frac{B-2A}{A+b}\xi+\frac{A}{A+b}=0 \tag{2.27}$$

yields the two eigenvalues ξ_1 and ξ_2:

$$\xi_1\left(A\right)=-\frac{B-2A}{2\left(A+b\right)}-\sqrt{\left(\frac{B-2A}{2\left(A+b\right)}\right)^2-\frac{A}{A+b}}, \tag{2.28}$$

$$\xi_2\left(A\right)=-\frac{B-2A}{2\left(A+b\right)}+\sqrt{\left(\frac{B-2A}{2\left(A+b\right)}\right)^2-\frac{A}{A+b}}. \tag{2.29}$$

For $A=0$ the second eigenvalue is zero while the first eigenvalue reduces to $-\frac{B}{b}$. As A increases the eigenvalues move closer together until the point A_1^* where the term under the root becomes negative and both ξ_1 and ξ_2 become complex:

$$A_1^*=\frac{B^2}{4\left(B+b\right)}. \tag{2.30}$$

At A_1^* both eigenvalues are equal and take a value:

$$\xi_1\left(A_1^*\right)=\xi_2\left(A_1^*\right)=\frac{B^2+2Bb}{2\left(B^2+2Bb+2b^2\right)}<1. \tag{2.31}$$

Because both eigenvalues are smaller than one, the steady state at the fundamental price will be stable at A_1^*. Therefore if the parameters in an isolated spot market are such that the steady state is unstable, it will become stable when the speculative influence A increases. [11]

[11] This will happen at some point before A reaches the value in Eq. (2.30). This point is given by $A_2^*=\frac{1}{4}\left(B-b\right)$.

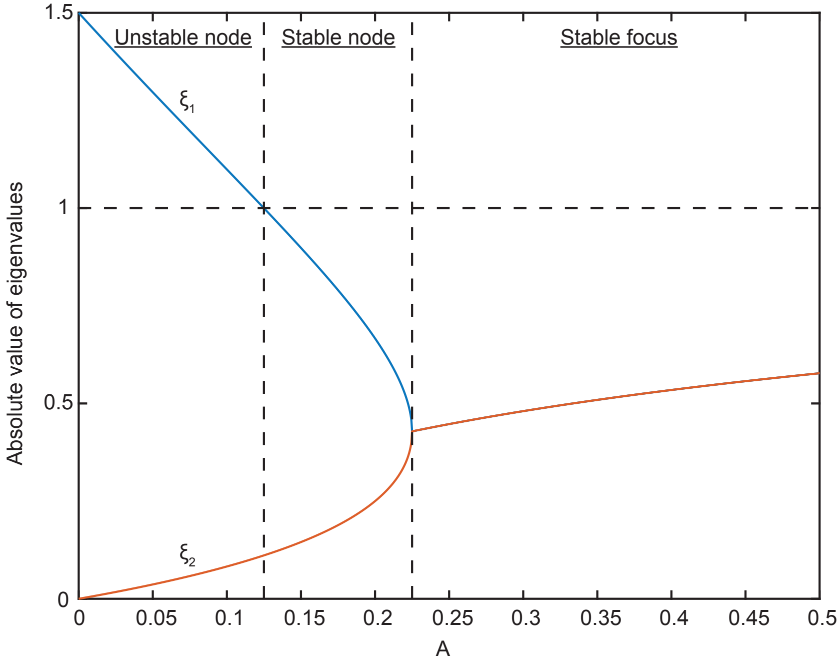


Figure 2.5: The absolute values of the eigenvalues ξ_1 and ξ_2 of the map corresponding to the model with naive agents and $\lambda = 0.25$. When all eigenvalues have absolute values smaller than one, the steady state at the fundamental price is stable. The regions for A for which this holds are marked 'Stable node' and 'Stable focus'. The latter arises if the two eigenvalues are complex.

Figure 2.5 shows a plot of the absolute values of the eigenvalues as a function of A for the case of 4 producers and 4 speculators ($K = H = 4$) and supply/demand parameter values $a = 12$, $b = 1$, $c = 1.5$, $d = 6$, and $\lambda = 0.25$. These values are different than used in the experiment, where we wanted to avoid a round number for the fundamental price. However, the conclusions of our analysis are equally valid for those values. In the rest of this appendix, unless explicitly mentioned, we will use the same settings in graphs and simulations. At these settings the fundamental price $p^* = 6$ and the slope of the supply curve $B = 1.5$. Three regions are indicated: an unstable node, a stable node, and a stable focus region. Figure 2.6 presents a simulated time series for one value of A within each region. In these simulations the standard deviation of the noise term is $\sigma_\epsilon = 0.1$.

In the first region, where both eigenvalues are real, the steady state is unstable. As a consequence in each next period the price lies further away from the fundamental price p^*. The first 15 periods of the time series in Fig. 2.6(a) illustrate this. After this point divergence stops and the time series shows convergence to a stable two-cycle. Also in the second region both eigenvalues are real. However, here the steady state is stable. Figure 2.6(b) shows a possible time series of prices in case $A = 0.2$. The scale is 5% of the one in Fig. 2.6(a). If it weren't for the demand shocks each period, one would see the prices rapidly converging, each iteration being closer to p^*. In the third region the steady state is also stable, but the eigenvalues are complex. With two complex eigenvalues, prices may not converge to the fundamental price directly, but show a damped oscillation towards it (hence a stable focus instead of a stable node). This is exactly the expected behavior of prices when storage is cheap. Figure 2.6(c) shows an example of a time series for $A = 10$.

The analysis above shows that when all agents are naive a larger influence of the futures market can only increase stability, not decrease it. However, does this also mean that price volatility decreases with larger A? This is a question that cannot readily be answered from the stability analysis. Therefore we will compare the variances of prices in simulated time series to address this. A simple measure is the variance of the prices in a series compared to the variance of the demand shocks (σ_ϵ^2):

$$\rho = \frac{\mathrm{Var}\,(p_t)}{\sigma_\epsilon^2}. \tag{2.32}$$

Each simulated time series had sufficient length (10000 periods) such that possibly different dynamics in the first few periods could be neglected.

The results, ρ as a function of A, are plotted in Fig. 2.7 for several values of λ. Consistent with the results from the stability analysis, when speculative influence is small the relative variance decreases rapidly with increasing A. Fig. 2.7 shows that this decrease continues also after the steady state has become stable. Even after the two eigenvalues have become complex, and their absolute values start increasing again (around 0.22 for $\lambda = 0.25$) the relative variance keeps decreasing with A. However, whether this trend continues to infinity does not become clear from the simulations (also not for simulations that extend to larger values of A). In general, the simulations support the intuition that with naive agents price volatility decreases with increasing influence of futures market trading.

2.B.3 Trend-following expectations

Compared to the naive expectations, stable prices near the fundamental value are much less likely when agents use a trend-following forecasting strategy. A trend-following strategy by producers tends to create even stronger price swings than the naive predictions.

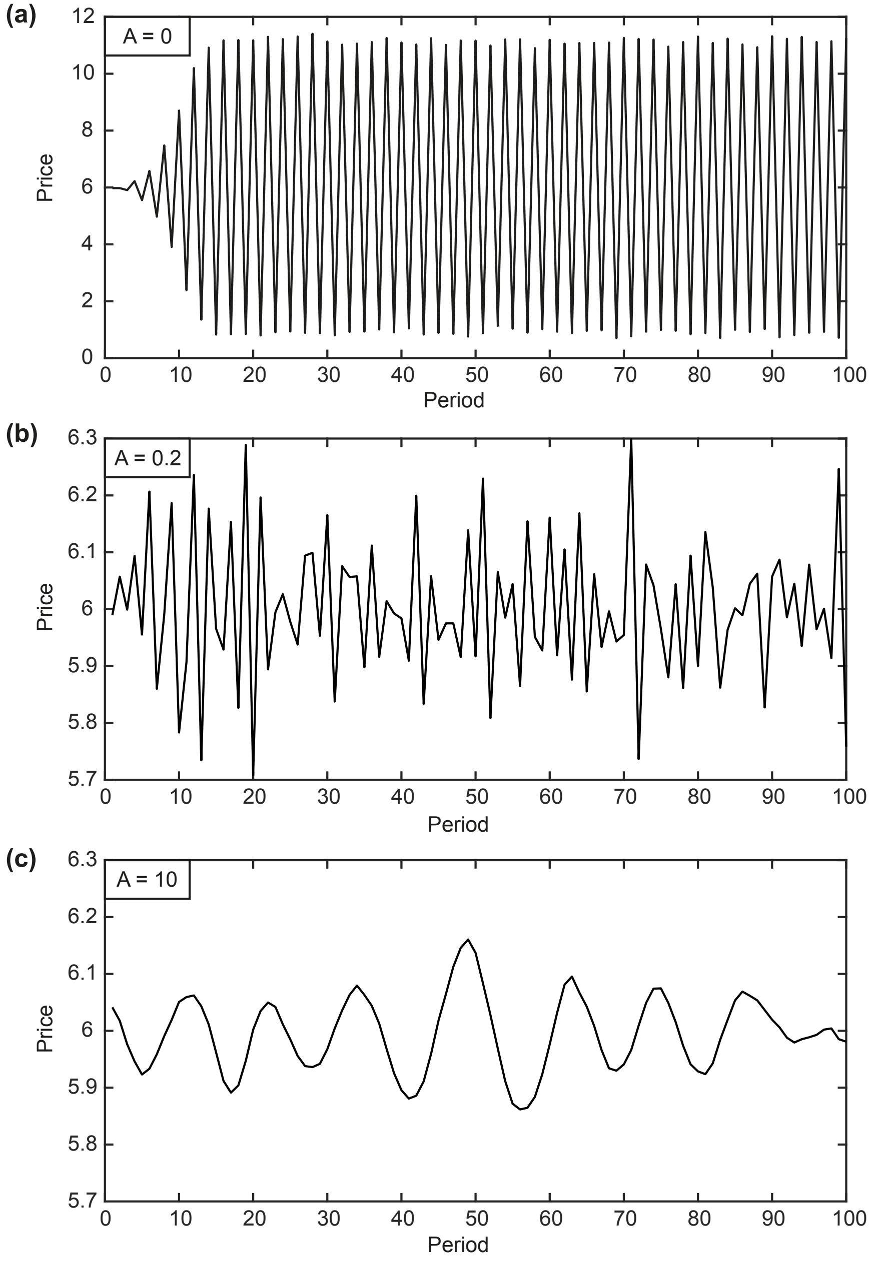


Figure 2.6: Time series of prices for naive expectations. For increasing values of the futures market influence A the price dynamics changes from a stable two-cycle with alternately very high and very low prices (a), to a stable steady state with small price variations around the fundamental price (b) and (c). The vertical scale in (b) and (c) is 5% of the scale in (a).

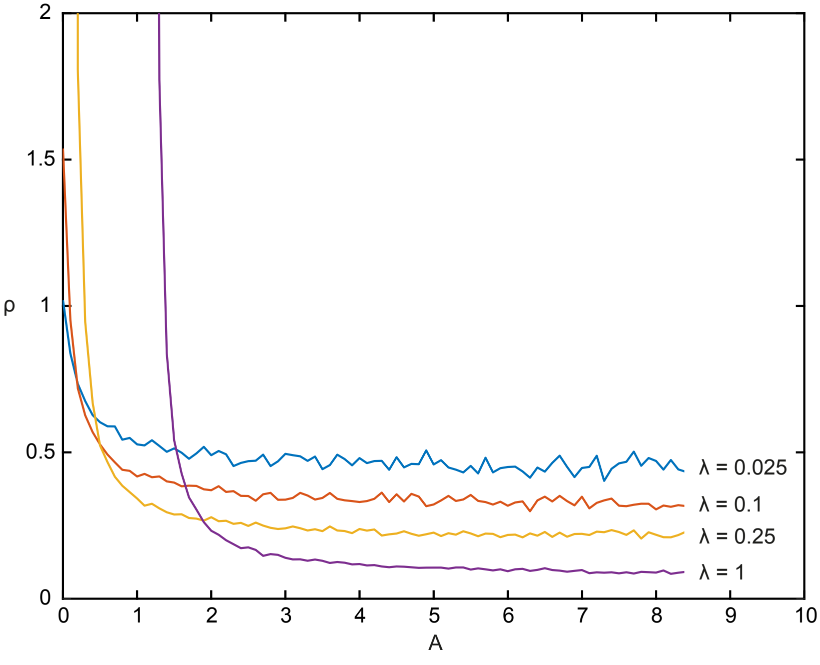


Figure 2.7: Variance of prices relative to the variance of the external noise process in the model with naive expectations. For each value of λ shown, the variance decreases with futures market influence A.

Now, when a positive demand shock drives prices upwards, producers will expect an even higher price next period, leading to an even larger production. Hence the drop in price will also be larger then, giving rise to an even lower prediction for next period's price by the producers. Again if speculative influence is small, the speculators may get the trend approximately right, lowering price volatility and increasing the stability of the system. However, when speculative influence grows this changes quickly. As spot prices start to follow the futures prices closer, a trend set by the speculators will not reverse easily, causing large inventory deviations and prices far from the fundamental value.

A trend-following forecasting strategy for the producers can be written as follows:

$$p^{e,p}_{k,t} = p_{t-1} + \alpha\left(p_{t-1} - p_{t-2}\right) = \left(1+\alpha\right)p_{t-1} - \alpha p_{t-2},$$

where α can be any positive number. In literature on heuristic switching models trend-following expectations with values of α of 0.4 and 1.3 have also been called weak trend rule (WTR) and strong trend rule (STR) (Anufriev and Hommes, 2012a,b). In the model discussed here the speculators make two-period ahead forecasts. There are various ways in which a trend-following strategy for two-period-ahead forecasts can be defined. Here we choose the speculators to expect that the most recent price change they observed will repeat itself twice:

$$p_{k,t}^{e,s} = p_{t-2} + 2\alpha\left(p_{t-2} - p_{t-3}\right) = \left(1 + 2\alpha\right)p_{t-2} - 2\alpha p_{t-3}.$$

With the above defined forecasting strategies the price dynamics of Eq. (2.14) becomes:

$$\begin{aligned} p_t = {} & \frac{a - Kc - Kc\tanh\left(\lambda\left(\left(1+\alpha\right)p_{t-1} - \alpha p_{t-2} - d\right)\right)}{A+b} \\ & + \frac{A\left(2\left(1+\alpha\right)p_{t-1} - \left(1+4\alpha\right)p_{t-2} + 2\alpha p_{t-3}\right)}{A+b} + \frac{\epsilon_t}{A+b}. \end{aligned} \tag{2.33}$$

This equation allows for a similar analysis of steady state stability as with naive expectations. There is one important difference: for trend-following expectations the new price depends on the past three prices instead of the past two. This results in a 3-D map for prices from one period to the next:

$$\begin{aligned} G_{\lambda,A}\left(x,y,z\right) = \Bigg(& y, z, \frac{a - Kc - Kc\tanh\left(\lambda\left(\left(1+\alpha\right)z - \alpha y - d\right)\right)}{A+b} \\ & + \frac{A\left(2\left(1+\alpha\right)z - \left(1+4\alpha\right)y + 2\alpha x\right)}{A+b}\Bigg). \end{aligned} \tag{2.34}$$

Here x, y, and z represent the last three prices in time series, with z being the most recent.

Also for a 3-D map the stability of the steady state at the fundamental price depends on the eigenvalues of the Jacobian at p^*:

$$\begin{aligned} JG_{\lambda,A}\left(p^*,p^*,p^*\right) &= \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ \frac{2\alpha A}{A+b} & \frac{\alpha Kc\lambda}{(A+b)\cosh^2(\lambda(p^*-d))} - \frac{(1+4\alpha)A}{A+b} & -\frac{(1+\alpha)Kc\lambda}{(A+b)\cosh^2(\lambda(p^*-d))} + \frac{2A(1+\alpha)}{A+b} \end{pmatrix} \\ &= \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ \frac{2\alpha A}{A+b} & \frac{\alpha B-(1+4\alpha)A}{A+b} & -\frac{(1+\alpha)(B-2A)}{A+b} \end{pmatrix}. \end{aligned} \tag{2.35}$$

Only if all (up to three) eigenvalues have absolute values smaller than one the steady state is stable. The characteristic equation is:

$$\zeta^3 + \frac{(1+\alpha)(B-2A)}{A+b}\zeta^2 + \frac{(1+4\alpha)A - \alpha B}{A+b}\zeta - \frac{2\alpha A}{A+b} = 0. \tag{2.36}$$

Although analytical solutions for the eigenvalues exist, they are too long to reproduce here. Instead they are plotted in Fig. 2.8 as a function of A for three different values of α: 0 (naive expectations), 0.4 (WTR), and 1.3 (STR). The stability for the case $\alpha = 0$ was discussed before: if not yet stable for $A = 0$, the steady state will become stable for some value of A and it will remain stable also if A is increased further. This changes when the trend-following component in the forecasts becomes stronger. When agents use the strong trend rule (Fig. 2.8(c)) the steady state will be unstable for any A. The case in between, for $\alpha = 0.4$, shows a richer picture. As with naive expectations increasing A can make the steady state stable. However, further increases may undo this again. Unlike with naive expectations, the focus does not remain stable for large A.

Figure 2.9 shows simulated time series for several values of A in case agents use the weak trend rule ($\alpha = 0.4$). The dynamics for $A = 0$ shows a stable two-cycle, similar to the one for naive expectations (compare Fig. 2.6(a)), but with even larger price swings. At $A = 0.25$ the dynamics takes place around the stable steady state. However, there is still a pronounced alternation in prices visible at most times, which indicates strong negative first-order autocorrelation. For $A = 0.9$ the fast, alternating dynamics is replaced by slower oscillations that are close to a four-cycle. This difference is due to the change of a stable node (real eigenvalues) to a stable focus (2 complex and 1 real eigenvalue). For the largest value of A the steady state has become unstable again (Fig. 2.9(d)). Prices still show the slower oscillations also present in the stable focus, but now the amplitude of these slower oscillations diverges.

Finally, Fig. 2.10 shows, both for the weak and the strong trend rule, plots of the relative variance ρ in simulated time series as function of A. As expected, at the value of A where the steady state becomes stable (unstable) one can observe a large decrease (increase) in the relative variance. However, all plotted curves (for several values of λ) are U-shaped. This means that in general for trend-following forecasting strategies, the volatility first decreases with increasing A and then increases again. The existence of U-shaped volatility curves has important implications. It shows that under some circumstances it is possible that increased influence of future market trading leads to larger price volatility on the commodity spot markets, despite the experience that the introduction of futures market generally reduces price volatility.

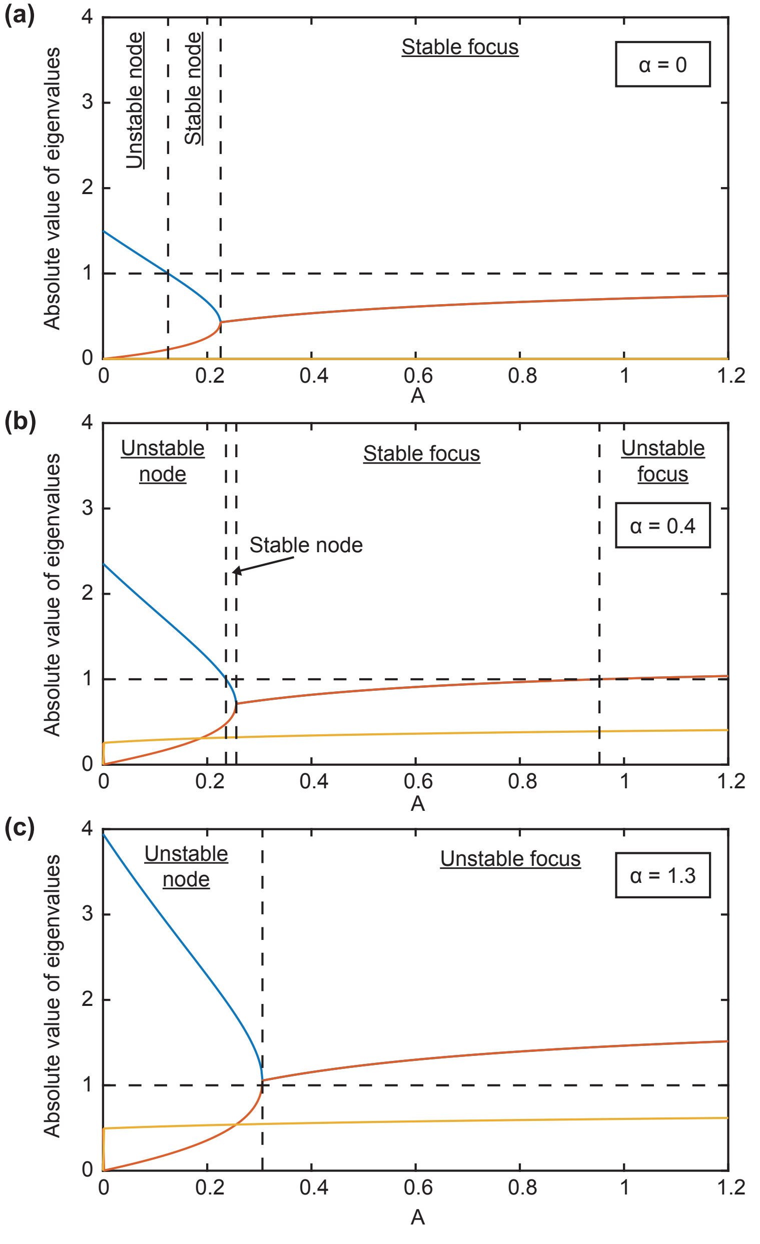


Figure 2.8: The absolute values of the eigenvalues of the map corresponding to the model with several types of trend-following agents and $\lambda = 0.25$. When all eigenvalues have absolute values smaller than one, the steady state at the fundamental price is stable. (a) repeats the case of naive agents ($\alpha = 0$). The cases for WTR ($\alpha = 0.4$) and STR ($\alpha = 1.3$) are shown in (b) and (c) respectively.

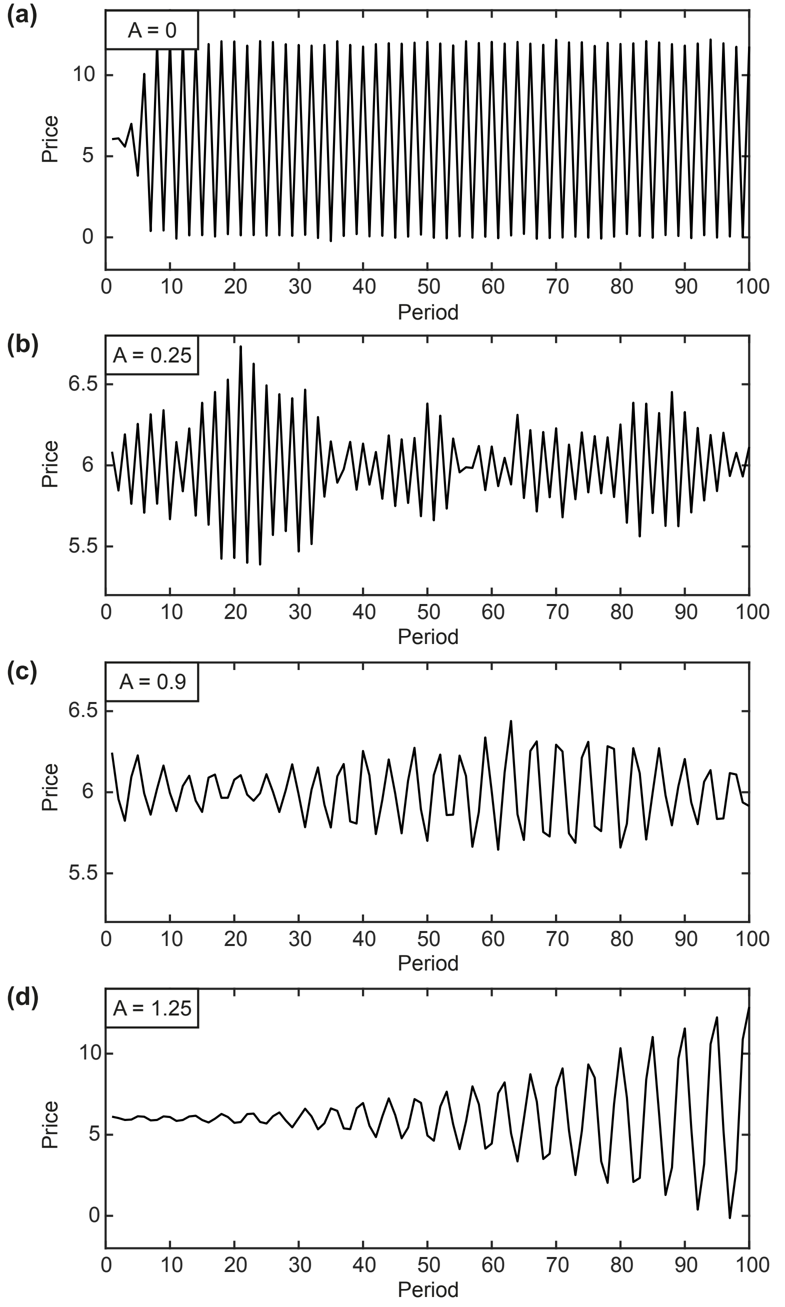


Figure 2.9: Time series of prices for agents following a weak trend rule ($\alpha = 0.4$). For increasing values of the futures market influence A the price dynamics changes from a stable two-cycle with alternately very high and very low prices (a), to a stable steady state with small price variations around the fundamental price (b) and (c) and finally to an unstable steady state again (d). The vertical scale in (b) and (c) is 10% of the scale in (a) and (d).

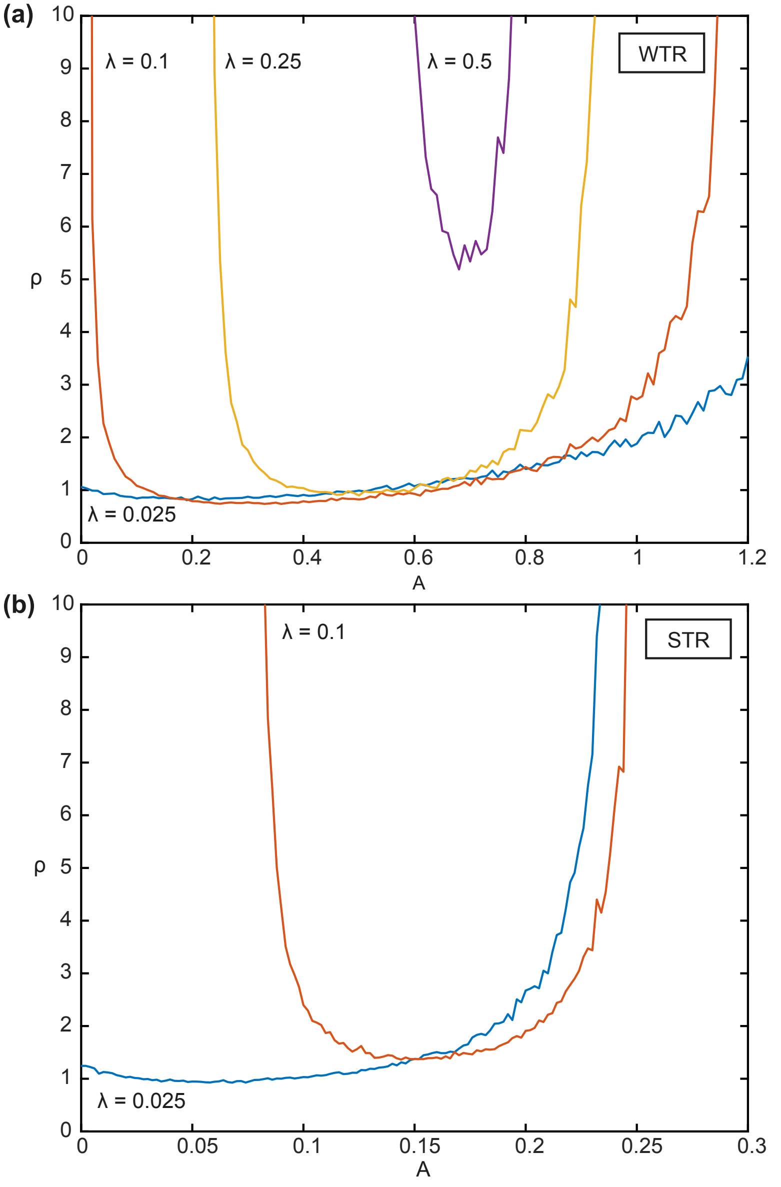


Figure 2.10: Variance of prices relative to the variance of the external noise process in the model with trend-following expectations. Both curves for the weak trend rule (a) and the strong trend rule (b) are shown. All curves are U-shaped, meaning that the relative variance first decreases with increasing A and then increases again when A gets too large.

2.B.4 Rational expectations

Compared to these two boundedly rational strategies, the case for rational agents will be a bit more complicated. Rational agents are different because each of their forecasts has to be equal to the expected value of the price in that period. Moreover, the agent should either be aware of the forecasting strategies used by all other market participants or should be able to assume that the rational expectations hypothesis holds in order to perform the calculation of the expected value. However, the (average) expectations of others also depend on (other) expectations and it is not clear a priori how many of these need to be taken into account by a rational agent. This gives rise to the question whether it is reasonable to expect that it is within an agent's ability to form rational expectations. At the end of this section I will try to address this question.

Intuitively, the first consequence of a *single* negative demand shock in period t is that inventory holders will take advantage of the difference between the (low) spot price and (higher) futures price and store a bit extra of the commodity. Because the extra stored produce will be taken off the spot market, prices will not be as low as without storage. Of course the extra inventory will increase supply in the next period, which causes the prices in period $t+1$ to be lower than they would otherwise have been. A rational producer will take this into account, expecting prices to be somewhat lower than the equilibrium price also in the next period. As a result production will also be lower than if the equilibrium price would be expected (see Eq. (2.1)). However, the total supply, the extra inventory of period t and the production in period $t+1$, still exceeds the total demand at the equilibrium price. It has to, because consistency imposes that in expectation the lower price expected by the producers needs to be realized.

At the start of the period $t+1$ the speculators are also aware that there has been a shock and they will deduce that something extra has been stored, and that the producers lowered production, but not enough to expect the equilibrium price to be realized later that period. Because of the extra supply in period $t+1$ it is reasonable for the speculators to expect the price to be higher in the next period ($t+2$). However, they know that their expectation will cause part of the supply in period $t+1$ to be stored for sale in period $t+2$, so they expect a higher price, but still below the equilibrium price. The lower futures price will reduce the fraction of extra produce going into storage somewhat compared to the previous period in which the demand shock was not anticipated by the speculators. Because all expectations are equal to the expected values for the prices, if there is no new demand shock that period, the producers will later make the same prediction for the price in period $t+2$.

In periods $t+2$ and later, a very similar scenario as in period $t+1$ will take place, each time with a smaller amount being stored and prices closer to the equilibrium price. As a consequence the effect of a single shock is smeared out over many future periods. In the full model there is a demand shock every period, each of which will affect future periods as well. There are two ways for rational agents to deal with this. The first is to keep track of the current inventory deviation. Combining this with knowledge of the equilibrium price enables them to calculate the exact rational expectations forecast. Alternatively they could take into account the full history of prices, making their predictions a function of the equilibrium price and all previous prices. The second strategy may, however, still be very useful if the weights are such that in practice only the most recent price or the two most recent prices need to be taken into account. Overall, one would expect that the high accuracy of the rational predictions would lead to a very efficient use of storage and that spot prices vary less as storage becomes cheaper or the risk premium goes down.

With a non-linear supply function such as Eq. (2.1) the prediction functions will in general also be non-linear, which makes it very difficult to find a closed form solution. However, if the volatility is low and prices stay close to the equilibrium price a linearized version of the model can be a very close approximation. Let $x_t = p_t - p^*$ be the price deviation from equilibrium and $x^{e,p}_{k,t} = p^{e,p}_{k,t} - p^*$ and $x^{e,s}_{h,t} = p^{e,s}_{h,t} - p^*$ be the predictions of this deviation by a producer and speculators, respectively. Then Eq. (2.14) can be written:

$$\begin{aligned} x_t &= \frac{c\sum_{k=1}^{K}\left(\tanh\left(\lambda\left(p^*-d\right)\right)-\tanh\left(\lambda\left(x^{e,p}_{k,t}+p^*-d\right)\right)\right)+A\bar{x}^{e,s}_{t+1}-I_{t-1}}{A+b}+\frac{\epsilon_t}{A+b} \\ &\approx \frac{-B\bar{x}^{e,p}_t+A\bar{x}^{e,s}_{t+1}-I_{t-1}}{A+b}+\frac{\epsilon_t}{A+b}, \end{aligned} \tag{2.37}$$

where B is again the slope of the supply curve at the equilibrium price and $\bar{x}^{e,p}_t$ and $\bar{x}^{e,s}_t$ are the average predictions of the producers and speculators. The approximation follows from a Taylor series expansion around $x^{e,p}_{k,t} = 0$ of the hyperbolic tangent function or can be obtained from deriving Eq. (2.14) with a linear supply function. The resulting Eq. (2.37) looks exactly the same as the price equation for a model with inventory speculation in the classic article by Muth (1961). The one crucial difference, however, is that here the speculators predict two periods ahead instead of one.

Following the rational expectations hypothesis by Muth (1961), I define the agents' rational expectations as:

$$\bar{x}^{e,p}_{k,t} = \mathrm{E}_{\mathrm{t}-1}\left[x_t\right], \qquad \bar{x}^{e,s}_{k,t} = \mathrm{E}_{\mathrm{t}-2}\left[x_t\right].$$

Using these in the linearized version of the model (Eq. (2.37)) and taking on both sides the expected value at $t-1$ yields:

$$\mathrm{E_{t-1}}\left[x_t\right] = \frac{-B\mathrm{E_{t-1}}\left[x_t\right] + A\mathrm{E_{t-1}}\left[x_{t+1}\right] - I_{t-1}}{A+b}$$
$$\Leftrightarrow \qquad \mathrm{E_{t-1}}\left[x_t\right] = \frac{A\mathrm{E_{t-1}}\left[x_{t+1}\right] - I_{t-1}}{A+B+b}. \tag{2.38}$$

We can then use Eq. (2.12) to rewrite Eq. (2.38) in terms of the expected change in inventories:

$$\mathrm{E_{t-1}}\left[x_t\right] = \frac{1}{B+b}\left(\mathrm{E_{t-1}}\left[I_t\right] - I_{t-1}\right). \tag{2.39}$$

Since I_{t-1} describes the full state of the economy in this model, it must be possible to write any prediction as a function of solely I_{t-1}. This includes $\mathrm{E_{t-1}}\left[I_t\right]$. Let

$$\mathrm{E_{t-1}}\left[I_t\right] = g\left(I_{t-1}\right). \tag{2.40}$$

Using Eq. (2.39) again allows to solve for $g\left(I_{t-1}\right)$:

$$g\left(I_{t-1}\right) = \mathrm{E_{t-1}}\left[I_t\right] = A\left(\mathrm{E_{t-1}}\left[x_{t+1}\right] - \mathrm{E_{t-1}}\left[x_t\right]\right)$$
$$= \frac{A}{B+b}\left(g\left(g\left(I_{t-1}\right)\right) - 2g\left(I_{t-1}\right) + I_{t-1}\right)$$
$$\Leftrightarrow \qquad g\left(g\left(I_{t-1}\right)\right) - \left(2 + \frac{B+b}{A}\right)g\left(I_{t-1}\right) + I_{t-1} = 0 \tag{2.41}$$

The solution to Eq. (2.41) is of the form:

$$g\left(I_{t-1}\right) = \mu I_{t-1}, \qquad \mu \in \mathbb{R}. \tag{2.42}$$

Solving for μ gives:

$$\mu_1 = 1 + \frac{B+b}{2A} - \sqrt{\left(1 + \frac{B+b}{2A}\right)^2 - 1} \tag{2.43}$$
$$\mu_2 = 1 + \frac{B+b}{2A} + \sqrt{\left(1 + \frac{B+b}{2A}\right)^2 - 1} \tag{2.44}$$

There are thus two solutions. The first, μ_1, is bound between zero and one and is in line with the intuition outlined above. For this solution the equilibrium price is always a stable focus. The second solution, μ_2, is always larger than one and therefore an explosive solution. Its existence as a rational solution is a reminder that this model exhibits both positive and negative feedback. In the rest of this work I will not consider μ_2 in more detail and assume that the rational expectations forecast uses μ_1.

Substituting the results above in Eq. (2.39) gives the expected value of the price deviation x_t in terms of I_{t-1}:

$$\mathrm{E}_{\mathrm{t}-1}\left[x_t\right] = \frac{\mu_1 - 1}{B+b} I_{t-1} = \left(\frac{1}{2A} - \sqrt{\frac{1}{A\left(B+b\right)} + \frac{1}{4A^2}}\right) I_{t-1}. \tag{2.45}$$

The two-period-ahead prediction follows readily as:

$$\mathrm{E}_{\mathrm{t}-2}\left[x_t\right] = \frac{\mu_1 - 1}{B+b} \mathrm{E}_{\mathrm{t}-2}\left[I_{t-1}\right] = \mu_1 \frac{\mu_1 - 1}{B+b} I_{t-2} = \mu_1 \mathrm{E}_{\mathrm{t}-2}\left[x_{t-1}\right]. \tag{2.46}$$

It is worth noting that the result in Eq. (2.46) is equivalent to the rational expectations solution for speculative storage by Muth (1961). However, the two-period-ahead forecasting by the speculators prevents rational predictions based on the last price only, i.e. $\mathrm{E}_{\mathrm{t}-1}\left[x_t\right] \neq \mu_1 x_{t-1}$.

The proper prediction function using past prices can be obtained by expanding Eq. (2.45) by repeatedly using Eq. (2.12):

$$\begin{aligned}
\mathrm{E}_{\mathrm{t}-1}\left[x_t\right] &= \frac{\mu_1 - 1}{B+b} I_{t-1} = \frac{A\left(\mu_1 - 1\right)}{B+b}\left(\mathrm{E}_{\mathrm{t}-2}\left[x_t\right] - x_{t-1}\right) \\
&= \frac{A\left(1-\mu_1\right)}{B+b} x_{t-1} - \mu_1 \frac{A\left(1-\mu_1\right)}{B+b} \mathrm{E}_{\mathrm{t}-2}\left[x_{t-1}\right] \\
&= \frac{A\left(1-\mu_1\right)}{B+b} x_{t-1} - \mu_1 \frac{A\left(1-\mu_1\right)}{B+b}\left(\frac{A\left(1-\mu_1\right)}{B+b} x_{t-2} - \mu_1 \frac{A\left(1-\mu_1\right)}{B+b} \mathrm{E}_{\mathrm{t}-3}\left[x_{t-2}\right]\right) \\
&= \frac{A\left(1-\mu_1\right)}{B+b} \sum_{i=0}^{T}\left(-\mu_1 \frac{A\left(1-\mu_1\right)}{B+b}\right)^i x_{t-1-i} \equiv \sum_{i=0}^{T} \phi_i x_{t-1-i}.
\end{aligned} \tag{2.47}$$

Here T is the total number of past prices, excluding the most recent one. The ϕ_i are the weights that should be attached to all known prices to predict the next one:

$$\phi_i = \frac{A\left(1-\mu_1\right)}{B+b}\left(-\mu_1 \frac{A\left(1-\mu_1\right)}{B+b}\right)^i. \tag{2.48}$$

They alternate between positive and negative. Note that already for moderate values of A the weights on older prices exceed the weights on the newer ones (in absolute terms). This makes a rational prediction strategy based on previous prices problematic as even the slightest error will make the forecast inaccurate.

Fig. 2.11 shows simulated time series for three values of A and Fig. 2.12 shows how the relative variance ρ of such series changes with A. All simulations show relatively low volatility as ρ is close to one for $A = 0$ and dropping rapidly afterwards. In fact, with

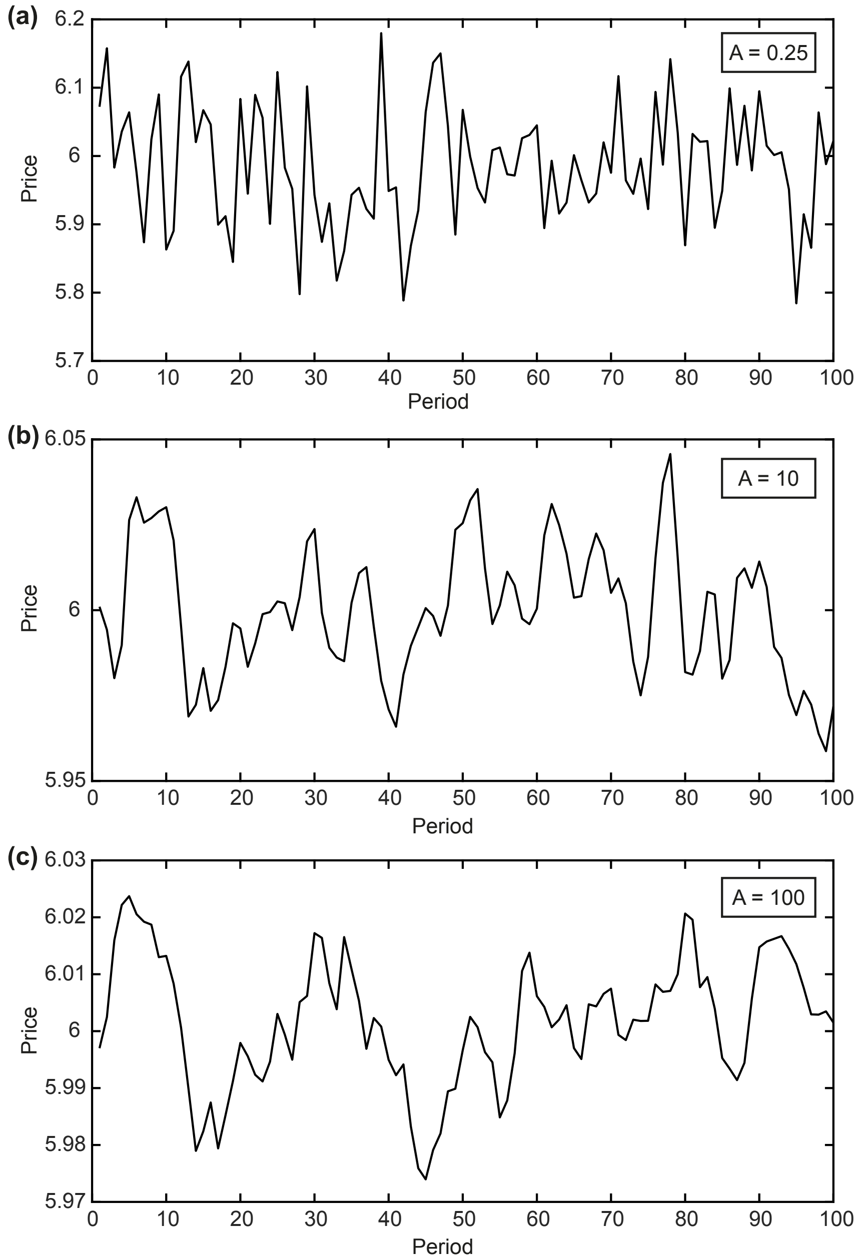


Figure 2.11: Three time series of prices for rational expectations: for $A = 0.25$ (a), $A = 10$ (b), and $A = 100$ (c). In general the amplitude of the price deviations decreases with larger A, while the persistence increases. For larger A the prices converge back to the equilibrium slower.

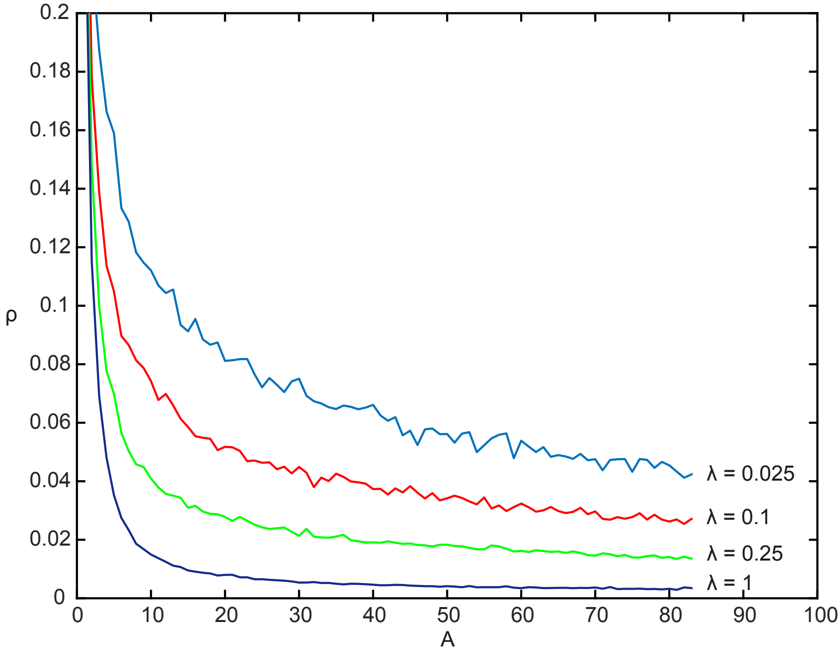


Figure 2.12: Variance of prices relative to the variance of the external noise process in the model with rational expectations. All relative price variances are close to one for $A = 0$, but decrease rapidly when A increases. The decrease is stronger for larger values of λ. Compared to other forecasting strategies, volatility is considerably lower with rational expectations.

similar parameters other forecasting strategies produce considerably more volatile prices. The time series also show that for larger A the prices are more persistent, i.e. it takes longer for a deviating price to converge back to equilibrium. This is understandable in situations in which storage is very cheap. Demand shocks will be spread out over many periods.

Appendix 2.C Futures prices in the experiment

The futures prices follow from Eq. 2.11, which contains three parameters that we did not specify prior to running our experiment: γ, ϕ, and σ. The coupling parameter A, by means of Eq. 2.13 fixes the relation between them, leaving two degrees of freedom. Therefore, to calculate futures prices for our experimental markets, we need to make some additional assumptions. The first assumption we make, is to set σ equal to the average standard deviation of the spot prices that we observed in each treatment: 2.4, 1.3, 10.3, and 48.5 for the treatments with $A = 0.01$, $A = 0.5$, $A = 10$, and $A = 30$, respectively. If we then choose $\phi = 0.00005$, we get $\gamma = 99.99928$ for $A = 0.01$, $\gamma = 1.99998$ for $A = 0.5$, $\gamma = 0.09867$ for $A = 10$, and $\gamma = 0.003930$ for $A = 30$. Fig. 2.13 shows the spot and futures prices together for each market.

Appendix 2.D Graphs of individual forecasts

Figures 2.14 to 2.17 provide plots of the prices in the spot markets along with the individual forecasts of these prices.

Appendix 2.E Individual forecasting strategies

Tables 2.3 to 2.6 contain the estimated parameters of the individual forecasting strategies.

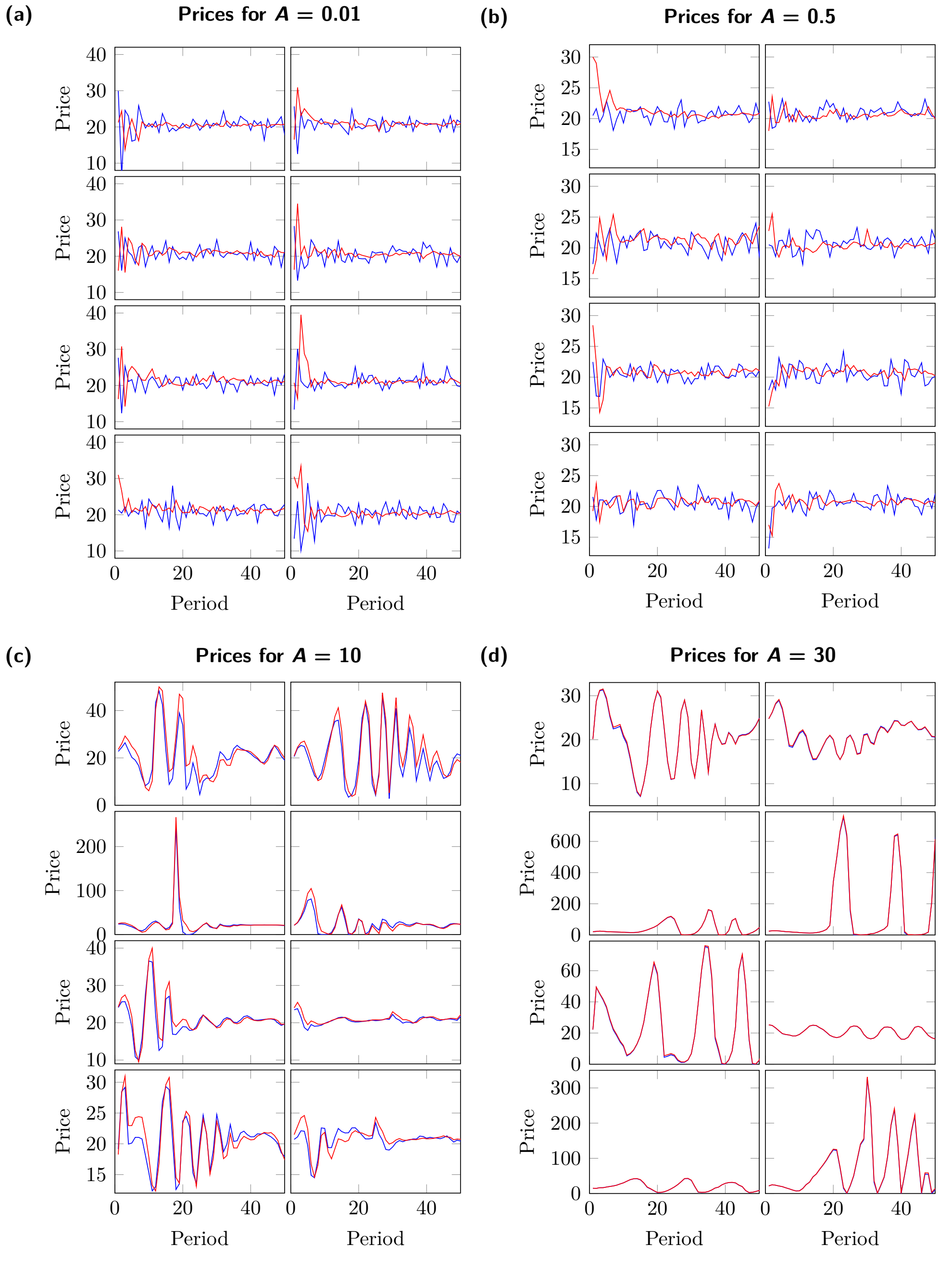


Figure 2.13: Plots of spot (blue) and futures (red) prices in different experimental spot markets. There are four treatments, differing only in the strength of the coupling between the spot and futures markets: $A = 0.01$ (a), $A = 0.5$ (b), $A = 10$ (c), $A = 30$ (d). Unlike the graphs in Fig. 2.3, the scales in these graphs are linear and can be different for different graphs.

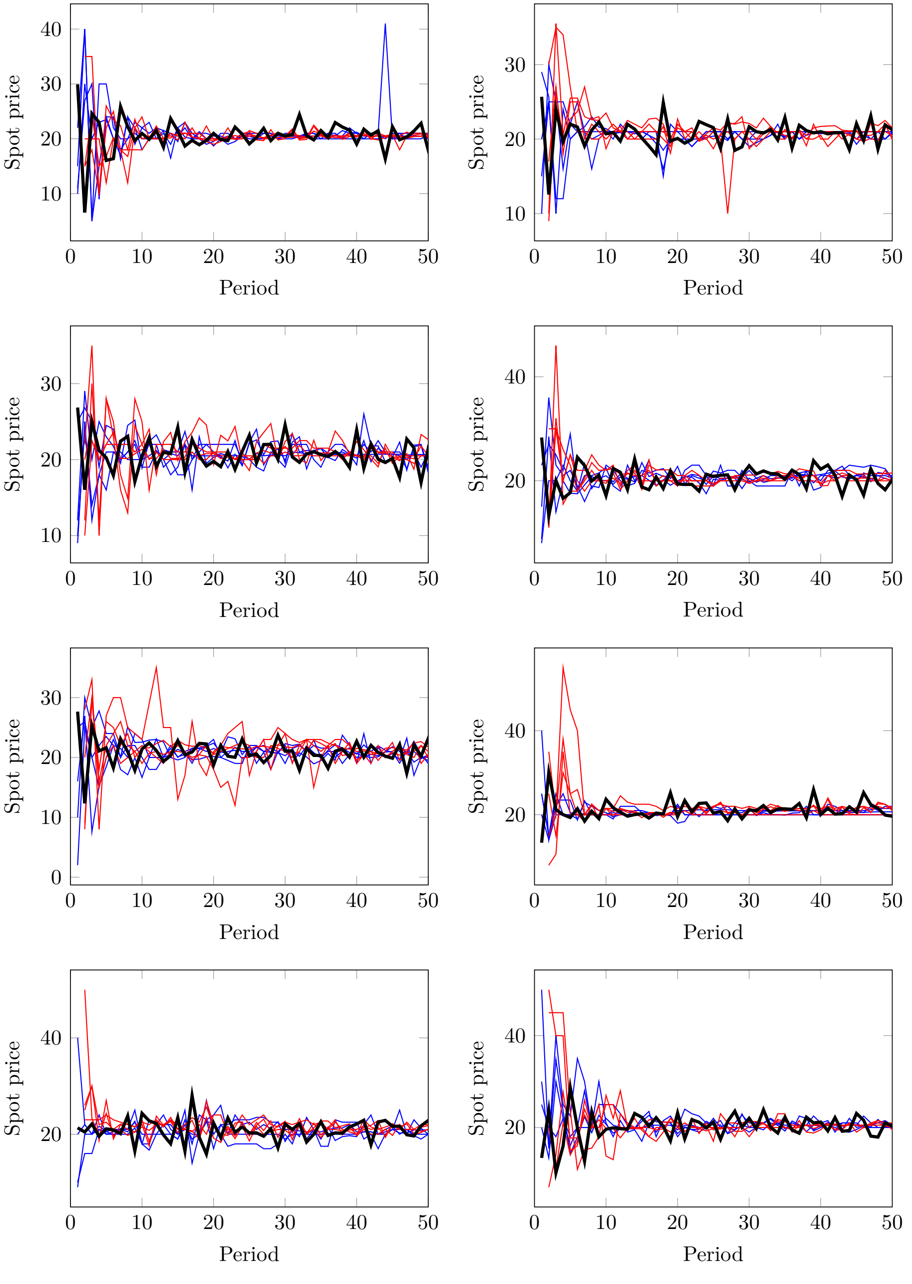


Figure 2.14: Spot prices (thick line) and individual forecasts of these prices (thin lines) in the almost isolated markets treatment ($A = 0.01$). Forecasts by advisors to producers (in blue) were produced one period before, while forecasts by advisors to speculators (in red) were produced two periods before. Unlike the graphs in Fig. 2.3, the scales in these graphs are linear and can be different for different graphs.

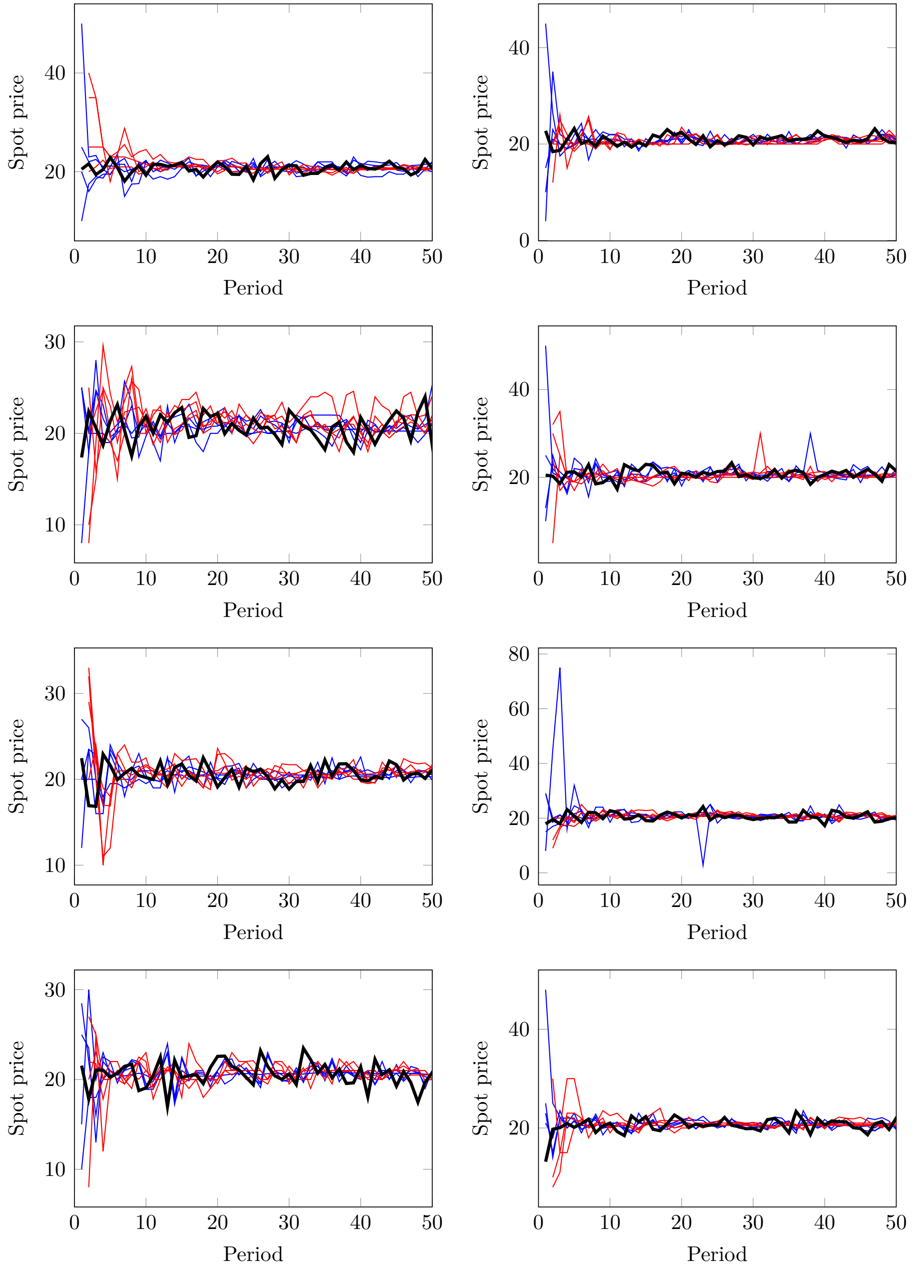


Figure 2.15: Spot prices (thick line) and individual forecasts of these prices (thin lines) in the weakly coupled markets treatment ($A = 0.5$). Forecasts by advisors to producers (in blue) were produced one period before, while forecasts by advisors to speculators (in red) were produced two periods before. Unlike the graphs in Fig. 2.3, the scales in these graphs are linear and can be different for different graphs.

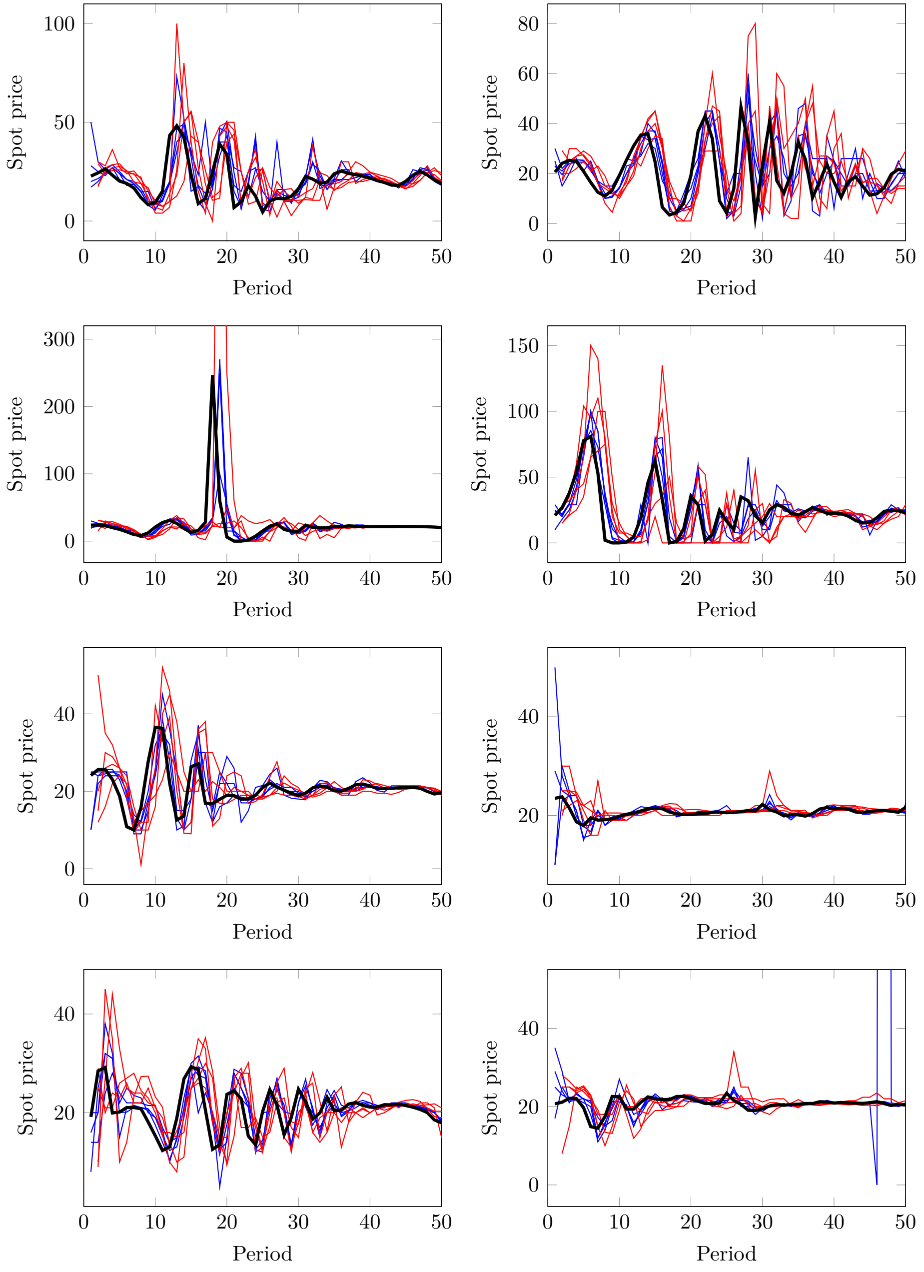


Figure 2.16: Spot prices (thick line) and individual forecasts of these prices (thin lines) in the strongly coupled markets treatment ($A = 10$). Forecasts by advisors to producers (in blue) were produced one period before, while forecasts by advisors to speculators (in red) were produced two periods before. Unlike the graphs in Fig. 2.3, the scales in these graphs are linear and can be different for different graphs.

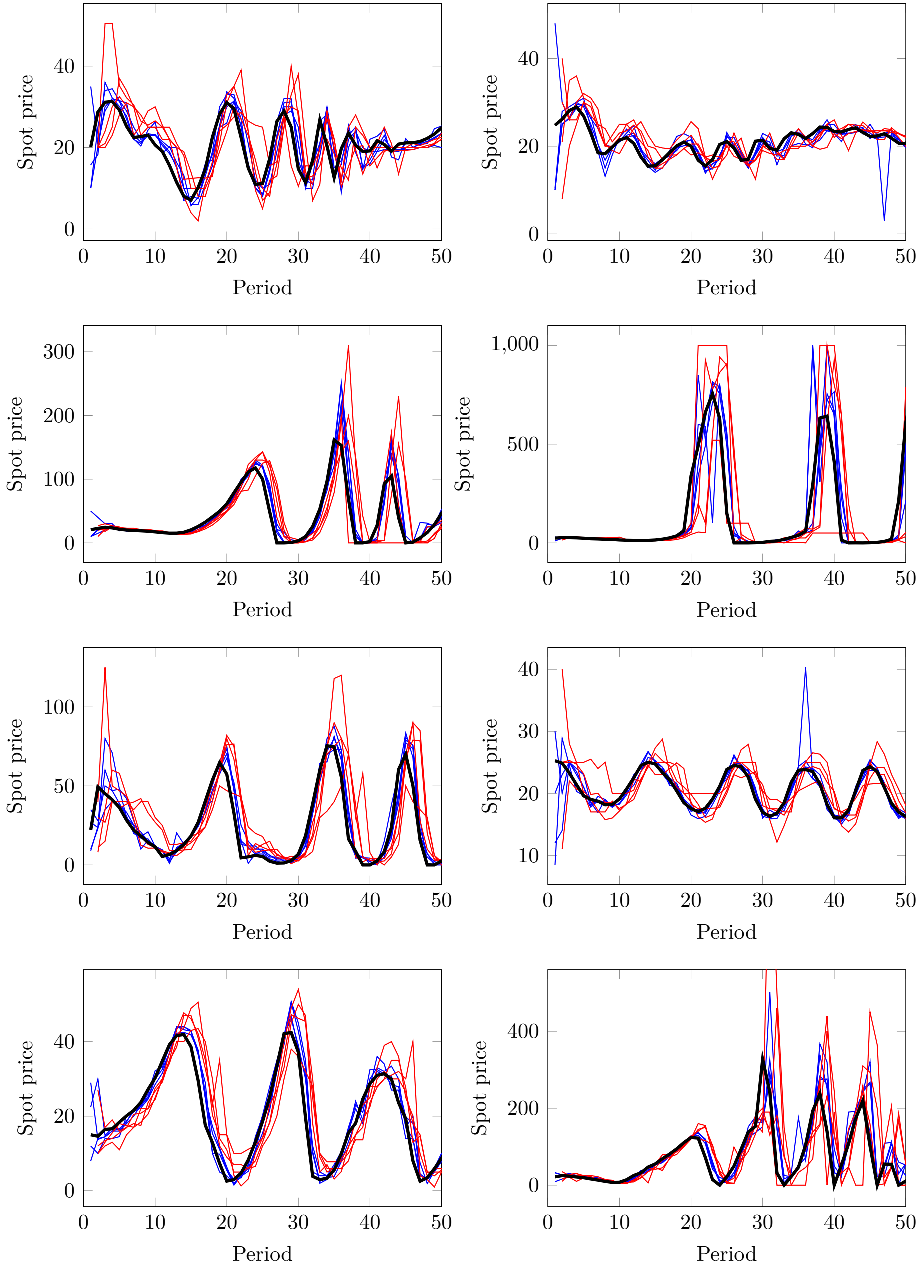


Figure 2.17: Spot prices (thick line) and individual forecasts of these prices (thin lines) in the very strongly coupled markets treatment ($A = 30$). Forecasts by advisors to producers (in blue) were produced one period before, while forecasts by advisors to speculators (in red) were produced two periods before. Unlike the graphs in Fig. 2.3, the scales in these graphs are linear and can be different for different graphs.

Table 2.3: Estimated parameters of the individual forecasting strategies of the participants in markets with $A = 0.01$.

Producers				Speculators			
Participant	α_1	α_2	β	Participant	α_1	α_2	β
P1	0.1	0	0	S1	0.08	0.58	0
P2	0	0	0	S2	0.23	0	−0.07
P3	0.21	0	0	S3	0	0	0.22
P4	0.27	0	0	S4	0.53	0	−0.16
P5	0.27	0	0	S5	0	0	0
P6	0.13	0.38	0	S6	0.34	0.54	0
P7	0.38	0.69	0	S7	0.31	0.3	0
P8	0.66	0.52	−0.16	S8	0.4	0	0
P9	0.61	0	0	S9	0.53	0	−0.22
P10	0.73	0	0	S10	0	−0.38	0
P11	0	0.47	0.15	S11	0.39	0	−0.08
P12	0.09	0	0	S12	0	0	0
P13	0.23	0	0	S13	0.4	0	0
P14	0.22	0.29	0	S14	0	0.7	0.2
P15	0	0.47	0	S15	0	0	0
P16	0	0	−0.23	S16	0.16	0	0
P17	0	0.3	−0.19	S17	−0.39	0.74	0
P18	0.69	0	0	S18	0	0	0
P19	−0.2	0	0	S19	−0.47	0	0
P20	0.58	0.66	0	S20	0	0	0
P21	0	0.32	0	S21	0.61	0.13	0
P22	0.08	0	0	S22	0.06	0	0
P23	0	0.43	0	S23	0.51	0	0
P24	0.18	0.61	−0.09	S24	0	0.47	0.13
P25	0	0	0	S25	0.56	0	0
P26	0.55	0.5	−0.31	S26	0	0	0.12
P27	0.76	0.37	0	S27	0.38	0	0
P28	0	0.48	0	S28	0	0	0
P29	0.12	0.3	−0.08	S29	0	0	0
P30	0	0.5	0.34	S30	0.48	0.5	−0.17
P31	0.68	0	−0.28	S31	0.42	0	0
P32	0	0	0	S32	−0.32	−0.2	0.12

Table 2.4: Estimated parameters of the individual forecasting strategies of the participants in markets with $A = 0.5$.

Producers				Speculators			
Participant	α_1	α_2	β	Participant	α_1	α_2	β
P1	0	0.43	0.27	S1	0.41	0	0
P2	0	0.41	0	S2	0.03	0.84	0
P3	0.43	0	0	S3	0.13	0	0
P4	0.45	0.23	0	S4	0.24	0.76	0
P5	0.44	0.24	0	S5	0.52	0	0
P6	0.82	−0.27	0	S6	0.2	0	0
P7	0.7	0	−0.34	S7	0.19	0	0
P8	0.33	0.51	0	S8	0.79	0	0
P9	0	0.65	0	S9	0.48	0	0
P10	0	0.49	0.23	S10	0.66	0.21	0
P11	0	0.36	0.41	S11	0.41	0	0
P12	0.78	0.43	0	S12	0.68	0	0
P13	0.81	−0.35	0	S13	0	1	0
P14	0.41	0.24	0	S14	0	0	0
P15	0.56	0	0	S15	0	0	0
P16	0	0.39	0.16	S16	0.31	0.42	−0.28
P17	0	0	0	S17	0.58	0.48	0
P18	0.99	0	0	S18	0	0	0
P19	0.24	0	0	S19	0	0	0
P20	0.17	0	0	S20	0.38	0	0
P21	0.84	0	0	S21	0.42	0	0
P22	0.21	0.41	0	S22	0.5	0.44	0
P23	0	0	0	S23	0.31	0	0
P24	0.62	0	0.21	S24	0	0	0
P25	0.59	0	0	S25	0	0	0
P26	0.3	0	0.15	S26	0.19	0.37	0
P27	0.66	−0.19	0	S27	0.32	0.38	0
P28	0.23	0	0	S28	0	0.29	0.37
P29	0.46	0	0	S29	0.52	0.37	0
P30	0.38	0	0.27	S30	0.14	0	0
P31	0.6	0	−0.17	S31	0.08	0.45	0
P32	0	0.54	0.31	S32	0.45	0.32	0

Table 2.5: Estimated parameters of the individual forecasting strategies of the participants in markets with $A = 10$.

Producers				Speculators			
Participant	α_1	α_2	β	Participant	α_1	α_2	β
P1	0.69	0	0.94	S1	0.47	0	0.57
P2	0.6	0	0.29	S2	0.68	0	0
P3	0.54	0	0.55	S3	0	0	0.89
P4	0.67	0	0	S4	1.01	0	0
P5	0.76	0	0	S5	0.51	0	1.1
P6	0.88	−0.34	0.45	S6	0	0.42	0
P7	0.76	0	0.43	S7	0	0	0
P8	0.88	0	0	S8	0	0	0.55
P9	1.19	−0.36	−0.16	S9	1.01	0	0
P10	0.97	0	0.05	S10	0	0.32	0.09
P11	1.01	0	0.09	S11	0	0.48	0
P12	0.36	0.23	0	S12	0	0.54	0
P13	0.69	0	0.69	S13	0.66	0.26	0
P14	0.88	0	1.12	S14	0	0.5	0.58
P15	0.8	0	0.4	S15	0.65	0	1.1
P16	1.3	−0.28	0	S16	0	0	1.01
P17	0.25	0	0.85	S17	0.7	−0.49	1.04
P18	0.76	−0.29	0.3	S18	0	0	1.23
P19	1.91	−0.52	−0.55	S19	0.22	0.31	0
P20	0.45	0	0.88	S20	0	0.83	0.67
P21	0.39	0.46	0.88	S21	0	0.57	0
P22	0.96	0	0.75	S22	0.5	0.26	0
P23	0.85	0.21	1.08	S23	0.63	0.36	0
P24	0.99	0	0	S24	0	0.62	0.39
P25	1.59	−0.4	0	S25	0	0	0.84
P26	1.3	−0.44	0	S26	0	0	0.49
P27	0.43	0	0.41	S27	0.77	0	0.63
P28	1.1	−0.23	0	S28	0.38	0	0.66
P29	0.5	0.32	0.93	S29	0	0.62	0.85
P30	0.96	0	0.29	S30	0	0.39	0
P31	0.8	0	0.96	S31	0	0.7	0
P32	0	0	0	S32	0.54	0	0.29

Table 2.6: Estimated parameters of the individual forecasting strategies of the participants in markets with $A = 30$.

Producers				Speculators			
Participant	α_1	α_2	β	Participant	α_1	α_2	β
P1	0.71	0	0.71	S1	0	0.48	0.78
P2	0.67	0	0.52	S2	0	0.55	0
P3	1.03	0	0.2	S3	0.78	0	0.77
P4	0.56	0.25	0.79	S4	0.43	0	0.61
P5	1.7	−0.73	0	S5	0	0.58	0.69
P6	0.73	0	0.83	S6	0	0.81	0
P7	0.33	0.53	0.67	S7	0	0.82	0
P8	1.01	0	0.53	S8	0.8	0	0.98
P9	1.04	0	0.7	S9	1.04	0	1.69
P10	1.65	−0.6	0.4	S10	1.82	−0.67	0
P11	0.95	0	0.83	S11	1.55	−0.38	1.03
P12	1.89	−0.9	0.37	S12	0	0.56	0.68
P13	1.53	−0.43	0	S13	0	0.78	0
P14	0.92	0	0.35	S14	1.03	0	0.37
P15	0.82	0.13	0.34	S15	1.02	0	0.8
P16	1.02	0	0.48	S16	0.32	0	0
P17	1.48	−0.48	0.32	S17	0.58	0	1.02
P18	1.34	−0.49	0.52	S18	1	0	0.64
P19	0.85	0	0.48	S19	0.59	0	0.2
P20	0.8	0	0.73	S20	0.89	0	0.87
P21	0.8	0	0.91	S21	0.84	0	0.66
P22	0.85	0	0.73	S22	0.6	0.35	1.3
P23	0	0.68	1.04	S23	0.65	0	0.94
P24	0.75	0	1.11	S24	0	0.69	0.55
P25	0.48	0.39	0.81	S25	0	0.87	0.81
P26	0.96	0	0.46	S26	0.96	0	0.53
P27	0.47	0.41	0.77	S27	0	0.83	0.97
P28	0.98	0	0.63	S28	0.91	0	0.61
P29	0.73	0	0.54	S29	0.61	0	0.88
P30	1.77	−0.53	0	S30	1.45	0	0
P31	0.86	0	0.33	S31	0	0.39	0.54
P32	0.71	0	0.34	S32	1.57	0	0

CHAPTER 3

The initial deposit decision and the occurrence of bank runs[1]

In studies of bank runs the initial deposit decision is typically not taken into account. The aim of this chapter is to investigate the effect of the initial deposit decision on subsequent withdrawal decisions with a laboratory experiment. Participants in the choice treatment first choose a bank and then decide whether to withdraw or not, while those in the baseline treatment only make the second decision. Despite a lower interest rate, 'safer' banks consistently attract almost half of the depositors in the choice treatment. Offering the deposit decision strongly reduces withdrawals in the riskier banks, but not in safer ones.

[1] Adapted from: de Jong, J.(2022). The initial deposit decision and the occurrence of bank runs. Working paper.

3.1 Introduction

Bank runs generally lead to poor outcomes for both the depositors and the shareholders of a bank and are thought to have played a pivotal role in the aggravation of the Great Depression in the 1930s (Bernanke, 1983). In contrast to what is usually assumed for firms, even a financially healthy bank may fail if depositors expect other depositors to withdraw their savings. This fundamental vulnerability is highlighted by Diamond and Dybvig (1983) who model the situation as a coordination game with two equilibria: a Pareto-optimal equilibrium in which only those depositors in immediate need of money withdraw and a bank run equilibrium in which all depositors withdraw. The model has inspired a large theoretical literature on bank runs and is more recently also being used in a growing number of experimental studies, looking at, among other things, the effectiveness of deposit insurance and suspension of convertibility (Madies, 2006; Davis and Reilly, 2016), the role of information, uncertainty, and sunspots (Schotter and Yorulmazer, 2009; Garratt and Keister, 2009; Kiss et al., 2012, 2018, 2022b; Shakina and Angerer, 2018; Arifovic and Jiang, 2019; **?**), the influence of a bank's vulnerability to early withdrawals (Arifovic et al., 2013), and the effects of a (possible) bank run on other banks (Chakravarty et al., 2014; Brown et al., 2017; Duffy et al., 2019; Shakina, 2019). Kiss et al. (2022a) provide an overview of experimental studies on bank runs.

The experiments to date have provided valuable insights on depositor behavior under many different circumstances. However, there is one aspect that is often mentioned[2], but has not received much detailed attention: depositors have chosen to entrust their savings to a particular bank and this decision is probably not independent from their later decision to withdraw or not. The goal of this chapter is to study the initial deposit decision and its effect on subsequent withdrawal decisions by means of a bank choice experiment. In this experiment participants are asked to choose between two banks: one that offers a high interest rate on deposits, but is more vulnerable to bank runs due to relatively illiquid investments ('risky bank'), and a less vulnerable bank with lower interest rates ('safe bank'). After all depositors have chosen a bank, they have the opportunity to withdraw their deposits immediately or leave them in the bank to collect interest.

The participants in the experiment are asked to make two types of decisions: deposit decisions and withdrawal decisions. The withdrawal decisions can be affected by the presence of an initial deposit decision through several channels. First of all, there may be a selection effect. Those for whom the gains do not outweigh the (strategic) uncertainty will not deposit in a risky bank in the first place. This could leave the population of depositors

[2]This includes Diamond and Dybvig (1983) themselves and later also Van Damme (1994) and Dufwenberg (2015).

in a risky bank less inclined to participate in a bank run than the general population. Another and perhaps even more important consideration is that the availability of different deposit options can solve the coordination problem. In case of a bank run, the risky bank pays out less than the safe bank would (under any circumstances). Therefore the bank run equilibrium ceases to exist in the risky bank and the only equilibrium left to coordinate on is the Pareto-optimal equilibrium. In line with these arguments the results of the experiment show a striking difference in the number of withdrawals between the treatments with and without bank choice. Those depositors who choose to deposit in the risky bank, rarely withdraw their deposits in the next period.

The deposit decisions themselves are also of interest. Theoretically, depositing in the risky bank is safe, because all depositors of the risky bank should coordinate on the Pareto-optimal equilibrium. This is also confirmed by the results of the experiment, which show that there are very few withdrawals from risky banks when a safer alternative is also available. However, the participants in the bank choice game do not show a clear preference for the risky bank. Depending on what the characteristics of the two options are, they choose the riskier high-interest bank only between 45% and 71% of the time.

This study builds on and is connected to a wider literature of experimental bank run studies. Only a few of these also feature an environment with multiple banks. Chakravarty et al. (2014) and Brown et al. (2017) study how observing withdrawals in one bank, affects withdrawals in another bank for cases in which bank fundamentals are linked and and cases in which they are not linked. Both find that when the fundamentals are linked, depositors are more likely to withdraw when they observe many withdrawals in the other bank, but only in the experiment of Chakravarty et al. (2014) does this also happen when fundamentals are not linked. Another paper, by Duffy et al. (2019), looks at the effect of the interbank network structure on the likelihood of contagion. They find that when liquidation costs are high, a complete network structure, in which all the banks are linked, is more robust to bank runs spreading from one bank to another than an incomplete network structure. For low liquidation costs no large effect of the network structure is observed. Finally, Shakina (2019) considers a situation with two banks in which depositors of one bank, next to the standard options of withdrawing and leaving the deposit in the bank, also have the option to withdraw and deposit in the other bank. The availability of this option leads to more bank runs in the first bank and fewer bank runs in the second bank, which may receive extra depositors. This study probably comes closest to the one in this chapter, but it focusses on the effect of a redeposit option instead of the initial deposit decision. As a consequence the experiment featured a very different design, with an asymmetry of the banks not in economic fundamentals, but in the fact that one bank can only lose depositors, while the other can also gain them.

Since bank run games are essentially coordination games, the experimental literature on coordination games is also relevant. In particular the paper by Cooper et al. (1992), who study a coordination game in which one of the two players has an outside option with a payoff in between the Pareto-dominated and the Pareto-dominant equilibrium payoffs. Unlike the bank choice game, these games have two Nash equilibria: one in which the outside option is chosen and one in which the players successfully coordinate on the Pareto-optimal equilibrium. The first of these can be eliminated using a forward induction refinement. Cooper et al. (1992) find that, after learning, row players choose to play the coordination game 60% of the time, 4 out of 5 times followed by successful coordination on the Pareto-dominant equilibrium. In contrast, without an outside option or with an irrelevant outside option, players do not manage to coordinate on this equilibrium. Note that these results are obtained after learning (only the second half of the played periods are analyzed in the paper). This contrasts with this chapter, in which the focus is on initial play (using a series of single-shot games).

3.2 The bank choice game

The basis for the bank choice game is the model by Diamond and Dybvig (1983). There are 3 periods $t = 0, 1, 2$. In period 0 each player is entitled to an endowment c, which can only be received in a bank account. Here the players can choose between two banks. After choosing they are free to withdraw their money in period 1, but if they wait until period 2 the bank promises to pay an interest rate $R_i > 1$ provided that it has the funds to pay out all depositors. These interest rates are typically different for the two banks. If in any period the available funds are insufficient to cover the banks immediate obligations, the bank is liquidated and the proceeds are divided equally among the depositors who made a withdrawal request.

Each bank B_i uses its depositors' money to finance a project that returns R_i in period 2 for each unit invested in period 0. If necessary the bank may liquidate (a part of) its stake in the project, but in that case it will only get $L_i < R_i$ per liquidated unit. I will assume that projects with lower liquidation values, have higher returns[3]. Therefore larger values of R always combine with smaller values L:

$$R_i > R_j \iff L_i < L_j. \tag{3.1}$$

[3]See Amihud et al. (2006) for theoretical underpinnings of this assumption and a review of the empirical evidence.

The players in this game do not have an explicit need to withdraw money in period 1. In the terminology of Diamond and Dybvig this means that they are all ‘patient’. However, they may still be better off withdrawing if other depositors in the bank withdraw. In period 1 they have to take a decision: they can either withdraw their complete deposit or leave everything in the bank (they cannot withdraw a part). If k_i out of N_i depositors of bank B_i withdraw money in period 1, the bank will continue to sell its stake in its project until it either raises enough to pay all its withdrawing depositors an amount c, or its stake is completely liquidated. If the latter happens, the funds raised through liquidation are equally divided among the withdrawing depositors. This means that the payoff to those who withdraw is

$$\pi_{withdraw} = \min\left(\frac{L_i N_i c}{k_i}, c\right). \tag{3.2}$$

If the bank had to completely liquidate its stake, those who decided to wait until period 2 receive nothing. If the liquidation was only partial, the part of the initial investment that remains is multiplied by R_i and divided over the remaining depositors. They therefore receive

$$\pi_{wait} = \max\left(\frac{\left(N_i - \frac{k_i}{L_i}\right) R_i c}{N_i - k_i}, 0\right). \tag{3.3}$$

The expressions $\pi_{withdraw}$ and π_{wait} are (non-strictly) decreasing functions of k_i that cross in a single point. A consequence of this is that the bank choice game can not have pure-strategy Nash equilibria in which different depositors in the same bank make different decisions. This can be understood by considering a situation in which some depositors withdraw and some others wait. In this case there are three possibilities: $\pi_{wait} < \pi_{withdraw}$, $\pi_{wait} > \pi_{withdraw}$, or $\pi_{wait} = \pi_{withdraw}$. In the first scenario, a depositor who chose to wait is not making a payoff-maximizing choice, while in the second and third scenarios a withdrawing depositor could have earned more by changing his or her strategy to waiting.

When all depositors in a bank either all withdraw or all wait, there are four possible payoffs for players of the bank choice game. Ranked from low to high: the bank run payoff in the risky bank, the bank run payoff in the safe bank, the maximum payoff in the safe bank, and the maximum payoff in the risky bank. When the banks are different, all these payoffs are necessarily different as well. This means that in a pure strategy Nash equilibrium all depositors deposit in a single bank. This cannot be the safe bank, because in that case becoming the single depositor in the risky bank and choosing to wait would yield a higher payoff. A bank run in the risky bank is also not a Nash equilibrium because then depositors could deviate to the safe bank to earn more. Therefore, when the banks are different the bank choice game has only one Nash equilibrium in pure strategies: all players deposit in the most risky bank and leave the deposit in the bank.

The bank choice game extends the Diamond-Dybvig model with an initial deposit decision, but there are also a few other important differences. The most important one is that there are no ‘impatient’ depositors. This is a crucial element of the risk-sharing problem that banks can help to solve. However, it does not play a role in the coordination problem that is created by the demand deposit solution and therefore it is not included in the bank choice game. The absence of impatience is also the reason that it is not made possible for the players to invest directly in the project. This would allow players to trivially avoid the coordination problem that is the focus of this study. A second difference is that in the bank choice game the potential losses for depositors that choose to wait is generated by the losses from liquidation and not by the interest paid to early withdrawers. This makes the game also suitable for studying situations with high strategic uncertainty in which only a small number of withdrawals leads to losses for depositors who decided to wait. Without liquidation losses this would only be possible with a bank that offers a very high interest rate over the first period and very little over the second and this is unnatural. Finally, in the bank choice game players do not have the possibility to divide their endowments between different options or withdraw a fraction of it in the first period. This simplifies the game by reducing the number of choices of players and therefore also the number of choices by others that players need to consider.

3.3 Experimental design

3.3.1 Task

In the experiment participants play the bank choice game. In period 0 they are presented with two banks, Square Bank and Round Bank, and have to choose the one in which they will receive their endowments. Figure 3.1 shows an example of the screen on which the participants have to make their choices. The banks can differ in their values of R and L or be the same. In total there are five types of banks, which differ primarily in the critical fraction of depositors that can withdraw before withdrawing becomes a dominant choice for the others. For example, in a type 1 bank, the values of R and L are chosen such that if 1 out of 6 depositors withdraws, any other participant would maximize his or her payoff by withdrawing as well. In a type 2 bank 1 depositor may withdraw without this tipping point being reached, but not 2. In general the type number corresponds to the number of depositors that need to withdraw in order to make withdrawing dominant for the others. The values of R and L for each bank type are shown in Table 3.1, together with the

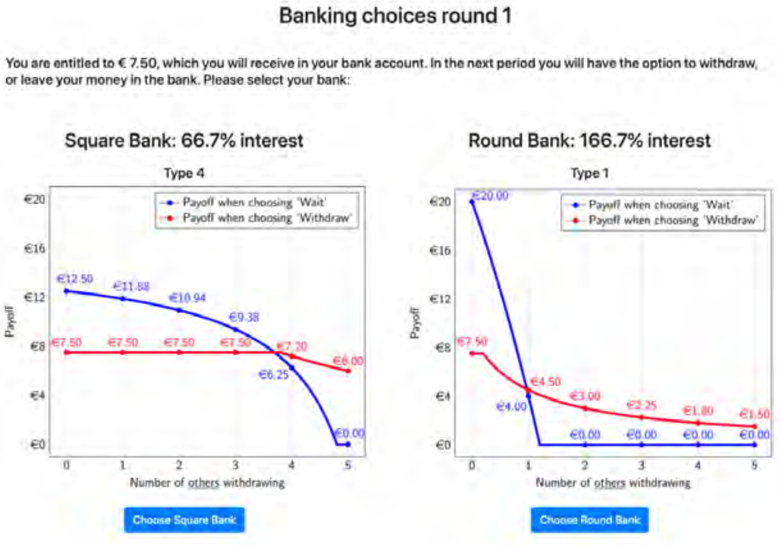


Figure 3.1: Example of a screen the participants see in period 0, when they have to make a choice between two banks.

earnings of the participant given his or her choice and the choices of the other depositors. The participants receive this information in the form of a graph. The graphs for each bank type are provided in Appendix 3.A. After all participants have made their choices, the experiment moves to period 1. Here the participants see again the payoff graph of the bank they chose and are asked if they want to withdraw or leave their deposits in ("wait").

In total, the experiment consists of 15 rounds. In each round the participants have to choose from a different combination of bank types, including some combinations in which the two banks are of the same type[4]. Determination of outcomes and payoffs only takes place at the very end of the experiment. This makes it possible to randomize the order in which the bank combinations appear on an individual level. It also means that the participants are not informed about the outcome or their earnings at the end of a round, which minimizes order effects. The most risky bank of the pair sometimes appears on the right side of the screen and sometimes on the left side. Also this is randomized on the level of individual participants.

At the end of the experiment there are two pools of participants for each combination

[4]In principle we would not expect any effect of having an initial deposit decision or not when all options are identical, except when the act of choosing itself can make a difference.

Table 3.1: Payoffs (in euros) for each of the five types of banks, depending on how many of the other depositors withdraw and whether the participant decides to wait or withdraw him or herself in period 1.

# of others withdrawing	Type 1 $R = 2.66$ $L = 0.2$		Type 2 $R = 2.33$ $L = 0.4$		Type 3 $R = 2$ $L = 0.6$		Type 4 $R = 1.66$ $L = 0.8$		Type 5 $R = 1.33$ $L = 0.93$	
	Wait	Run	Wait	Run	Wait	Run	Wait	Run	Wait	Run
0	20.00	7.50	17.5	7.50	15.00	7.50	12.50	7.50	10.00	7.50
1	4.00	4.50	12.25	7.50	13.00	7.50	11.88	7.50	9.86	7.50
2	0.00	3.00	4.38	6.00	10.00	7.50	10.94	7.50	9.64	7.50
3	0.00	2.25	0.00	4.50	5.00	6.75	9.38	7.50	9.29	7.50
4	0.00	1.80	0.00	3.60	0.00	5.40	6.25	7.20	8.57	7.50
5	0.00	1.50	0.00	3.00	0.00	4.50	0.00	6.00	6.43	7.00

of bank types: those who deposited in the square bank and those who deposited in the round bank. These pools are then split up in groups of 6 and possibly for each pool one left-over group with fewer than 6 participants. To make the situation in the left-over groups as similar as possible to the situation in the complete groups, the empty spots are filled with computer players that copy the withdrawal decisions of randomly selected participants in other banks of the same type. These are individuals who made the same deposit choice when presented with the same two bank types, but they either are in one of the complete banks in the same session or were participants in a previous session. The only situation in which an incomplete bank is formed is when fewer than 6 people in any of the sessions up to that point made a particular deposit choice. In that case the payoffs still follow from Eqs. 4.1 and 4.2, but with N_i smaller than 6. Participants learn how many depositors there were in their bank in each round, how many withdrew and how much they earned, but not if some of their chosen banks were completed with computer players or not.

3.3.2 Treatments and procedures

To isolate the effect of the initial deposit decision, the experiment consists of two treatments: choice and control. In the choice treatment participants play the full bank choice game, as described in the text above. The control treatment is identical, except that the participants are not given the choice to deposit in either the Square bank or the Round bank. Instead, their endowments are deposited in the banks chosen by choice treatment participants in an earlier session. Each control treatment participant is matched with one choice treatment participant and is presented exactly the same banks as their match chose (in the same order). The control treatment participants are not informed of the existence of the choice treatment and the matching procedure. They simply start in period 1 with their endowments in either a Round bank or a Square bank of a particular type. The screen presents the payoff graph for this particular type and the participants can choose to withdraw or wait.

At the start of the experiment participants receive instructions both on paper and on screen and the experiment only starts when all participants in a session answered a set of control questions correctly. When all rounds of the experiment have finished the participants are asked to complete two risk elicitation tasks, a 2/3-of-average number guessing game, and a questionnaire. The first risk elicitation task is the low payoff multiple price list (MPL) task used by Holt and Laury (2002). The second is the "bomb" risk elicitation task (BRET) by Crosetto and Filippin (2013). The number guessing game is the one by Nagel (1995) and its aim is to access the Depth of Reasoning. The MPL task appeared first, followed by the number guessing game and the BRET. Only after all tasks are completed, the participants are informed about their earnings in each round and in each of the additional tasks. The computer then randomly selects one round of the main experiment for payment and the final screen shows the total earnings.

The experiment took place in April and May 2019 at the CREED laboratory of the University of Amsterdam. It was programmed in oTree (Chen et al., 2016) and incorporated existing apps for the additional tasks (Holzmeister and Pfurtscheller, 2016; Holzmeister, 2017). In total there were 210 participants, 107 in the choice treatment and 103 in the control treatment[5]. All were students, the majority (62%) in an economics or business program. 51% of the participants were female. Sessions lasted approximately 1.25 hours and on average the participants earned €18.37.

3.4 Results and discussion

3.4.1 Bank choice and withdrawal decisions

A first question to ask is what participants choose in the different banks in the control treatment. In the control treatment the participants receive their deposits in the bank type chosen by their matches in the choice treatment. They therefore play the classic bank run game, with two Nash equilibria. Based on experiments by Arifovic et al. (2013) one

[5]The last 4 participants in the choice treatment never got matched to control treatment participants and are therefore excluded from the analysis in the next section

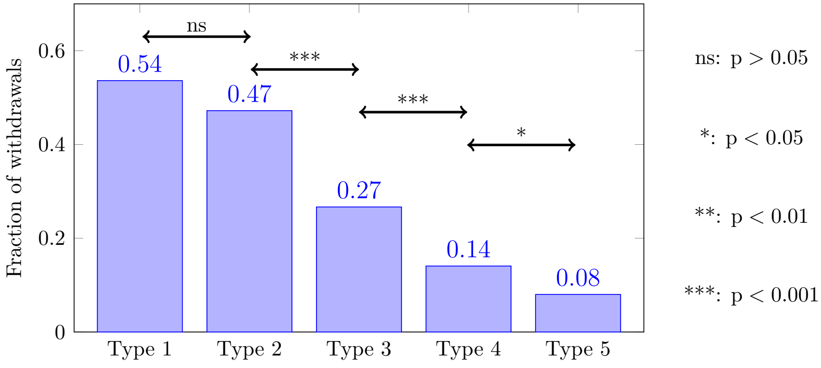


Figure 3.2: Fraction of withdrawals in period 1 in the control treatment, where participants cannot choose a bank. The stars above the arrows indicate which differences are significant in a Mann-Whitney U test.

would expect coordination on the run equilibrium in very risky banks and coordination on the Pareto-optimal equilibrium in the safest banks.

Figure 3.2 shows the fraction of withdrawals in the first period for each type of bank[6]. As expected, withdrawals in banks of type 4 and 5 are quite low at 14% and 8%, respectively. This increases to 27% for type 3 banks, 47% for type 2, and 54% for type 1 banks. All increases are significant ($p < 0.05$) in a Mann-Whitney U test, except for the one between type 2 and type 1 banks. Surprisingly, the participants in this experiment never fully coordinate on the run equilibrium, not even in the riskiest banks. This contrasts with the results of Arifovic et al. (2013), who also study the effect of different levels of strategic uncertainty on withdrawing decisions, but use interest to early withdrawers instead of liquidation losses to generate this strategic uncertainty. A possible explanation is that for very risky banks the payoffs in the run equilibrium are reduced to a small fraction of the endowment, due to the banks having to liquidate at a loss. At the same time these banks offer a very high return if everyone coordinates on the good equilibrium. It seems that many participants find it worth taking this gamble.

In contrast to the situation in the control treatment, the bank choice game played by the participants in the choice treatment has only one Nash equilibrium. To coordinate on it, participants should first choose to deposit in the risky bank and consequently leave their deposits in. Fig. 3.3 shows that the first step is often not taken. When presented the option to choose between two banks of a different type approximately half of the

[6]In the control treatment participants see most bank types multiple times. In this analysis all withdrawal decisions of all participants are pooled for each bank type.

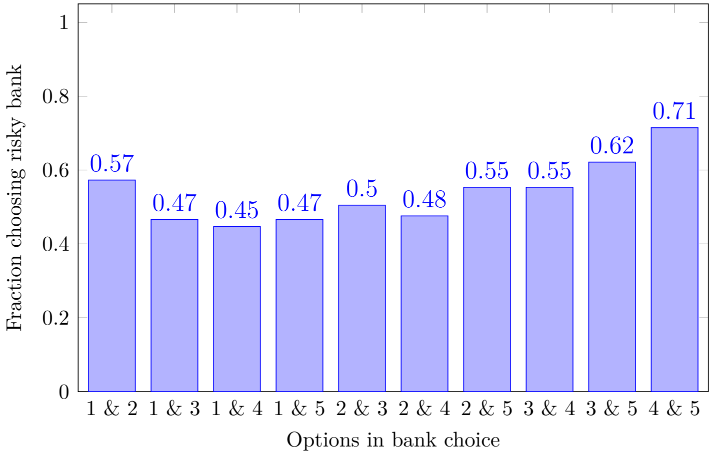


Figure 3.3: Fraction of participants choosing the riskier bank when offered a choice between two banks of different types.

participants choose the more risky bank with the higher interest rate and the other half chooses the safer bank. This is remarkably stable for different pairs of bank types. Only when two very safe banks are involved, types 3 and 5 or types 4 and 5, does the fraction choosing the risky bank rise above 60%. This is somewhat similar to the finding by Cooper et al. (1992) that almost 40% of participants choose a fixed payment over playing a coordination game with one higher-payoff and one lower-payoff equilibrium when given the choice.

The fact that in all cases both banks attract a significant fraction of the depositors opens the door for selection effects to play a role. One could hypothesize that now either the resolution of the coordination problem or a population of more risk tolerant depositors or both could drive down withdrawals in the riskier bank. Figure 3.4 shows the fraction of depositors that withdraw in period 1 from the riskier bank after choosing it (choice treatment) or when not having a choice (control treatment). The treatment effect is very strong. For banks of type 1 and 2 the fraction of participants who withdraw in the first period is reduced by a factor 3 or more in the choice treatment compared to the control treatment. On average fewer than 1 out of 6 depositors withdraw after choosing a riskier bank. For banks 3 and 4 the difference is less pronounced, because they already face fewer withdrawals in the control treatment. However, also there the effect is in most cases significant at the 5% level (sign test, two-sided), except when the choice was between a type 4 and a type 5 bank.

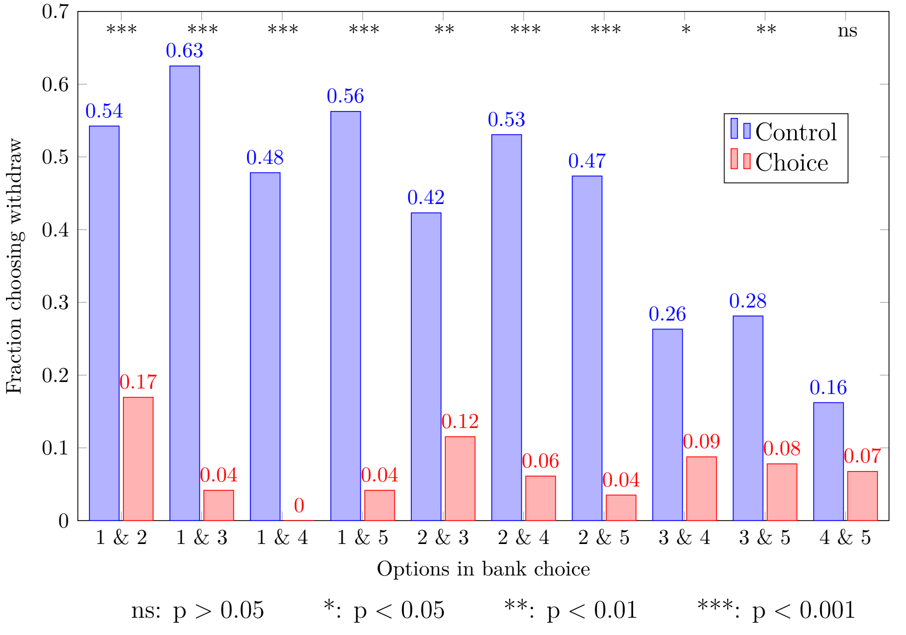


Figure 3.4: Fraction of participants withdrawing from the riskier bank (of the two shown on the horizontal axis) in the control treatment (blue) and in the choice treatment (red). The stars above the bars indicate which differences are significant in a sign test.

An interesting question is what happens after participants decide to deposit in the safer alternative. If selection effects play a role and the safe bank attracts relatively more risk averse depositors, it is conceivable that here *more* people will withdraw than in the control treatment. Fig. 3.5 shows that in general this is not the case. For none of the choice pairs the effect is significant at the 5% level (sign test, two-sided) and also when all the data is pooled, there is no significant effect ($p = 0.24$).

Figures 3.4 and 3.5 only show results from choices between banks that are not of the same type. The reason is that selection effects and a solution to the coordination problem, the proposed mechanisms through which the initial deposit decision could affect withdrawal decisions, do not work if the two options are identical. The expectation is therefore that there will be no treatment effect for identical options. Surprisingly, the results for identical options in Figure 3.6 show an effect for banks of type 1 and 2 that is (close to) significant in a sign test ($p = 0.07$ and $p = 0.02$). Participants who chose these banks are about a third less likely to withdraw compared to participants who could not choose. A possible explanation is that the act of choosing itself can already have an

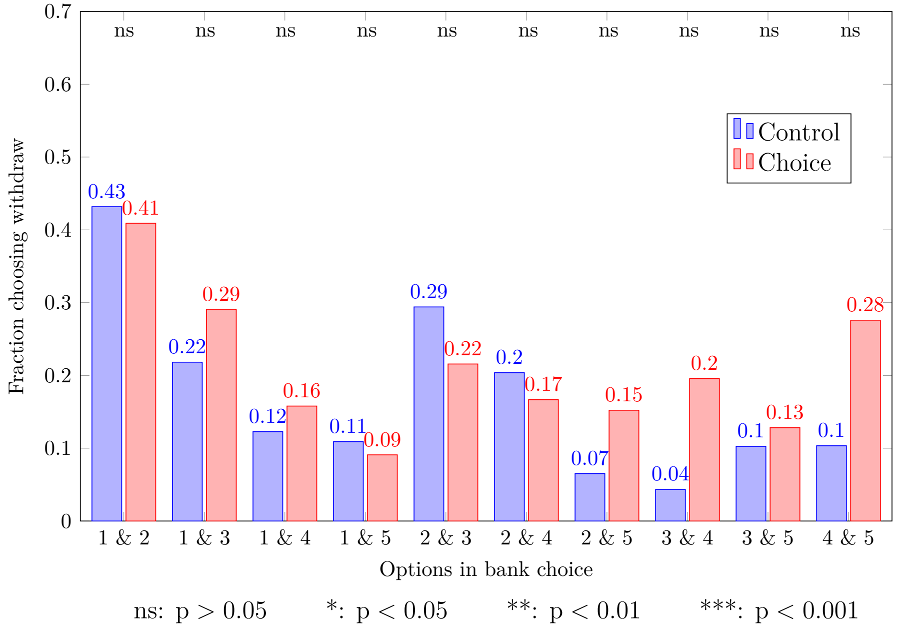


Figure 3.5: Fraction of participants withdrawing from the safer bank (of the two shown on the horizontal axis) in the control treatment (blue) and in the choice treatment (red). The stars above the bars indicate which differences are significant in a sign test.

effect.

3.4.2 Empirical best responses

With the participants in this experiment not coordinating on a particular equilibrium, the question arises which responses are empirically best (in the sense that they maximize the expected payoff). To establish an answer, I will use the choices by the participants in the experiment to estimate the probability that a depositor that is randomly drawn from the population, withdraws ($p_{withdraw}$). In the control treatment the participants encountered most banks multiple times and they did not always make the same decision[7]. Therefore, in this case $p_{withdraw}$ is the average of the probabilities of the individual participants withdrawing from a bank of a certain type (calculated as the number of times that a participant withdrew from a bank of a certain type divided by the number of times the participant acted as a depositor in a bank of that type). Table 3.2 shows the $p_{withdraw}$ that

[7]One possible reason is that the participant is indifferent between withdrawing and waiting for that particular bank type

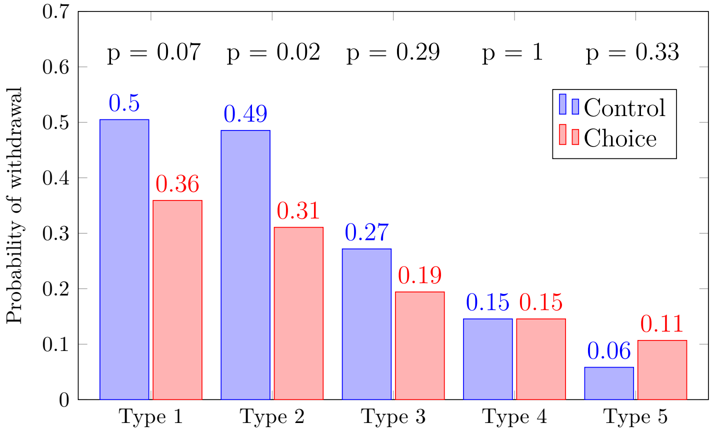


Figure 3.6: Fraction of participants withdrawing for each bank type when they have a choice between two banks of that same type (choice treatment, blue) and when they have not been given a choice (control treatment, blue). The stars above the bars indicate which differences are significant in a sign test.

are estimated in this way in the 2nd column. As expected, the probability of a random individual withdrawing is highest for a bank of type 1 and lowest for a bank of type 5.

Given a withdrawal probability $p_{withdraw}$, it is possible to calculate expected payoffs for withdrawing and waiting in a bank with five other depositors:

$$\mathbb{E}\left(\pi_{withdraw}\right) = \sum_{k=0}^{5} \binom{5}{k} p_{withdraw}^{k} \left(1 - p_{withdraw}\right)^{5-k} \min\left(\frac{45 L_i}{k+1}, 7.5\right), \tag{3.4}$$

$$\mathbb{E}\left(\pi_{wait}\right) = \sum_{k=0}^{5} \binom{5}{k} p_{withdraw}^{k} \left(1 - p_{withdraw}\right)^{5-k} \max\left(\frac{7.5\left(6 - \frac{k}{L_i}\right) R_i}{6-k}, 0\right). \tag{3.5}$$

Here R_i and L_i are the return and liquidation values of the chosen bank's investments. The 4th and 5th columns of Table 3.2 list the expected payoffs for waiting and withdrawing for each bank type. The decisions that yield the highest expected payoffs are indicated with an asterisk. The results show that someone who is interested in maximizing expected earnings in a bank run game should withdraw from banks of types 1 and 2 and wait in banks of types 3, 4, and 5.

In the choice treatment participants encounter a particular combination of bank types only once and in each case the participant pool splits in two populations: one that chooses the safe bank and one that chooses the risky bank. In each population a particular fraction

Table 3.2: Estimated withdrawal probabilities for each bank type and expected payoffs for each decision that a participant can take (wait or withdraw) in the bank run game and the bank choice game with two identical banks. An asterisk (*) indicates which decision yields the highest expected payoff.

	Withdrawal probability		Expected payoffs			
			Single bank		Two identical banks	
Bank type	Single bank	Two identical banks	wait	withdraw	wait	withdraw
1	0.55	0.36	0.80	2.67*	3.26	3.69*
2	0.45	0.31	4.83	5.63*	8.21*	6.42
3	0.27	0.21	11.48*	7.38	12.32*	7.44
4	0.14	0.14	11.98*	7.50	11.99*	7.50
5	0.08	0.10	9.94*	7.50	9.92*	7.50

of participants decides to withdraw and this fraction is a good estimate of the withdrawal probability of a random depositor in that bank. Table 3.3 lists these estimates in the 3rd and 4th columns. The table also provides expected payoffs, calculated with Eqs. 3.4 and 3.5, for each of the four combinations of choices that a player can make: wait in risky bank (5th column), withdraw from risky bank (6th column), wait in safe bank (7th column), or withdraw from safe bank (8th column). An asterisk again marks the choice combination that yields the highest payoff. In contrast with the bank run game, withdrawing is never rewarded with the highest expected payoff in a bank choice game with different banks. For all combinations of bank types the expected payoffs are maximized by waiting in the risky bank.

Although this result does not extend completely to bank choice games in which the deposit options are identical, the addition of a deposit decision still causes differences with important consequences. The 3rd column of Table 3.2 shows the withdrawal probabilities after a randomly selected individual has to choose between two identical banks and the 6th and 7th columns show the expected payoffs for waiting and withdrawing in this case. Comparing to the bank run game, in which a payoff-maximizing player should withdraw in banks of types 1 and 2, this is now only optimal for banks of type 1. Moreover, the difference in expected payoffs for type 1 banks is much smaller than in the equivalent bank run game.

Table 3.3: Estimated withdrawal probabilities and expected payoffs for each pair of banks in the bank choice game and for each combination of choices that a participant can make (bank choice decision and withdrawal decision). An asterisk (*) indicates which decision combination yields the highest expected payoff.

Bank type		Withdrawal probability		Expected payoffs			
Risky bank	Safe bank	Risky bank	Safe bank	Risky bank wait	Risky bank withdraw	Safe bank wait	Safe bank withdraw
1	2	0.17	0.40	9.51*	5.35	6.15	5.97
1	3	0.04	0.31	16.87*	6.90	10.86	7.33
1	4	0.02	0.17	18.35*	7.19	11.88	7.50
1	5	0.04	0.09	16.93*	6.91	9.93	7.50
2	3	0.11	0.24	14.28*	7.33	11.92	7.41
2	4	0.06	0.17	15.81*	7.45	11.85	7.50
2	5	0.03	0.17	16.58*	7.48	9.86	7.50
3	4	0.08	0.18	14.04*	7.50	11.81	7.50
3	5	0.08	0.12	14.18*	7.50	9.90	7.50
4	5	0.07	0.26	12.28*	7.50	9.75	7.50

3.4.3 Additional tasks and questionnaire

To investigate the role of a possible selection effect the participants completed three additional tasks: the multiple price list (MPL) task (Holt and Laury, 2002), the bomb risk elicitation task (BRET) (Crosetto and Filippin, 2013) and a number guessing game in which the person closest to two-thirds of the average wins a price (Nagel, 1995). The expectation was that participants who choose the more risky bank are more risk tolerant, have a higher Depth of Reasoning, or both. However, there were no significant differences in MPL and number guessing scores and very few in the BRET scores (see Appendix 3.C for the results). This could mean that there is either no selection effect or that the populations differ in a dimension not captured by one of the additional tasks[8].

The answers to one of the questions in the final questionnaire provides additional insight on the relation between bank runs and the initial deposit decision. This question is: "Did you ever switch banks in real life, and if so, what was the reason?". 201 participants answered this question and 70% reported to have never switched banks. Although the participant population in this experiment is quite young, 22 years on average, this number

[8]Other experimental bank run studies also don't find differences in risk aversion scores between people that choose to withdraw and people that choose to wait (Kiss et al., 2014, 2016, 2018; Shakina, 2019), but there is some indication that loss aversion plays a role in these type of coordination games (Trautmann and Vlahu, 2013; Kiss et al., 2018).

does not stand out: the low mobility of consumers in the retail banking sector is well documented and often considered undesirable (van der Cruijsen and Diepstraten, 2017). There is therefore an active discussion of policies to reduce the (perceived) barriers to switch banks, which, if successful, would effectively increase the number of people who consciously make a deposit decision. This chapter shows that such policies do not only stimulate bank choice decisions, but may also affect subsequent withdrawal decisions.

3.5 Conclusion

Theoretically, whether a bank run occurs or not can depend critically on the initial deposit decision of the depositors. The bank choice experiment in this chapter is meant to assess to what extent the presence of an initial deposit decision affects withdrawals. It provides some participants with two options to receive an endowment in, a risky bank with a high interest rate and a safe bank with a low interest rate. After they have chosen a bank, these participants can either withdraw or leave the money in the bank and receive interest. Other participants cannot choose a bank. They receive their endowments in a certain type of bank and can only decide to withdraw their money or not.

Contrary to the theoretical prediction, about half of the participants who can choose a bank in the experiment chooses the safer option for their deposits. Only when both banks are very safe the fraction of participants choosing the safest option goes down a bit. Participants who choose the risky option rarely withdraw afterwards. Compared to the situation in which participants are not offered a choice, the number of withdrawals dropped by 67% or more for the most risky bank types. At the same time, the number of withdrawals from the safer bank is not significantly different from the number of withdrawals in the case that participants could not choose.

The results show that the initial deposit decision has a strong impact on the withdrawal behavior of depositors in more risky banks. The very low fraction of withdrawals from those banks in the experiment contrasts with the intuition and earlier results that institutions with low liquidity levels are automatically more at risk of facing a bank run. On the other hand, if we generalize the result of this chapter too much, we should not observe any panic-based bank runs in the modern setting with an ecosystem of many banks and this, in turn, does not correspond to what we see. The challenge is now to understand what drives bank runs in a world with initial deposit decisions and how this relates to the liquidity level of institutions. The bank choice game can be extended such that it is ideally suited for this purpose.

Appendix 3.A Payoff plots for each type of bank

Figure 3.7 shows five graphs, one for each type of bank, of the payoffs of a participant as a function of the number of other depositors that withdraw and the participant's own choice.

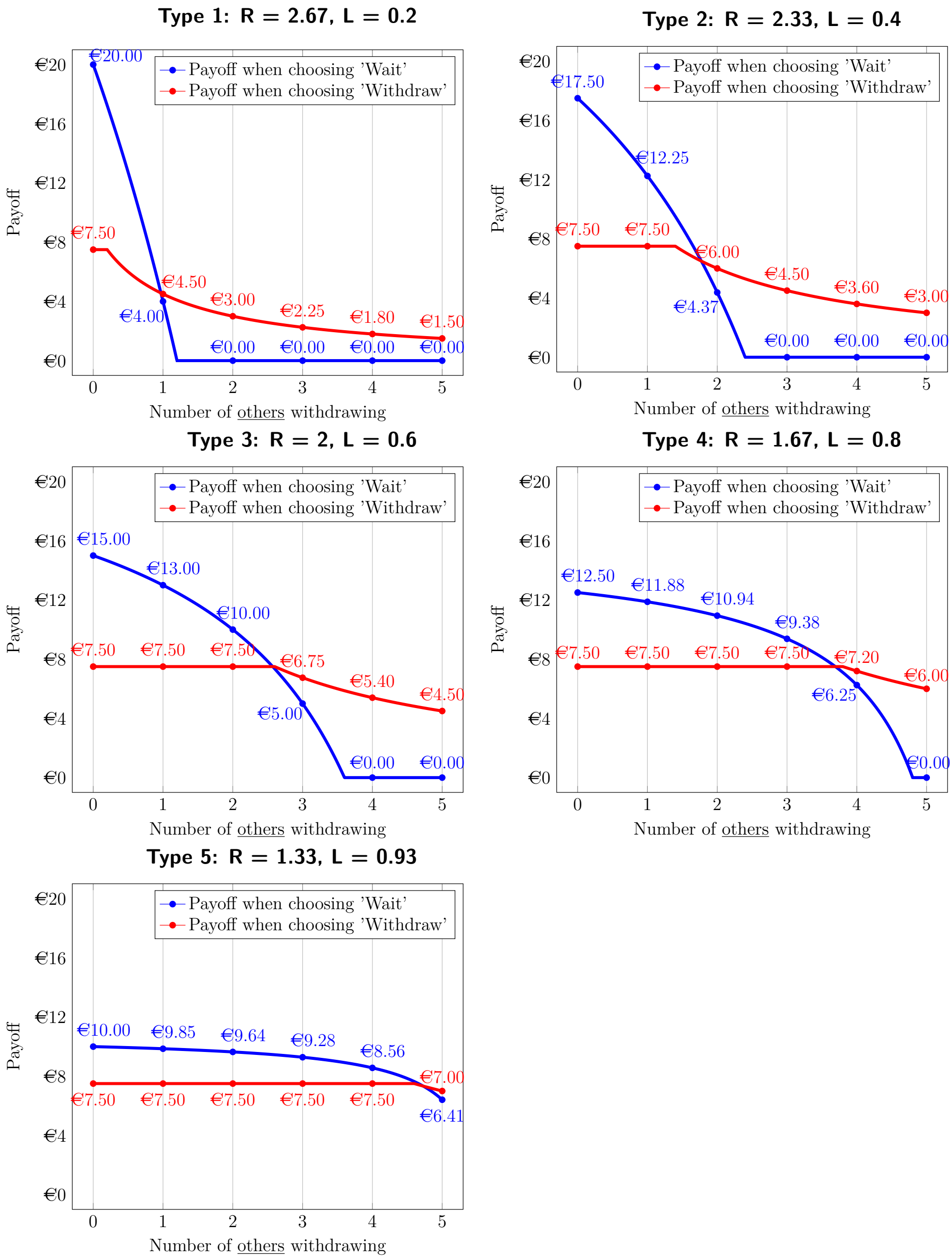


Figure 3.7: Payoff graphs of the five types of banks in this experiment. These were the graphs used to explain the payoffs to the participants and the relevant graph(s) were shown on every page on which the participants needed to take a decision.

Appendix 3.B Instructions to participants

3.B.1 Choice treatment

General information

This part of the experiment consists of 15 rounds. In each round you have to make two choices. First you select the bank in which you want to receive your endowment of €7.50. You can choose between two options: Round Bank and Square Bank. These banks may be of a different type or not.

Next you are given the choice to either withdraw this endowment immediately, or wait and collect the interest that the bank offers. Note, however, that the interest rates that the banks in this experiment advertise with, are only correct if none of the depositors withdraws early. If there are early withdrawers, the amount of interest received will be lower. If too many depositors withdraw early, the bank will not be able to fully pay back some of its depositors anymore and will thus go bankrupt. In that case depositors are served in the order in which they requested a withdrawal. This means that first the ones who chose to immediately withdraw get some money. If anything is left, this will be divided by the depositors who chose to wait.

The depositors

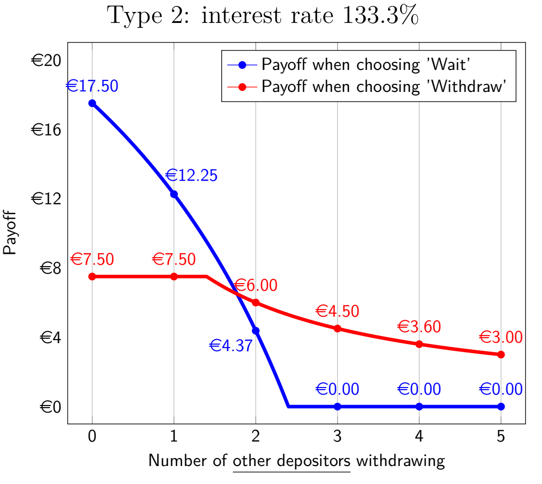
After all participants have made their choices, banks of 6 depositors are formed. Those participants who chose for Round Bank will be in a bank with other participants who chose Round bank and the same is true for the participants who chose Square bank. Because the number of participants who make a particular choice is often not an exact multiple of 6, there can be one Round Bank and one Square bank that initially have fewer than 6 depositors. To provide the participants in those banks with the same experience as the ones in the full banks, the empty spots are filled with computer players who copy the behavior of participants that made the same choice but happen to be in another group of 6. The copied participants can be individuals in the same or in a previous session.

Types of banks

Not all banks are equally vulnerable to bankruptcy. The banks with the highest interest rates are also the ones that are most vulnerable. In this experiment there are 5 types of banks. Type 1 has the highest interest rate (166.7%), but already goes bankrupt if 1 out of 6 depositors withdraws early. For a type 2 bank (interest rate 133.3%) this happens when 2 out of 6 depositors withdraw. In fact, the number of the type corresponds to the number of depositors that need to withdraw such that the remaining depositors will not receive their full deposit back.

Example

The graph on the right provides an example for a bank of type 2. It shows the payoffs of the decision maker (you) for the choices of waiting (blue line) and of withdrawing (red line). Apart from the choice of the decision maker, payoffs also depend on the decisions of the 5 other depositors in the bank. The horizontal axis depicts how many of them choose to withdraw.



Suppose that 1 out of 5 other depositors withdraws and you decide to wait. In this case you and the other 4 depositors who wait get €12.25 and the depositor who withdraws gets €7.50. If in the same situation you choose to withdraw instead, you and the other depositor who withdraws get €7.50. Note that in that case the 4 depositors who do wait get €4.37, because now from their perspective 2 other depositors are withdrawing. We can also consider a situation in which 3 out of 6 other depositors withdraw. In that case depositors who choose to wait get nothing. If you decide to withdraw here you get €4.50.

Results and payoffs

In this experiment participants are not informed about the outcomes until all parts of the experiment are completed. Then also the payoffs become known. At the end, for each participant 1 of the 15 rounds will be randomly selected for payment.

Summary

In each of the 15 rounds you have to choose a bank to receive your endowment in. Banks with lower type numbers provide higher interest rates, but are also more vulnerable to bankruptcy if depositors withdraw early. After you have chosen a bank, you are given the opportunity to withdraw immediately, or leave your money in the bank to collect interest.

Depositors who withdraw receive no interest. However, in case of bankruptcy they receive a larger part of their endowments back than those who chose to wait. You will learn the outcomes of all rounds at the end of the experiment.

3.B.2 Control treatment

General information

This part of the experiment consists of 15 rounds. In each round you will receive an endowment of €7.50 as a deposit in a bank account. You are given the choice to either withdraw this endowment immediately, or wait and collect the interest that the bank offers. Note, however, that the interest rates that the banks in this experiment advertise with, are only correct if none of the depositors withdraws early. If there are early withdrawers, the amount of interest received will be lower. If too many depositors withdraw early, the bank will not be able to fully pay back some of its depositors anymore and will thus go bankrupt. In that case depositors are served in the order in which they requested a withdrawal. This means that first the ones who chose to immediately withdraw get some money. If anything is left, this will be divided by the depositors who chose to wait.

The depositors

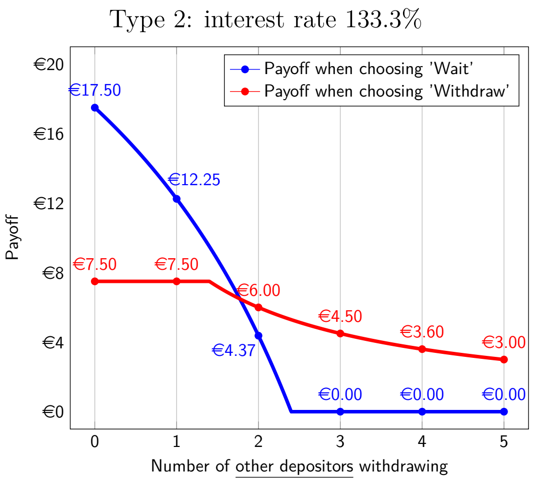
Banks typically have 6 depositors. However, because the number of participants with a deposit in a certain type of bank is often not an exact multiple of 6, there can be banks that initially have fewer than 6 depositors. To provide the participants in those banks with the same experience as the ones in the full banks, the empty spots are filled with computer players who copy the behavior of participants that have a deposit in the same type of bank but happen to be in another group of 6. The copied participants can be individuals in the same or in a previous session.

Types of banks

Not all banks are equally vulnerable to bankruptcy. The banks with the highest interest rates are also the ones that are most vulnerable. In this experiment there are 5 types of banks. Type 1 has the highest interest rate (166.7%), but already goes bankrupt if 1 out of 6 depositors withdraws early. For a type 2 bank (interest rate 133.3%) this happens when 2 out of 6 depositors withdraw. In fact, the number of the type corresponds to the number of depositors that need to withdraw such that the remaining depositors will not receive their full deposit back.

Example

The graph on the right provides an example for a bank of type 2. It shows the payoffs of the decision maker (you) for the choices of leaving the endowment in the bank (blue line) and of withdrawing (red line). Apart from the choice of the decision maker, payoffs also depend on the decisions of the 5 other depositors in the bank. The horizontal axis depicts how many of them choose to withdraw.



Suppose that 1 out of 5 other depositors withdraws and you decide to wait. In this case you and the other 4 depositors who wait get €12.25 and the depositor who withdraws gets €7.50. If in the same situation you choose to withdraw instead, you and the other depositor who withdraws get €7.50. Note that in that case the 4 depositors who do wait get €4.37, because now from their perspective 2 other depositors are withdrawing. We can also consider a situation in which 3 out of 6 other depositors withdraw. In that case depositors who choose to wait get nothing. If you decide to withdraw here you get €4.50.

Results and payoffs

In this experiment participants are not informed about the outcomes until all parts of the experiment are completed. Then also the payoffs become known. At the end, for each participant 1 of the 15 rounds will be randomly selected for payment.

Summary

In each of the 15 rounds you receive a deposit in a bank account and are asked if you want to withdraw this money immediately or leave the money in the bank to collect interest. Banks with lower type numbers provide higher interest rates, but are more vulnerable to bankruptcy if depositors withdraw early. Depositors who withdraw receive no interest. However, in case of bankruptcy they receive a larger part of their endowments back than those who chose to wait. You will learn the outcomes of all rounds at the end of the experiment.

3.B.3 Multiple price list task

In the following, you'll face 10 decisions listed on your screen. Each decision is a paired choice between "Option A" and "Option B". While the payoffs of the two options are fixed for all decisions, the chances of the high payoff for each option will vary.

After you have made all of your choices, one of the 10 decisions will be randomly chosen for your payment. For the option you chose, A or B, in this decision, it will be randomly determined (according to the corresponding probabilities) whether the low or high outcome will constitute your payoff.

To summarize: You will make 10 choices; for each decision you will have to choose between "Option A" and "Option B". You may choose A for some decision rows and B for other rows. When you are finished, one of the 10 decisions will be randomly picked for your payoff. Then a random number will be drawn to determine your earnings for the option you chose in that decision.

3.B.4 Number guessing game

You are in a group of x[9] people. Each of you will be asked to choose a number between 0 and 100. The winner will be the participant whose number is closest to 2/3 of the average of all chosen numbers.

The winner will receive €20. In case of a tie, the €20 will be equally divided among winners.

3.B.5 Bomb task

In the following, you will see a 10x10-matrix containing 100 boxes on your screen.

As soon as you start the task by hitting the 'Start' button, one of the boxes is collected per second. Once collected, the box is marked by a tick symbol. For each box collected you earn 0.1.

[9] This game was played with the whole session. The number of players therefore differed per session.

Behind one of the boxes hides a bomb that destroys everything that has been collected. The remaining 99 boxes are worth 0.1 each. You do not know where the bomb is located. You only know that the bomb can be in any place with equal probability.

Your task is to choose when to stop the collecting process. You do so by hitting 'Stop' at any time. **Note that you cannot restart the process afterwards. Hitting 'Stop' marks your final choice.** If you collect the box where the bomb is located, the bomb will explode and you will earn zero. If you stop before collecting the bomb, you gain the amount accumulated that far.

At the end of the task boxes are toggled by hitting the 'Solve' button. A dollar sign or a fire symbol (for the bomb) will be shown on each of your collected boxes.

Appendix 3.C Results of additional tasks

After playing 15 rounds of the bank choice game, the participants were asked to complete 3 additional tasks before learning their payoffs. These were a multiple price list (MPL) task (Holt and Laury, 2002), the bomb risk elicitation task (BRET) (Crosetto and Filippin, 2013) and a number guessing game in which the person closest to two-thirds of the average wins a price (Nagel, 1995). Figures 3.8 to 3.10 show the average scores of participants choosing a riskier bank and the average scores of participants choosing a safer bank next to each other. There are no significant difference in the MPL and number guessing scores (Mann-Whitney U test, two-sided). Also the number of boxes collected in the bomb task is in most cases not significantly different, except when both options are relatively safe banks (types 3, 4, and 5). Here for two out of three combinations participants that choose the safer bank also collect significantly fewer boxes, indicating that they are more risk averse.

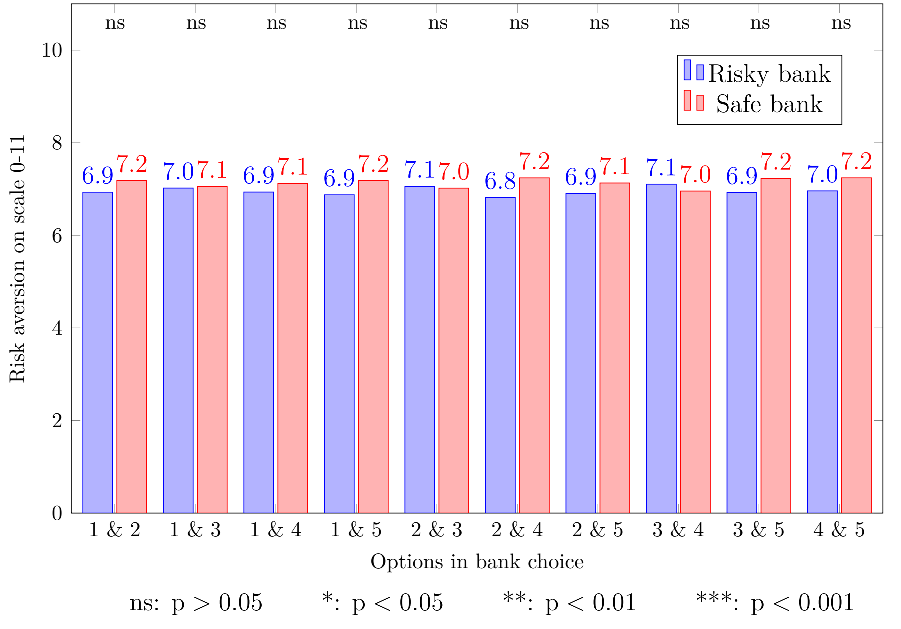


Figure 3.8: Average multiple price list (MPL) test scores for participants who choose the riskier bank (blue) and the safer bank (red) of the two options. A higher score means that a participant is more risk averse. Mann-Whitney U tests show no significant differences in the average scores of participants who chose different banks.

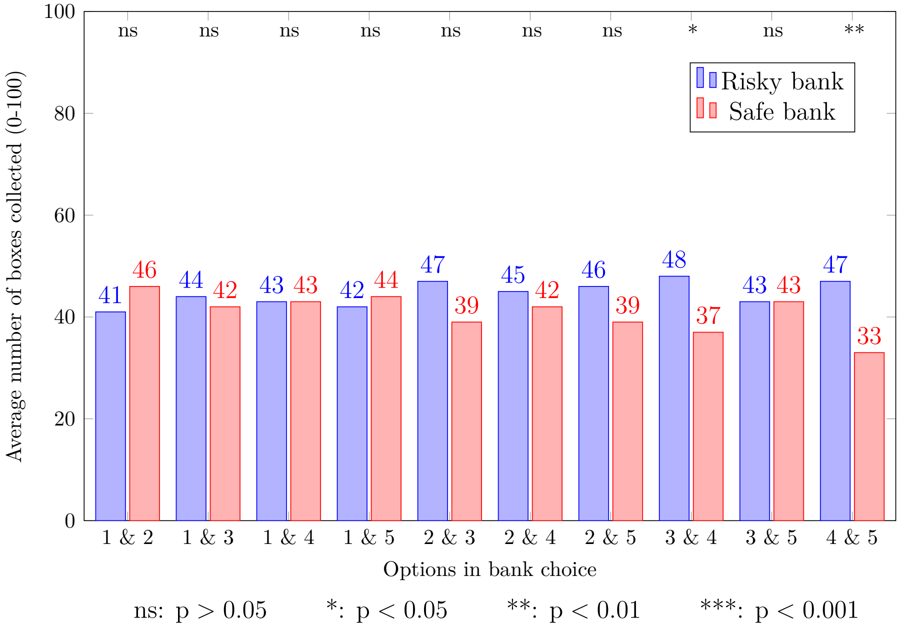


Figure 3.9: Average bomb risk elicitation task (BRET) scores for participants who choose the riskier bank (blue) and the safer bank (red) of the two options. The score for an individual is the number of boxes collected (out of 100) and the lower the score, the more risk averse the participant is. Mann-Whitney U tests show no significant differences in the average scores of participants who chose different banks for all combinations, except 3&4 and 4&5.

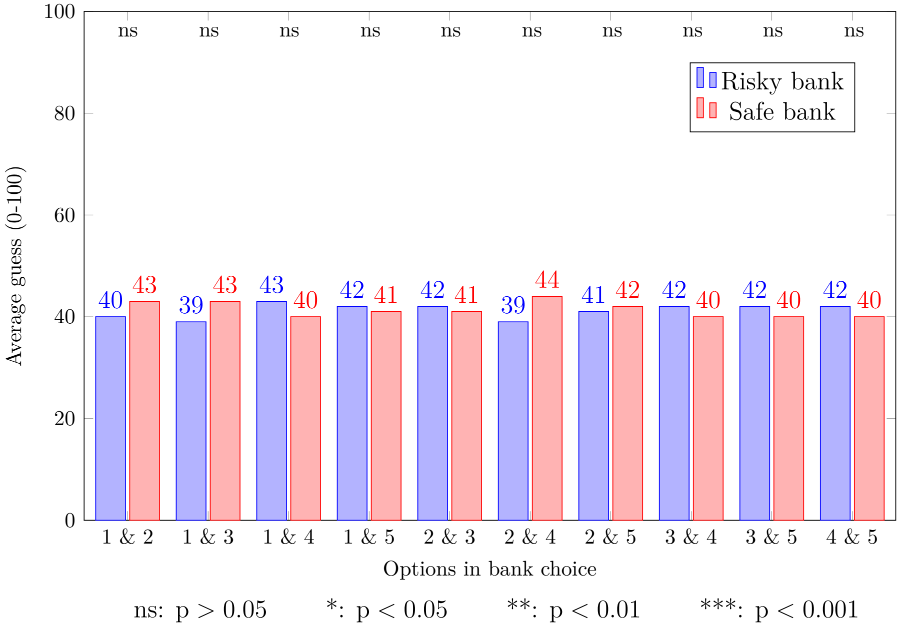


Figure 3.10: Average number guessed in the number guessing game by participants who choose the riskier bank (blue) and the safer bank (red) of the two options. In the number guessing game the person who guesses the number (between 0 and 100) that is closest to two-thirds of the average wins a price. A lower number is associated with higher Depth of Reasoning. Mann-Whitney U tests show no significant differences in the average scores of participants who chose different banks.

CHAPTER 4

Bank choice, bank runs, and coordination in the presence of two banks[1]

We investigate learning in a repeated bank choice game, in which agents first choose a bank to deposit in and then decide to withdraw that deposit or not. This game has a single pure-strategy Nash equilibrium in which all agents deposit in the bank that offers the highest return (interest), even though it may be more vulnerable to bankruptcy if some agents withdraw early. The experiment in Chapter 3 showed that in a single-shot game people do not coordinate on the Nash equilibrium, but distribute themselves rather evenly over the two banks. In this chapter we use an individual evolutionary learning algorithm to model under which circumstances and with which beliefs agents can learn to play the Nash equilibrium in the repeated game and compare the results with an experiment. We find subjects coordinating on the Nash equilibrium under low and medium risk, but efficient coordination fails under high risk (irrespective of whether subjects have full or only partial information).

[1]Adapted from: Arifovic, J., de Jong, J., Kopányi-Peuker, A (2022). Draft.

4.1 Introduction

Since the seminal paper by Diamond and Dybvig (1983) it has become common to describe bank runs as one of the equilibrium outcomes of a coordination game. In these models patient depositors have to decide to withdraw their deposits (optimal in the bank run equilibrium in which all others also withdraw) or leave the money in (optimal when others of the same type also refrain from withdrawing, the 'good' equilibrium). The pre-deposit game, in which an agent chooses whether or not to deposit money in the bank, is often not explicitly modeled even though it can be an important element of decision making. One can argue whether deposit decisions should be included or not, but the consequences of including it can be large. It imposes strict limits on sunspot solutions (Peck and Shell, 2003) and in the most simple case discussed in Chapter 3, in which agents do not receive any signals between the deposit and withdrawal decisions, bank run equilibria could even disappear. As most previous papers focus on withdrawal decisions, research on the pre-deposit game is still scarce.

In this chapter we run simulations with an individual evolutionary learning (IEL) algorithm and we conduct laboratory experiments to study learning in the bank choice game, which includes deposit decisions. In the game we allow agents to repeatedly choose the bank they want to deposit in from two available banks, and subsequently decide whether they want to withdraw their deposits, or not. The banks differ in their riskiness and the interest rate they offer. One of the banks promises a higher interest rate (risky bank) but becomes insolvent already with a lower fraction of early withdrawals, while the other offers a lower interest rate, but is less vulnerable to early withdrawals (safe bank). Theoretically there is only one pure-strategy Nash equilibrium in the one-shot game with two different banks (and also in the finitely repeated game) and it offers the agents the highest possible return: they all deposit in the risky bank, and do not withdraw their money. Despite this, the experiment in Chapter 3 shows that only about half of the subjects play according to the Nash equilibrium strategy in the one-shot game, whereas others mainly deposit in the safe bank. This far-from-equilibrium situation raises questions about how choices would evolve dynamically if agents are allowed to learn. The most important ones are whether those who initially deposit in the safe bank can learn to deposit in the risky bank to increase their earnings, whether risky banks can remain solvent over time, and how the dynamics depend on the riskiness of the bank and on the information agents receive about the history.

To answer these questions we consider two information environments and vary the riskiness of the banks. In the first information setting agents receive information about the number of depositors and withdrawals in both banks (full information) at the end of each round, while in the second they only learn the fraction of agents withdrawing in the bank they deposited in (partial information). Full information is more common in previous bank run experiments, as subjects exactly know with how many other individuals they form a bank, and they also receive information from which they can infer the number of withdrawals in the bank after each round.[2] Given that belief-updating is not straightforward when agents face partial information we decided to investigate the effect of information structure on the dynamics. Furthermore, we consider the partial information environment more realistic, thus more relevant to investigate.

In the second treatment-dimension we vary the vulnerability of the banks, i.e. what fraction of agents is needed so that the bank becomes insolvent. Even though the riskiness of the banks should not make a difference in theory, coordination on the equilibrium and learning might be more difficult in the presence of very risky banks. As soon as the level of coordination required for the bank to remain solvent approaches the level of the 'noise' in the decision making, the coordination cannot be sustained. Moreover, agents may anticipate this noise and choose a different strategy from the beginning. To investigate this question we applied three different bank combinations in our experiment (low risk, medium risk and high risk). IEL includes some randomness in the decision making through its experimentation component. Therefore, the simulations also predict differences in learning for these three different conditions.

Our experimental results reveal small differences in behavior depending on the information structure, which leads us to conclude that participants can be quite sophisticated in their beliefs-updating. Furthermore, we only observe a consistent failure to coordinate on the Nash equilibrium in sessions with the most vulnerable banks. In the majority of other sessions the decisions converge to the Nash equilibrium rather quickly. This convergence seems faster and more complete when participants receive information about the outcomes in both banks. However, we do not have enough data to assess the significance of this difference. The IEL simulations can predict our experimental results well when we use an initialization that is close to the initial behavior in the experiment, and assume sophisticated beliefs-updating.

This chapter contributes to two main strands of the literature. First, we add to the bank run literature by investigating dynamics in a repeated bank run game with the deposit decision included. Here we build on Chapter 2, in which the one-shot bank choice game with 15 different bank combinations is investigated. In this chapter we conduct 3 bank combinations in total in a repeated interaction, and we also vary the information

[2] See for example Arifovic et al. (2013), Arifovic et al. (2023), or for a review of the experimental bank run literature Kiss et al. (2022a).

structure. Even though we are not the first to vary bank characteristics or information structures across treatments, or having multiple banks, to the best of our knowledge we are the first investigating these characteristics together with a choice in which bank to deposit the endowments. In their study of the effect of bank characteristics on withdrawals, Arifovic et al. (2013) introduced the coordination parameter η as the fraction of depositors that need to forego withdrawing ('wait') to make waiting the payoff-maximizing strategy. They consistently find coordination on the good equilibrium for $\eta \leq 0.5$, coordination on the bank run equilibrium for $\eta \geq 0.8$, and mixed results in between. The information variation in our experiment is only possible in a multi-bank setup and has not been looked at before. There are experiments in which subjects might not have perfect information about others' withdrawal decision. However, these experiments are mainly conducted on sequential withdrawal decisions, and the information provision concerns observations *within a round*. For examples see Schotter and Yorulmazer (2009), Kiss et al. (2012), Kiss et al. (2014), and Davis and Reilly (2016). In the majority of cases the visibility of others' actions leads to fewer withdrawals. Finally,Shakina (2019) also considers a multi-bank setting, but her experiment focusses on the redeposit decision instead of the pre-deposit game. She finds that a redeposit option leads to more withdrawals from banks that cannot receive new depositors and fewer withdrawals from banks that are on the receiving end. For an extensive review of the general experimental bank run literature, see Kiss et al. (2022a).

Second, this chapter also contributes to further development of the IEL algorithm. Agents that use the IEL algorithm in their decision making maintain a collection of strategies of which they continuously evaluate the performance. Each period the collection is updated through experimentation and the replacement of poorly performing strategies by better performing ones. IEL has been successfully used to explain results in several experiments, including call markets experiments (Arifovic and Ledyard, 2007), public goods experiments (Arifovic and Ledyard, 2011), and bank run experiments (Arifovic, 2019). However, in these experiments subjects always received enough information to be able to calculate foregone payoffs and evaluate strategies. To use IEL with an environment in which agents only receive partial information (in our case about their own bank), one needs to extend the algorithm with beliefs about the missing pieces of information (here: about what happened in the other bank). We explore several possibilities to do this and find that a variant in which agents form very sophisticated beliefs is closest to the experimental results.

The rest of the chapter is organized as follows. In Section 4.2 we describe the bank choice game. Section 4.3 presents the simulations in more details together with their results. Section 4.4 describes the experimental design. In Section 4.5 we discuss the experimental results and compare them to the simulations. Section 4.6 concludes.

4.2 The bank choice game

There are N players who play a repeated version of the bank choice game described in Chapter 3. Each round consist of 3 periods: period 0, 1 and 2. In period 0, players can decide between two banks in which they can deposit their money (the endowment cannot be received as 'cash'). The initial deposit is c. After everyone has chosen a bank, the players enter a typical bank run game in which they are asked whether they want to withdraw their money or not. Important is that the banks to choose from are different. Some banks invest such that the return R in period 2 is higher, but at the cost of a lower liquidation value L in period 1. Banks with a high R and low L are the more vulnerable or 'risky' banks, while banks with lower R and higher L are 'safer'. We assume that $R_r > R_s > 1 > L_s > L_r$ where r stands for the riskier bank, and s stands for safer bank.

After players make their decisions, earnings in each bank are determined by the payoff function:

$$\pi_{withdraw} = \min\left(\frac{L_k c}{f_k}, c\right), \tag{4.1}$$

$$\pi_{wait} = \max\left(\frac{\left(1 - \frac{f_k}{L_k}\right) R_k c}{1 - f_k}, 0\right). \tag{4.2}$$

Here f_k is the fraction of depositors in bank k who choose to withdraw from the bank. When none of the depositors withdraw $\pi_{wait} > \pi_{withdraw}$ and when all depositors withdraw $\pi_{wait} < \pi_{withdraw}$. There is a single value of f_k for which waiting and withdrawing yields the same payoff, denoted by f_k^*. If the fraction of depositors withdrawing is less than f_k^*, 'wait' becomes payoff dominant. f_k^* is thus a measure of the vulnerability of the 'good' equilibrium in the bank run game. The higher f_k^* is, the less vulnerable the bank is.[3] The bank choice game (with two banks) has only one pure-strategy Nash equilibrium, in which all players deposit in the risky bank and wait. This is also the single Pareto optimal outcome and it yields the maximum payoff to all participants. Hence the single pure-strategy Nash equilibrium of the repeated game is simply that all players coordinate on the stage game equilibrium in every round.

In this chapter we will often use particular combinations of L and R for the banks.

[3]This f_k^* parameter is closely related to the coordination parameter η_k from Arifovic et al. (2013). In fact, $f_k^* = 1 - \eta_k$.

Table 4.1: Bank types

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5
R	3.00	2.67	2.33	2.00	1.67	1.33
L	0.10	0.20	0.40	0.60	0.80	0.93
f^*	0.103	0.135	0.276	0.429	0.615	0.778

Notes: Bank types with the parameter values for return R and liquidation value L, and the fraction of depositors f^* needed to withdraw such that depositors are indifferent between wait and withdraw.

These combinations (or bank types) are listed in Table 4.1, together with the values of their coordination parameters. Types 1 to 5 were also used in Chapter 3.[4] We also add an extra type, type 0, which is more vulnerable than type 1.

4.3 Simulation design and results

4.3.1 Individual Evolutionary Learning

The advantage of IEL compared to other learning models is that it needs relatively few free parameters to describe learning dynamics in repeated games with more than two players relatively well (Arifovic and Ledyard, 2011). In IEL each agent starts round t with a private set of strategies that is inherited from the previous period. This set S^i_{t-1} has a fixed size M and each place m in the set can contain any strategy available to the agent. Strategies in the set are therefore typically not unique. At the end of the round one of the strategies in the set will be selected to be played, but before that the set can undergo changes due to two processes: experimentation and replication.

In the bank choice game strategies naturally contain two elements: a bank choice and a withdrawal decision. Each element of each strategy in the set is (independently) subject to experimentation with probability ρ. When experimented upon, the element changes. How it changes, depends on the application. In our simulations we limit the strategies available to the agent to only the four pure strategies of the one-shot game and then experimentation simply leads to switching of the choice in the respective element, e.g., risky bank instead of safe bank or waiting instead of withdrawing.

After the experimentation process is complete, all strategies in the set are evaluated

[4] In Chapter 3 the type number coincided with the number of withdrawals that would drive a bank with 6 depositors to insolvency. The banks we study here will not always have 6 depositors, so the type number does not have any special significance beyond the fact that a higher number corresponds to a safer, less vulnerable bank.

in terms of the payoffs that the agent believes they would have generated if they would have been selected in the previous round (calculation of foregone payoffs $\tilde{\pi}$). Agents thus consider a situation in which only their strategy in round $t-1$ is (possibly) different, but the actions of all other agents remain the same. The information that they receive about other agents' actions may or may not be sufficient to calculate the foregone payoffs with certainty. We assume that agents calculate the actual foregone payoffs when they have information about both the number of depositors and the number of withdrawals (full information). In other cases the foregone payoffs depend on the beliefs of the individual agents.

The idea of replication is that strategies with a higher foregone payoff have a higher probability of becoming more common in the set, pushing out worse performing strategies. In IEL this is implemented in the form of a tournament. For each place m in the new, updated set S_t^i two strategies $s_{v,t-1}^i$ and $s_{w,t-1}^i$ are randomly selected and the one with the highest foregone payoff fills the spot:

$$s_{m,t}^i = \begin{Bmatrix} s_{v,t-1}^i \\ s_{w,t-1}^i \end{Bmatrix} \quad \text{if} \quad \begin{Bmatrix} \tilde{\pi}\left(s_{v,t-1}^i, B_t^i\right) \geq \tilde{\pi}\left(s_{w,t-1}^i, B_t^i\right) \\ \tilde{\pi}\left(s_{v,t-1}^i, B_t^i\right) < \tilde{\pi}\left(s_{w,t-1}^i, B_t^i\right) \end{Bmatrix} \tag{4.3}$$

The final step is to select the strategy to be played in round t. This is determined by a random draw from S_t^i with weights equal to the foregone payoffs of the strategies.

IEL as outlined above requires assumptions about the set size J, the initialization (the initial strategy set and the actions in round 1, and under some circumstances initial beliefs), and the experimentation rate ρ. Furthermore, we need to specify how beliefs are formed in case the agents are not informed about the number of depositors in each bank and the number of withdrawals. For the set size we choose $J = 100$, in line with what has been used for IEL simulations of other games. Together with probabilistic choice, the experimentation rate is the main source of noise in the agents' decision making. We therefore use several values to understand the impact of this parameter on the decision dynamics and in particular on convergence. As initialization, rather than choosing an initial strategy set and actions, we choose the probabilities p_j with which the agents select each of the four possible actions in the first round. These probabilities are then used to construct the initial strategy set.[5]

[5] The procedure is to randomly determine each strategy in the set independently based on the probabilities p_j (the set can only contain pure strategies). This means that the initial strategy sets are actually random variables, which are independently determined for each agent. The chosen action in round 1 is one of the strategies in this set (random draw with equal weights).

4.3.2 Beliefs under partial information

In our simulations we consider both cases in which agents know of each bank how many agents deposited there and how many withdrew in the previous round (full information) and cases in which agents only learn about the fraction of withdrawals in the bank in which they had deposited (partial information). In the latter cases the foregone payoffs are mostly determined by beliefs. The choice of what these beliefs should be, is far from trivial. One option is to assume that agents are *naive* in their beliefs and ignore their own influence on the outcome in their own bank. They will thus calculate the foregone payoffs of the alternative action (withdrawing instead of waiting or waiting instead of withdrawing) in their last chosen bank as if that would not change the overall withdrawal fraction in the bank. Beliefs still have to be formed for the other bank, in which the agent did not deposit and about which she does not receive any information in that round. Here, agents could treat depositing in the bank as *neutral*, i.e. yielding the initial endowment, or they could use the last observed withdrawal fraction in that bank and calculate foregone payoffs using that (*last-known*).[6]

Another possibility is to assume that agents are *sophisticated* in their beliefs about the number of depositors and withdrawers in both banks. Sophisticated agents will never hold beliefs that contradict available information. They know that there are I other agents and that the number of depositors can therefore never exceed I. The fraction they observe for their last chosen bank further restricts the number of depositors that are possible. For example, if the fraction of withdrawals is $\frac{1}{3}$, the number of depositors in that bank needs to be a multiple of 3. We next assume that sophisticated agents' beliefs about the number of depositors in the bank chosen in round $t-1$ is as close as possible to number of depositors they believed the bank had in round $t-2$. This means that if they believed that the number of depositors was 2 in round $t-2$ and they observe a withdrawal fraction of $\frac{1}{3}$ for round $t-1$, they will believe that there are 3 depositors in that bank in period $t-1$ and that one of these depositors withdrew. Beliefs about the number of depositors in the last chosen bank immediately fixes the beliefs about the number of depositors in the other bank as well, but not necessarily the number of withdrawals there. Here we assume that agents will use the fraction of deposits they believed to be withdrawn in round $t-2$, apply this fraction to the new number of depositors believed to be there in round $t-1$ and round the result to the nearest integer.[7] So in total we consider 3 cases in our simulations: naive neutral, naive last-known, and sophisticated.

[6] In case an agent never deposited in a certain bank, their belief about the withdrawal fraction is equal to the value with which a single agent withdraws from that bank in round 1. This is an initialization value and all agents are assumed to know it.

[7] In case two integers are equally close, the agent randomly chooses one of them.

4.3.3 Simulation results

Figure 4.1 condenses the most important results of our simulations, showing information about the average strategies in rounds 26 to 50 of the repeated bank choice game. The experimentation rate ρ was set equal to 0.05, which we believe to be a realistic value, and is within the range of values used in previous studies. In Appendix 4.B we provide the results for other experimentation rates ($\rho = 0.01$ and $\rho = 0.10$). All data shown is from an average of 100 simulation runs with 12 agents.

There are 8 tables, each showing results for all different combinations of bank types 0 to 5 (details about these types are given in Table 4.1). The tables on the left represent simulations in which agents start by fully randomizing, with equal probabilities, their bank choice ($f_b = 0.5$) and withdrawal choices from the safe and risky banks ($f_s = 0.5$ and $f_r = 0.5$). It is a default option often chosen to initialize the IEL algorithm. However, the single-shot experiments in Chapter 3 already revealed that the number of withdrawals in the risky bank is very low. Therefore we also show, in the tables on the right, simulations in which the agents that start the first round by depositing in the risky bank initially have a low probability of withdrawing ($f_r = 0.1$). The different rows show variations in information and beliefs, with full information simulations in the top row and partial information simulations with the sophisticated, naive-lastknown, and naive-neutral beliefs in the other rows.

The individual cells of the tables each show two pieces of information: the average fraction of agents that withdraw from their bank (shading) and a measure of how many agents deposited in the risky bank (the number). The darkest shading (red) corresponds to more than 90% withdrawals, while with no shade (white) less than 10% is withdrawn on average. The numbers range from 0 (all deposit in the safe bank) to 12 (all deposit in the risky bank). This means that in a white cell with a number 12, agents converge to waiting in the risky bank (the Nash equilibrium) in almost all simulations. Similarly, a red cell with the number 0 means that agents converge to withdrawing in the safe bank in almost all simulations.

A first thing to note is the large impact of the initialization, a sign that path-dependence plays an important role in the dynamics. Regardless of the information or the beliefs, a reduction in the number of withdrawals from the risky bank in the first round helps to prevent runs 25 rounds later. Information and beliefs are also important, particularly when the initialization is not favorable ($f_r = 0.5$). Under those circumstances agents in the IEL simulations only manage to converge to the Nash equilibrium under full information. With partial information there are also few withdrawals for combinations with at least one relatively safe bank (type 4 or 5), but only agents with sophisticated

Fraction of withdrawals: >90% 50-90% 10-50% <10%

$\rho = 0.05$

Full info — Initialization $f_r = 0.5,\ f_s = 0.5$

	0	1	2	3	4	5
0	4	2	4	8	12	12
1		4	3	7	12	12
2			4	7	11	12
3				5	12	12
4					6	12
5						6

Full info — Initialization $f_r = 0.1,\ f_s = 0.5$

	0	1	2	3	4	5
0	5	6	8	10	12	12
1		5	10	11	12	12
2			6	12	12	12
3				6	12	12
4					8	12
5						6

Partial info Sophisticated — Initialization $f_r = 0.5,\ f_s = 0.5$

	0	1	2	3	4	5
0	10	6	6	6	7	7
1		10	6	6	7	7
2			10	7	7	7
3				6	7	8
4					6	10
5						6

Partial info Sophisticated — Initialization $f_r = 0.1,\ f_s = 0.5$

	0	1	2	3	4	5
0	9	6	7	9	9	9
1		8	9	9	10	10
2			7	11	11	11
3				8	12	12
4					9	12
5						8

Partial info Naive-lastknown — Initialization $f_r = 0.5,\ f_s = 0.5$

	0	1	2	3	4	5
0	6	0	0	0	0	0
1		6	0	0	0	0
2			6	0	0	0
3				6	1	1
4					6	8
5						6

Partial info Naive-lastknown — Initialization $f_r = 0.1,\ f_s = 0.5$

	0	1	2	3	4	5
0	6	0	0	0	0	0
1		9	6	7	7	8
2			11	11	11	11
3				11	12	12
4					10	12
5						9

Partial info Naive-neutral — Initialization $f_r = 0.5,\ f_s = 0.5$

	0	1	2	3	4	5
0	6	6	6	5	1	0
1		6	6	5	2	0
2			6	4	1	0
3				5	3	1
4					5	4
5						6

Partial info Naive-neutral — Initialization $f_r = 0.1,\ f_s = 0.5$

	0	1	2	3	4	5
0	6	6	6	4	2	1
1		9	8	7	4	4
2			11	9	8	7
3				10	9	8
4					9	8
5						8

Figure 4.1: IEL simulation results. Each table shows information about the average strategies in rounds 26 to 50 for all combinations of the 6 bank types defined in Table 4.1. The color represents the average fraction of withdrawals from both banks and the number represents how many of the 12 agents choose to deposit in the risky bank.

beliefs seem to be able to learn to deposit in a riskier bank (type 0, 1, 2, or 3).

With a favorable (and more realistic) initialization the differences are not nearly as large. Particularly striking is the similarity between the full info simulations and the partial info simulations with sophisticated beliefs. The only difference here seems to be that convergence to the Nash equilibrium is not always complete, either because some agents in the group do not learn it or because some groups do not converge to it (we will come back to this point later). Simulations with naive-lastknown beliefs differ primarily from these two when a bank of type 0 is present (agents never deposit in it if they have an alternative) and in simulations with naive-neutral beliefs the Nash equilibrium choice is much less common. A common element of all tables is that there are more withdrawals when the banks that agents can choose from get riskier.

The majority of the simulations do not result in the (almost certain) convergence to a particular strategy. There are two possible causes of their in-between values. It may be that the individual runs of the simulation simply do not converge to any strategy or there is a lot of variation between the runs, with some runs converging and some others not, or to another strategy. To test this we checked for convergence in every single run using the following criterium for convergence:

1. A minimum of 90% of the agents (which is 11 out of 12 in a simulation with 12 agents) choose the same strategy for two consecutive rounds at some point in the first 50 rounds.

2. In at least 75% of the rounds between the first of the two consecutive rounds mentioned above and the the end of round 50, agents coordinate on this strategy (with a minimum of 90% of the agents choosing this strategy).

We find that it is very common that runs do not converge to any strategy. However, there are also many simulations for which some runs converge to one strategy and other runs to another strategy. The only strategy that runs rarely converge to is withdrawing in the risky bank. Simulations for which only some runs converge are also common.

The convergence tests also provide us with information about how quickly the agents converge to a strategy. For convergence to the Nash equilibrium strategy, both the initialization and the information plays a large role. When the fraction of withdrawals in the risky bank starts low ($f_r = 0.1$), convergence often occurs within 4 or 5 rounds, When half of the first-round depositors in the risky bank withdraws, convergence is less common and requires full information. It also takes about twice as long (7 to 10 rounds). With the favorable initialization ($f_r = 0.1$) we also see convergence to the Nash equilibrium strategy when one of the banks is very risky (type 0 or 1) and agents have partial information.

Under those circumstances agents need sophisticated beliefs to succeed in coordinating on the Nash equilibrium and it takes a few more rounds (also 7 to 10 rounds).

4.4 Experimental design

4.4.1 Main design

In the experiment 12 subjects form one group, and play repeatedly the game discussed in Section 4.2. Subjects start each round with the same initial endowment of 75 points, and face the same decision: first they have to choose between two banks where they want to deposit their endowment. After choosing their bank, they decide whether to wait or withdraw their funds from the chosen bank. Between the bank choice and withdrawal decisions subjects do not receive any information about what others are doing. In particular, they have to make their withdrawal decisions without knowing how many others are in the same bank. After each round subjects receive information about their own payoffs, and - depending on the treatment - they get feedback about either their chosen or both banks. The banks that subjects can choose from are called Round Bank and Square Bank. The Round Bank is always the riskier bank that has a higher potential maximum payoff as well. The Square Bank is the safer bank with a lower potential maximum payoff. In each round subjects face the same two bank types, each chosen from Table 4.1. One of two is always a type 1 bank, the type of the other depends on the treatment. In Section 4.4.2 we discuss the treatments in more detail.

Subjects' payoffs in each round depend on their own choices, the number of others in their chosen banks, and the number of withdrawals in that bank. Payoffs are determined by the formulas (4.1) and (4.2). Subjects are not given the exact formulas, but they are presented with payoff graphs, in which they can see the payoffs for the different actions given the fraction of withdrawals in the chosen bank. Given that the number of people in a bank may vary, as it is a decision subjects make, we opted for presenting the payoffs as a function of the fraction of withdrawals. Subjects' total payoff of the bank choice game is their cumulative payoff across the 50 rounds.

For each decision subjects have 1 minute to submit their choices. If they do not submit anything within that time, they do not earn anything in that round. If subjects do not choose a bank in time, then the program skips the withdrawal decision, and subjects are proceeding to a wait page telling them they have not chosen a bank. Payments for the other subjects are then determined by excluding those who have not chosen a bank. If subjects do not make a withdrawal decision, then they again earn nothing for the

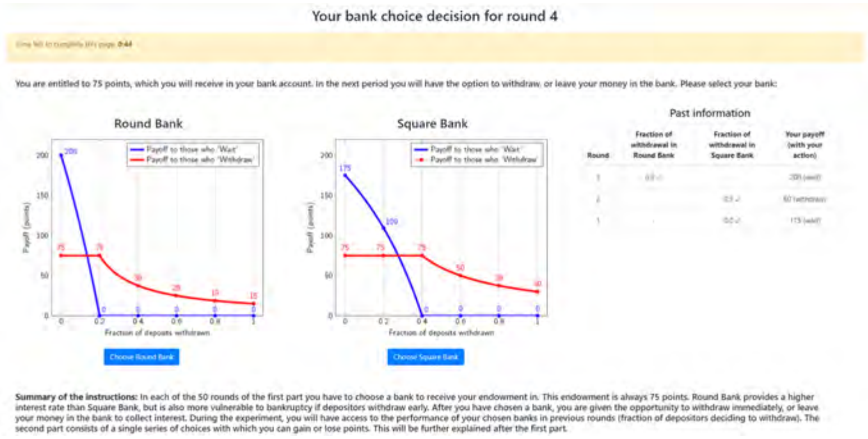


Figure 4.2: Screenshot of the bank choice decision (partial information)

given round, and their decision counts as 'wait' for those in the same bank, as they do not withdraw their funds. If a subject does not make decisions for three rounds, they are excluded from the experiment, and will not get paid. This is known to subjects in advance.[8]

4.4.2 Treatments

We implement a 2x3 design, where we vary the information subjects receive as well as the combination of the different banks. In the *partial information* treatments subjects only receive information about what happened in *their chosen bank* in the previous rounds (see the history table in Figure 4.2). By contrast, in the *full information* treatments subjects receive more detailed information about their chosen bank as well as for the other bank. In particular, the fraction of withdrawals is presented as a fraction for both banks, where the denominator is the number of depositors in the given bank, and the numerator is the number of withdrawals in the given bank. Subjects' chosen bank is denoted with a tick in the table (see the history table on Figure 4.3).

On the other dimension we vary the combination of banks used as risky and safer bank. Here we implement three different riskiness level: *low risk*, *medium risk* and *high risk*. Common in all three treatments is that we take bank type 1 from Table 4.1, and combine it with a different bank. In the low risk treatment the risky bank is a type 1 bank

[8]Note that subjects still have around 4 minutes to solve connection issues or contact the experimenter should they encounter a problem without being excluded from the experiment, as they have 1 minute for each decision. If subjects do not choose a bank, the waiting page telling them they have not chosen a bank is also displayed for 1 minute (with a 'next' button) to give subjects time to solve possible problems.

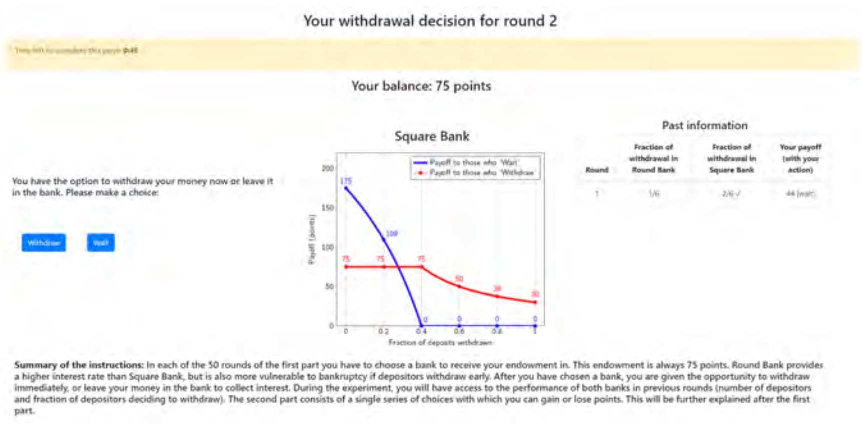


Figure 4.3: Screenshot of the withdrawal decision (full information)

Table 4.2: Bank combinations in the experiment

	low risk		medium risk		high risk	
	Round b.	Square b.	Round b.	Square b.	Round b.	Square b.
Bank type	1	4	1	2	0	1
Max. earnings	200	125	200	175	225	200
Liq. value	0.2	0.8	0.2	0.4	0.1	0.2

Notes: Maximum earnings can be reached if all depositors in the given bank decide to wait. It is calculated using the initial endowment of 75. Graphical representation of the payoffs can be found in Appendix 4.A.3.

and the safe bank is of type 4, which is a relatively safe type as 80% of the depositors need to withdraw before the bank becomes insolvent. In the medium risk treatment we combine bank type 1 (risky bank) with bank type 2 (safer bank). These two types are close to each other, resulting in moderately high risk. Finally, in high risk bank type 1 is actually the 'safer' bank, and it is combined with the even riskier bank type 0. Note that for this bank type a single withdrawal will already cause insolvency in most cases. Table 4.2 gives an overview of the different maximum earnings and liquidation values implemented in the experiment.

Based on the simulations and earlier bank run studies with different coordination parameters, we expect that the combination of banks affects the ability of subjects to learn the equilibrium of waiting in the risky bank. The safer the safe bank is, the more likely it is to end up in the Nash equilibrium of the game. Looking at the IEL simulations with pure random initial decisions, the expected outcome in the low risk and the medium risk treatments are different. However, if we look at the initialization in which agents wait with 90% probability after choosing the risky bank, we find that only in case of high risk agents cannot learn the Nash equilibrium. The second initialization, in which agents are more likely to learn the equilibrium is in line with observations from the one-shot game in Chapter 3.[9] This leads us to our first hypothesis:

Hypothesis 1 *The safer the safe bank is, the more likely it is that agents can learn the Nash equilibrium, i.e. waiting in the risky bank.*

Next to the variation in bank types, we consider different information settings. In the full information treatments subjects have the best chance to learn to wait in the risky bank. However, information this detailed is hardly observable in real life, so we decided to also investigate learning with just partial information about what happens in the banks. Giving only partial information makes coordination more difficult to subjects, as they need to try out each bank if they want to know how others behave in a particular bank. Therefore we expect similar or less coordination on the pure strategy Nash equilibrium with partial information. Also, in case participants do converge on using a certain strategy, it is expected to be slower than under full information. This leads us to our second and third hypotheses:

Hypothesis 2 *Partial information does not lead to more coordination on waiting in the risky bank.*

Hypothesis 3 *Partial information leads to slower convergence than full information.*

4.4.3 Loss aversion task

To better understand behavior in the bank choice game, we also implement a loss aversion task after the 50 rounds of the main experimental task.[10] Before the bank choice game subjects are aware that there is a second task they need to perform, but they do not know the nature of that task until they finish the first part. The second task consists of 6 lotteries, and subjects need to choose whether they want to play that particular lottery or not. After all subjects make their decisions, one of the lotteries and its realization is randomly drawn. Subjects who chose to play that lottery receive the corresponding earnings (which can be positive or negative), whereas subjects who decided not to play

[9] A type of forward-induction reasoning could underly the choices observed in that experiment. Intuitively, agents choose the risky bank only if they want to wait, to enjoy higher earnings, as withdrawing is safer from the safe bank.

[10] Previous studies (Trautmann and Vlahu, 2013; Kiss et al., 2018) show some correlation between loss aversion and decisions in bankrun games. Risk aversion does not seem to be a good predictor of behavior in these games (Kiss et al., 2014, 2016, 2018; Shakina, 2019), thus we decided to elicit only loss aversion from subjects.

the chosen lottery receive nothing. In all 6 lotteries the probability of winning 1350 points is 50%. With 50% probability however subjects can lose money. The lowest absolute loss is 150 points, and this increases to 1650 in steps of 300. For the exact payoffs see Appendix 4.A.4. We do not impose a time limit on this task.

4.4.4 Procedures

The experiment was programmed in oTree (Chen et al., 2016), and was run as an online experiment with subjects from the University of Amsterdam and Simon Fraser University in Vancouver between May and October 2021. In total 574 subjects participated in 48 sessions. Subjects were mainly students in various fields. Most subjects (46.1%) studied economics or business economics, followed by natural sciences, mathematics, computer science or engineering (13.7%) and social sciences (excluding economics and psychology - 11.3%). 56% of the subjects were female, 43% were males (8 subjects either stated other or did not want to answer). The average age was 21.8 years.[11] None of the subjects participated more than once. Sessions took on average one hour with average earnings of 14.90 euros in Amsterdam and 19.90 dollars in Vancouver (including a participation fee of 5 euros, 7 dollars, respectively). Subjects earnings consist of their cumulative point earnings of the 50 rounds of bank choice game, their earnings from the loss aversion task plus the participation fee. Point earnings from the experiment were exchanged to euros or dollars with 675 points for 1 euro, and 450 points for 1 dollar.

In most sessions 12 subjects participated from one of the two locations.[12] We collected 4 groups per treatment per location, resulting in 8 independent observations per treatment. Subjects were one-by-one admitted to a zoom session where we checked their ID, renamed them, and placed them back into the waiting room. Once we prescreened all participants, we admitted all of them in the zoom session, and sent away subjects if more than 12 had shown up. The remaining participants were sent a unique oTree link via private chat. Subjects were only allowed to communicate with the experimenter via the private chat, but not with each other. Subjects read the experimental instructions at their own pace, and had to correctly answer understanding questions before starting the bank choice game. Both the instructions and the understanding questions are reproduced in Appendix 4.A. After everybody correctly answered all questions, subjects played the

[11] Comparing subjects' gender, age and field of study across treatments with a Kruskal-Wallis test reveals no significant differences across treatments ($p > 0.58$).

[12] In three sessions one participant left the experiment during the instructions, in three additional sessions one participant left the experiment during the bankrun game, and in two sessions we started with 11 subjects due to low show-up. The program did not depend on the exact number of subjects, and could handle drop-outs. The 574 subjects include the drop-outs as well.

bank choice game for 50 rounds. After the main game, subjects performed the loss aversion task (these instructions are also found in Appendix 4.A). Finally, subjects filled in a post-experimental questionnaire to provide more information about their strategies, and some demographics.

4.5 Experimental results

4.5.1 Coordination on the different outcomes

Figure 4.4 shows the evolution of strategies subjects chose in each round. There are four action combinations possible, each corresponding to a pure strategy of the bank choice game: depositing in the risky bank and waiting (red), depositing in the safe bank and waiting (green), depositing in the safe bank and withdrawing (blue), and depositing in the risky bank and withdrawing (black). The rows represent different information structure and source of data: full (Full) or partial (Part) information, and Exp denotes rows with experimental data, whereas IEL denotes rows with the corresponding simulations. For partial information we have three different possible beliefs, sophisticated (Soph), naive-lastknown (Naive-LK) and naive-neutral (Naive-N). The three columns show data on the three different levels of riskiness: low, medium and high risk.

The first thing to note is that in the low risk and medium risk treatments very few participants withdraw. In those treatments most groups converge to playing the Nash equilibrium strategy (with sometimes one or two participants deviating by depositing in the safe bank). In the high risk treatments we do not see any sign of convergence to the Nash equilibrium or to one of the withdrawal strategies. When we apply the convergence criteria outlined in Section 4.3.3, we indeed find that none of the high risk sessions converges to any strategy in 50 periods, compared with 6 out of 8 (low risk, full information), 2 out of 8 (low risk, partial information), 5 out of 8 (medium risk, full information), and 4 out of 8 (medium risk, partial information) in the other treatments. In Appendix 4.C we provide the data for each of the individual experimental sessions. Second, the IEL simulations describe the experimental data relatively well when agents have sophisticated beliefs under partial information, or possess full information. Naive beliefs provide a much worse fit.

As we can see from Figure 4.4, the dynamics seem to be different for high risk compared to the two other risk types. However, the differences seem to be less pronounced looking across information structures, even though there seems to be a slight advantage of having full information for coordination. Table 4.3 quantifies the differences across treatments by

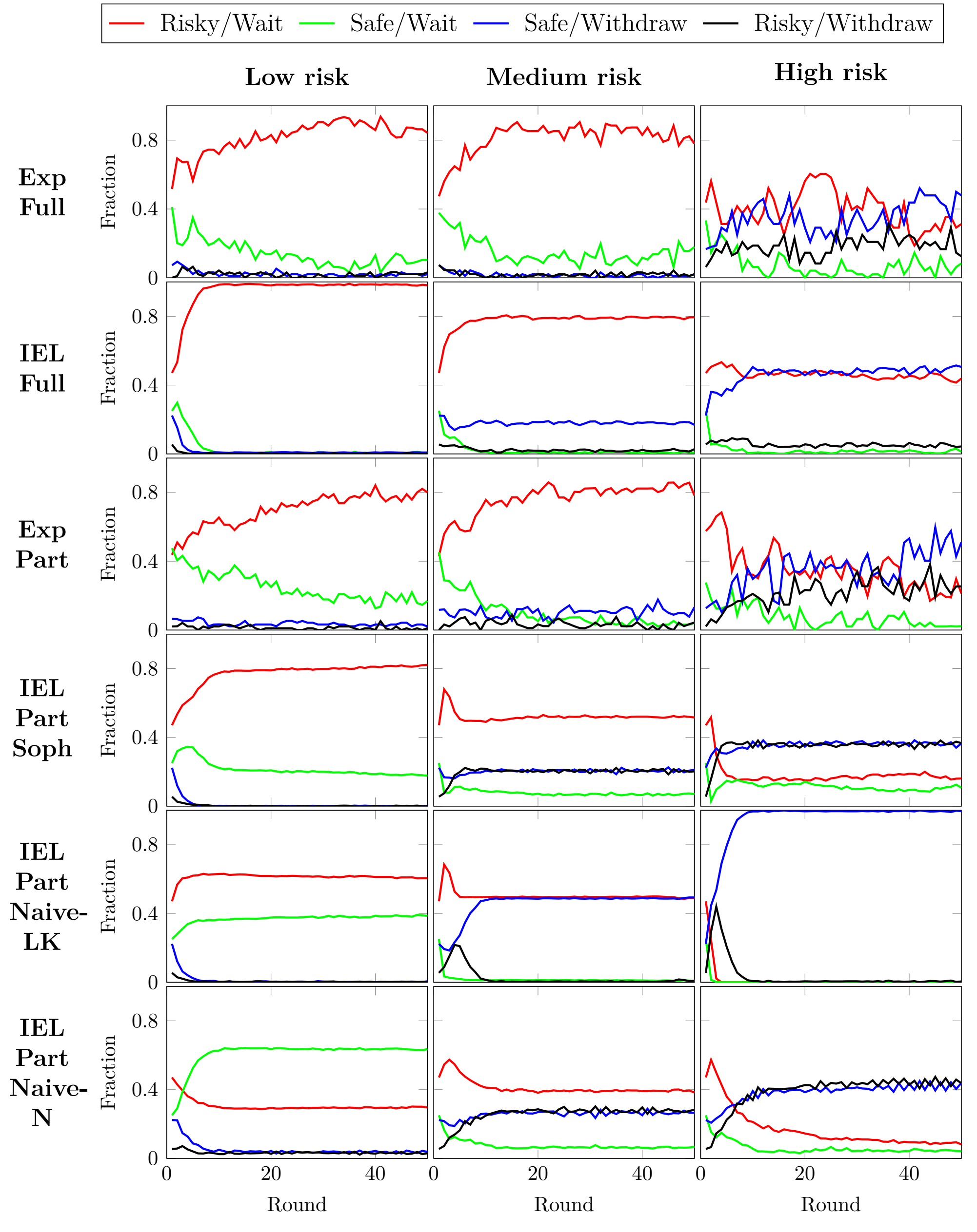


Figure 4.4: Strategies in the experiment and predicted by IEL

Table 4.3: Average bank choices and withdrawal rates for the whole experiment

	Low risk	Medium risk	High risk
Panel A: Bank choice decision - risky bank			
Partial info	0.71 (0.45)	0.80 (0.40)	0.51 (0.50)
Full info	0.84 (0.37)	0.83 (0.37)	0.55 (0.50)
Panel B: Withdrawal rate in the safer bank			
Partial info	0.13 (0.33)	0.50 (0.50)	0.84 (0.37)
Full info	0.15 (0.35)	0.10 (0.30)	0.70 (0.46)
Panel C: Withdrawal rate in the riskier bank			
Partial info	0.02 (0.14)	0.04 (0.19)	0.42 (0.49)
Full info	0.02 (0.15)	0.02 (0.15)	0.31 (0.46)

Averages and standard deviations (in brackets) calculated on the individual level.

showing descriptive statistics of different aggregate measures of behavior. In particular, Panel A contains the average choice of the risky bank throughout the entire experiment. Panel B contains the average withdrawal rate in the safe banks, and Panel C the average withdrawal rate in the risky bank. For all the analyses presented in this section we pool the data across the two locations because we are interested in the treatment effects in general, and the purpose of the experiment is not to investigate location differences. We do find some differences though and we present those in Appendix 4.D.

To test the differences seen on Figure 4.4 and in Table 4.3, we investigate treatment effects by means of pooled panel logit regressions. Table 4.4 presents the results of these regressions for the likelihood of depositing in the risky bank (columns (1) and (2)), and for the likelihood of withdrawing (columns (3) and (4) - here also controlling for the chosen bank in the given round). In the first column for both dependent variables we are only interested in the average treatment effects, but not for path dependency, thus we do not control for history in the bank. However, as path dependency can play a crucial role here, in the second column for both dependent variables we include the last withdrawal fraction in the *chosen* bank. This information is available in both information treatments, whenever subjects chose a bank in the previous round, and given the group interaction, it seems to be a more relevant piece of information than subjects' own previous decision.[13]

The regression results in Table 4.4 reveal that both information and riskiness affect the decisions. With a few exceptions, most effects are strongly significant. First of all, under full information subjects are more likely to choose the risky bank than under

[13]Including this variable instead of own previous decisions makes it also possible to use a simpler model, as we do not need to estimate a dynamic model then.

Table 4.4: Panel logit regressions – all data

Dependent variable:	Deposit in risky bank		Withdrawal decision	
	(1)	(2)	(3)	(4)
Withdrawing fraction$_{t-1}$		-2.647^{***}		3.660^{***}
		(0.058)		(0.073)
Deposit in risky bank$_t$			-2.059^{***}	-1.531^{***}
			(0.039)	(0.045)
Full information	0.748^{***}	0.510^{***}	0.178	0.251^{*}
	(0.051)	(0.055)	(0.101)	(0.110)
High risk	-0.886^{***}	0.715^{***}	3.587^{***}	1.703^{***}
	(0.044)	(0.057)	(0.078)	(0.088)
Medium risk	0.490^{***}	0.782^{***}	1.385^{***}	0.687^{***}
	(0.049)	(0.055)	(0.083)	(0.096)
Round	0.015^{***}	0.016^{***}	0.015^{***}	0.008^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Full * high	-0.565^{***}	-0.650^{***}	-0.792^{***}	-0.412^{***}
	(0.066)	(0.072)	(0.112)	(0.123)
Full * medium	-0.534^{***}	-0.763^{***}	-1.589^{***}	-0.849^{***}
	(0.074)	(0.082)	(0.137)	(0.155)
Constant	0.527^{***}	0.576^{***}	-2.278^{***}	-2.701^{***}
	(0.040)	(0.042)	(0.076)	(0.081)
Observations	28,399	23,749	28,399	27,749
Log Likelihood	−15,832.92	−13,242.63	−9,164.49	−7,124.891

Notes: ***: significant on 0.1%-level, **: significant on 1%-level, *: significant on 5%-level. Columns (1) and (2) show the results of pooled logit regressions with the bank choice decision as dependent variable (1 = risky bank, 0 = safe bank). Columns (3) and (4) show the results of pooled panel logit regressions for the withdrawal decisions as dependent variable (1 = withdraw, 0 = wait). Deposit in risky bank is 1 for choosing the risky bank in the given round, 0 otherwise. Full information is 1 for the full info treatments, 0 otherwise. High risk is 1 for the high risk treatments, 0 otherwise. Medium risk is 1 for the medium risk treatments, 0 otherwise. Full information is interacted with the medium and high risk dummies. Lagged variable for the withdrawing fraction in the chosen bank is included. Standard errors are clustered on the session level, and are in brackets.

partial information. Consistent with the averages in Panel A of Table 4.3, the effect of information is significantly smaller for medium and high risk treatments compared to the low risk treatment (see interaction terms between the treatment dummies).[14] In fact, by running the logit regressions separately on each subsample of medium or high risk, we find that full information facilitates the choice of the risky bank, but only if we do not control for history in the bank as in column (2). When controlling for history, full information does not have an effect under high risk, and has a negative effect under medium risk (see regression outputs in Table 4.11 in Appendix 4.E). This might be due to the fact, that

[14] Table 4.9 in Appendix 4.E provide additional specifications for robustness checks. In one of these we exclude the interaction term between the treatment dummies. Also then full information has a positive effect on choosing the risky bank.

path dependency has a much stronger effect on decisions, thus once subjects coordinate on the Nash equilibrium (which is easier under full information), they change their decisions less often. However, under partial information they need more time to coordinate, thus there they might choose the risky bank more often irrespective of the withdrawal rate in the hope of coordination and higher earnings.

First turning our attention to the relative risk, we can see that under partial information medium risk increases the probabilities of choosing the risky bank and of withdrawing compared to low risk (see coefficient 'Medium risk'). Under full information however there is no significant difference between low and medium risk treatments. Looking at the effect of high risk compared to low risk we find that high risk decreases the probability of choosing the risky bank for both partial and full information. However, when controlling for the fraction of depositors running in the previous period this is only true in the full information treatment. Under partial information high risk increases the probability of choosing the risky bank. The explanation for this could be that subjects experiment more in the high risk treatment after the same withdrawal rate, because they have less information, but higher profits to earn. Withdrawal rates under high risk are always higher than under low risk, no matter which information setting we consider. Subjects are more likely to withdraw when facing this high risk.[15] Note that for withdrawal decisions we always control for the chosen bank in the given period. In line with the forward induction argument we find that subjects choosing the risky bank are less likely to withdraw their deposits. These observations lead us to our first result, which relates to Hypothesis 1.

Result 1 *We do not see a monotonic relationship between the level of coordination on the Nash equilibrium and the riskiness of the safest bank. Subjects in low and medium risk treatments coordinate more often on the Nash equilibrium without a clear ordering between the treatments. High risk leads to significantly less deposits in the risky bank and significantly higher withdrawal rates.*

Next we look at the effect of the information structure. Here we see that the effect of full information is significantly negative for the high and medium risk treatments (here we control for the chosen bank as well), but either insignificant or slightly positive for the low risk treatment. This means that in the treatments with more risk involved information helps subjects to coordinate on the risky bank, and facilitates waiting irrespective in which bank they are. This leads us to our second result, related to our second hypothesis.

[15] In order to draw conclusions about the the effect under full information we have run the same regressions on the subsample of all decisions under full information, as we did for riskiness. The results are reported in Table 4.10 in Appendix 4.E.

Table 4.5: Comparison of first rounds of convergence

	$\boldsymbol{t_c}$ full	$\boldsymbol{t_c}$ partial	$\bar{t}_c$ full	$\bar{t}_c$ partial	full vs partial
low risk	9, 11, 3, 4, 19, 26	7, 5	12	6	0.64
medium risk	12, 5, 4, 5, 15	13, 27, 8, 5	8	13	0.40
high risk	-	-	-	-	1

Result 2 *On average, full information leads to more coordination on waiting in the risky bank.*

Before turning to the speed of convergence, we briefly discuss the strengths of the different treatment effects by comparing coefficients with the regressions. High risk seems to have the strongest effect of all treatment dimensions, whereas there is no clear ordering between information structure and the differences between the other two riskiness levels. It is important to note that path dependence indeed plays a large role in our experiment, as expected (remember, IEL is also dependent on the intiialization). In fact the coefficient of the previous-period withdrawal fraction is highly significant for both the bank choice and the withdrawal decision. The more subjects withdrew in a given round, the less likely agents choose the risky bank (irrespectively where the withdrawal happened) and the more likely agents will withdraw their money. Note that a direct comparison between the magnitude of this coefficient and the treatment effect is less useful, as treatments are dummy variables, whereas the withdrawing fraction is variable taking values between 0 and 1. The impact of an additional subject choosing to withdraw depends on the number of depositors in the given bank.

To test our hypothesis on the speed of convergence, we check for each experimental session if convergence took place (according to our criterion in Section 4.3.3) and, for those that did, record the first round of convergence. Table 4.5 displays the lists of first convergence rounds ($\boldsymbol{t_c}$) for all treatments, their averages ($\bar{t}_c$), and the p-value of a Mann-Whitney U test comparing the results of full and partial information. Although the averages differ considerably from each other, we do not find any significant effects due to the low number of partial information sessions in which we observe convergence. Therefore we cannot draw any definite conclusions about whether the amount of information provided to the agents affects the speed of convergence or not.

Result 3 *We do not find a significant effect of the information structure (full or partial information) on the speed of convergence to any particular strategy.*

Table 4.6: First round decisions

	Low risk	Medium risk	High risk	L vs. M	L vs. H	M vs. H
Panel A: Bank choice decision - risky bank						
Partial info	0.46 (0.50)	0.43 (0.50)	0.44 (0.50)	0.72	0.83	0.88
Full info	0.52 (0.50)	0.55 (0.50)	0.51 (0.50)	0.66	0.94	0.61
p-value	0.43	0.11	0.34			
Panel B: Withdrawal rate in the safer bank						
Partial info	0.12 (0.33)	0.20 (0.41)	0.30 (0.46)	0.20	0.015**	0.20
Full info	0.15 (0.36)	0.16 (0.37)	0.32 (0.47)	0.81	0.05*	0.09
p-value	0.73	0.60	0.83			
Panel C: Withdrawal rate in the riskier bank						
Partial info	0.05 (0.21)	0.00 (0)	0.07 (0.26)	0.48	0.37	0.11
Full info	0.00 (0)	0.13 (0.34)	0.14 (0.35)	0.004**	0.005**	0.81
p-value	< 0.001***	0.015**	0.32			
Panel D: Comparison in withdrawal rates across bank types (p-values)						
Partial info	0.14	< 0.001***	0.004**			
Full info	< 0.001***	0.59	0.03*			

Notes: ***: significant on 0.1%-level, **: significant on 1%-level, *: significant on 5%-level. Standard deviations are in brackets. Panel D compares the withdrawal decisions across the two banks. All p-values are based on two-sided permutation tests with individuals as observations, and z-score for proportion test as test-statistics (with 100,000 permutations per test). For Panels A and D all subjects in the given treatment are considered. For Panels B and C only part of the population is used as observations, in particular those choosing the bank in consideration.

4.5.2 First round decisions

To get more insights in the observed dynamics, we turn to the beginning of the experiment. Did subjects decide differently in the first round already, or did they learn to converge to a given outcome later? Table 4.6 shows how subjects decide in the first round of the experiment. Given that in the first period all individual decisions are independent, we also provide test-statistics based on the permutation test on pairwise comparisons. Panel A presents the fraction of subjects choosing the risky bank in the first round. Panel B presents the withdrawal rates in the safer bank, whereas Panel C presents the withdrawal rate in the riskier bank. Looking at the bank choices in the first round, we see that in all treatments around half of the subjects (43-55%) decided to choose the risky bank regardless of the information and the relative riskiness of the two banks.[16]

Turning to the withdrawing decisions, we do not find substantial treatment differences

[16]None of the pairwise comparisons between treatments results in significant difference. In this section we used a permutation test based on the proportion test-statistics on individual level in order to get rid of the problem that the non-parametric ranksum test has with ties.

considering only the safer bank (see Panel B in Table 4.6). Subjects withdraw in 12-32% of the cases, and these differences are only significant when we compare the lowest riskiness to highest riskiness level. Remember that in this case the safer bank in the high risk treatment is much riskier than in the low risk treatment (see Table 4.2). Looking at the riskier bank (see Panel C in Table 4.6), we find significant differences under full information and also between the two lower risk treatments. In particular, under full information in the low risk treatment nobody withdrew from the risky bank in the first round, whereas 13-14% of the subjects withdrew in both in the medium risk and high risk treatments. Furthermore, nobody withdrew in the risky bank in the medium risk treatment under partial information which is a significantly lower withdrawal rate than in the full information treatment with the same riskiness. Finally, comparing the safer and riskier banks in the same treatments, in four out of the six treatments we see that subjects withdrew significantly less often in the risky bank than in the safe bank. The difference is highly significant ($p < 0.01$) for medium and high risk under partial information and for low risk under full information (see Panel D in Table 4.6 for the p-values). The forward induction argument intuitively explains our findings of more withdrawal from the safe bank, and it is also in line with the findings of Chapter 3.

Even though we do not see many significant treatment differences in the first round decisions, the resulting outcomes of these decisions are already different. While on average banks do not become insolvent with these average withdrawal rates under low risk, and medium risk, this is not the case for high risk.[17] For high risk most banks start with some withdrawal which can be detrimental for later rounds, as insolvency was more likely to occur.

In Table 4.6 we performed pairwise comparisons with subsamples of the data that only contained the two treatments we compared to each other. To further investigate the general treatment effects, we pooled all the data, and looked at logit regressions as well. This way we investigate the treatment effects also from a different angle. Table 4.7 reports the results of these logit regressions for the bank choice decision (column (1)) and for the withdrawal decisions in the first round (column (2)). From column (1) we see no treatment differences, confirming the picture Table 4.6 gave. Column (2) shows that choosing the risky bank significantly decreases the likelihood of withdrawing in the first round. Furthermore, being subject to high risk compared to low risk significantly increases the withdrawing probability consistent with the findings of Table 4.6. Further robustness checks showing the same treatment effects (including interaction terms between

[17]Note that for medium risk under full information the average withdrawal rate is above the insolvency threshold, but this average rate means less than 1 person withdrawing per bank. Given full information it is easier to learn for this single person to wait in the risky bank.

treatments and controls for demographics) are relegated to Table 4.12 in Appendix 4.E.

Table 4.7: Logit regressions for the first round decisions

	(1)	(2)
Dependent variable:	Deposit in risky bank	Wihdrawing
full information	0.324	0.249
	(0.168)	(0.250)
high risk	−0.042	1.194***
	(0.206)	(0.328)
medium risk	0.012	0.591
	(0.206)	(0.350)
Deposit in risky bank		−1.331***
		(0.282)
Constant	−0.216	−2.108***
	(0.169)	(0.309)
Observations	570	570
Log Likelihood	−392.907	−212.698

Notes: ***: significant on 0.1%-level,**: significant on 1%-level, *: significant on 5%-level. Coloumn (1) shows the result of a logit regression with the bank choice decision as dependent variable (1 = risky bank, 0 = safe bank). Column (2) shows the result of a logit regression for the withdrawal decisions as dependent variable (1 = withdraw, 0 = wait). Deposit in risky bank is 1 for choosing the risky bank in the first round, 0 otherwise. Full information is 1 for the full info treatments, 0 otherwise. High risk is 1 for the high risk treatments, 0 otherwise. Medium risk is 1 for the medium risk treatments, 0 otherwise. Heteroskedasticity-robust standard errors are in brackets.

4.6 Conclusion

Bank runs are relatively rare phenomena and there are few people that are subject to them more than once or twice in their lifetimes. This has led some authors to focus primarily on single-shot games or first-round decisions (e.g. Schotter and Yorulmazer, 2009 or Chapter 3 of this thesis). However, there are two reasons why learning can be important for studying bank runs. The first is that the bank run setting is only one specific example of a coordination problem. Coordination problems in general are quite common. People may learn from earlier (mis)coordination and apply this also when they are facing a decision to withdraw from a bank or not. The second reason is that as long as depositors manage to avoid bank runs, the coordination problem stays intact. This may be less relevant in a study that aims to look at the parameters that (consistently) trigger bank runs, but does become relevant when we broaden the analysis, for example by including deposit decisions. Unlike in many bank run experiments, the (fewer) withdrawals in the single-shot bank choice game, in which subjects make both a deposit and a withdrawal decision, rarely cause banks to become insolvent (Chapter 3). This is mainly because those who are reluctant to bear the strategic uncertainty that comes with the 'wait' decision initially avoid depositing in risky banks. About half the subjects leave a considerable amount of money on the table with this choice. Such initial situation is therefore also unlikely to persist and when depositors move from one bank to another (riskier) bank, it is natural for all depositors to reevaluate also the withdrawal decision again.

In this chapter we study dynamics and learning in the bank choice game both with a (repeated) bank choice experiment and with simulations. For the experiment we used the most basic version of the game. Subjects can choose between a 'risky' and 'safe' bank to deposit an initial endowment in and after making this choice they have to decide whether to withdraw that deposit or not. This is repeated for 50 rounds with the same two banks. As in the earlier single-shot study, both banks receive a similar share of depositors in the first round. In most sessions the initial withdrawals are also quite low. At this point we see few significant differences between treatments with different levels of riskiness of the two banks. However, this changes in subsequent periods. In sessions which combine low- or moderate-risk banks with high-risk banks, the majority of depositor groups converge on playing the single pure-strategy Nash equilibrium of the game: deposit in risky bank and not withdrawing. But in sessions with only high-risk banks subjects do not coordinate on any strategy, not even after 50 rounds.

In our experiment we also varied the amount of information that was shared with subjects at the end of each round. In the full information treatments subjects could see how many depositors each bank had and how many of those withdrew. In the partial information treatments they were only informed about the fraction of withdrawals in the bank that they deposited in. In the experiment we only noticed a minor impact of information on the subjects' decisions. However, this treatment variation has large consequences for the simulations with the individual evolutionary algorithm, because the partial information condition required us to extend the algorithm with beliefs. We tried several possible ways of introducing beliefs and found that the only way in which we can reproduce the experimental results is by assuming that agents are very sophisticated in their belief-updating.

Appendix 4.A Instructions

In this Appendix we reproduce the experimental instructions. In Section 4.A.1 the instructions for the bank choice game in treatment low risk, partial info is given for both locations. In Section 4.A.2 we list the differences between the different treatments to give a complete view of all instructions. Section 4.A.3 graphically presents the 4 different bank types we used in the experiment. Finally, in Section 4.A.4 the instructions for the loss aversion task is presented. These instructions were identical in all bank choice treatments.

4.A.1 Instructions for treatment LP

This subsection presents the instructions for the treatment low risk, partial information. The differences in locations only consist of a different exchange rate, and the different information needed to pay subjects out. These differences are added in italics in brackets in the text. Bold fonts were also bold in the experiment. The correct answers for the understanding questions are added in italics in brackets after each question.

PAGE 1

Welcome!

Today you participate in an experiment on economic decision making. In this experiment we use **anonymization** to ensure that neither the experimenters, nor the other participants know who is behind the decisions that you take. To be able to pay you, we will ask you for an [(Vancouver) ***email address*** / (Amsterdam) ***IBAN-number***], but not your name. Also, this information will be removed from the data set once your payment is processed.

Note that only those who **fully complete** the experiment **will get paid**. Therefore, if you experience errors or connection problems of any kind, contact the experimenters via the Zoom chat or, if that is not possible, send an email to [*email Vancouver* / *email Amsterdam*].

This page is followed by a page with instructions. Please read these instructions carefully and answer the five-question quiz on the following page in order to proceed to the experiment. On the quiz page, you can revisit the instructions by scrolling downwards. Once all participants have answered all quiz questions correctly, the experiment will start. At the end of the experiment, you will be asked to fill out a short questionnaire.

By clicking the button below, you consent to the collection of your participation data for the sole purpose of research. Thank you for your participation and good luck!

PAGE 2

Introduction

This experiment consists of two parts. The first part has 50 rounds in which you can earn points. The second part consists of a single page with choices with which you can win more points or lose some. When both parts are finished the total number of points that you earned is converted into [*dollars / euros*] at a rate of [*450 points for 1 dollar / 675 points for 1 euro*]. How much you will earn exactly depends on your choices and the choices of other participants, but it can add up to a considerable amount. Additionally, you will receive a [*$7.00 / €5.00*] participation fee.

General information

In each round of the first part you have to make two choices. First you select the bank in which you want to receive your endowment of 75 points. You can choose between two options: Round Bank and Square Bank. In Round Bank you can potentially earn more interest, but it is also more vulnerable when people withdraw early. In one of the sections below we will go into more detail about this tradeoff.

When everyone selected a bank, you are given the choice to either withdraw your endowment immediately, or wait and collect interest. If few people withdraw, you earn more by leaving the money in the bank. However, if many withdraw, the bank will not be able to fully pay out all depositors and those who decided to wait, lose their money.

In the next round you again start with an endowment of 75 points. Any money that you earned in the previous round is set aside to be paid out at the end of the experiment.

The depositors

You are participating in this experiment with 11 other participants. All receive the same endowment, are given the same information, and face the same choices as you are confronted with. Upon choosing a bank, some may decide to deposit at Round Bank and some others at Square Bank. Your payoff will only depend on your decision and the decisions of those who chose to deposit in the same bank. The decisions of those who deposited in the other bank will not affect your earnings in that round. At the time that you have to make the decision to withdraw or not, you do not know exactly how many others deposited in the same bank. At the end of the round you learn what fraction of the total depositors of your bank chose to withdraw their deposits.

The banks

The tradeoff between the interest rate and the bank's vulnerability is best explained using a graph. Below you find how much a depositor receives when choosing to withdraw (red curve) and choosing to wait (blue curve) as a function of the fraction of total deposits that is withdrawn in the particular bank in that period. The graph on the left is for Round Bank and the graph on the right for Square Bank.

Round bank **Square bank**

[Figures 4.A.1b and 4.A.1d appear here next to each other in the instructions.]

Let's start with Round Bank. When none of the depositors in Round Bank withdraws, they all receive 200 points. However, when a fraction of 0.2 of the depositors withdraws (that is 1 out of 5 depositors), those who withdraw receive 75 points and those who wait receive nothing. When more than a fraction of 0.2 of the depositors withdraws, those who withdraw receive less than 75 points, while those who wait still receive nothing.

In Square Bank the maximum earnings when everyone waits, are lower: 125 points. However, when a fraction of 0.2 of the depositors withdraws those who wait still receive 117 points. Only when a fraction of 0.8 of the depositors withdraws (4 out of 5 depositors), those who decided to wait receive nothing. So, although the maximum earnings in Square Bank are considerably lower, it is also considerably less vulnerable to early withdrawals.

Decision time

In each round you have enough but limited time to make your decisions. You have 1 minute to choose your bank, and then again 1 minute to choose whether you wait or withdraw your deposit. If you don't make at least one of your decisions on time, you earn nothing for the given round. You are not counted then as a depositor for the others either. If you don't make the bank choice decision on time, you will not see the screen for the second decision. If you fail to make at least one of your decisions in 3 rounds of the experiment, you cannot continue with the experiment, and you will not be paid at all.

Information

The graphs with the payoffs in the two banks will be visible on the screen when you have to choose a bank to deposit in. Next to the graphs a table with the past performance of the banks will be provided. It shows the fraction of depositors withdrawing in your bank. You will only see this information for one of the banks for each round: the one you chose in the given round. In case a bank attracted no depositors in a particular round, the fraction of withdrawing depositors cannot be calculated. In that case the fraction is represented by a dash ('-'). The last column of the table shows how many points you earned in that round.

Contact

During the experiment you can always contact the experimenter using the Zoom chat function. The experimenter will first try to help you via chat. If the problem cannot be resolved that way, you will be invited into a break-out room where full Zoom functionality can be enabled (including screen sharing if necessary). If for any reason you cannot contact us via Zoom, you can send an email to [*email Vancouver / email Amsterdam*].

Summary

In each of the 50 rounds of the first part you have to choose a bank to receive your endowment in. This endowment is always 75 points. Round Bank provides a higher interest rate than Square Bank, but is also more vulnerable to bankruptcy if depositors withdraw early. After you have chosen a bank, you are given the opportunity to withdraw immediately, or leave your money in the bank to collect interest. During the experiment, you will have access to the performance of your chosen banks in previous rounds (fraction of depositors deciding to withdraw). The second part consists of a single series of choices with which you can gain or lose points. This will be further explained after the first part.

On the next screen you are asked to answer some questions to test your understanding of the experiment.

PAGE 3

Understanding Questions

1. Suppose you end period 1 with earnings of 150 points. How many points can you deposit in the bank in period 2? [*Answer: 75*]

2. Suppose you do not choose a bank in a given period. What are your earnings in points in that period? [*Answer: 0*]

3. For this question you have to use the graphs provided in the instructions below. Suppose you choose the Square Bank. Next, you decide to wait, but some other depositors withdraw. The withdrawing depositors constitute a fraction of 0.2 of the total number of depositors in Square Bank in that round. What are your earnings in points in this period? [*Answer: 117*]

4. For this question you have to use the graphs provided in the instructions below. Suppose you choose the Round Bank with 4 other depositors. The earnings graph associated with Round Bank is shown above. You and another depositor decide to withdraw the deposit. What are your earnings in points in this period? [*Answer: 38*]

5. Do you receive information about the number of depositors in your chosen bank?

    a. No [*correct answer*]

    b. Yes

4.A.2 Differences in other treatments

In this subsection we detail out the differences between our treatments by listing the changes compared to the instructions in Section 4.A.1. We divide the differences into different risk levels and different information.
Different risk levels: For the different risk levels the following texts change:

- For medium risk we use bank types 1 (Figure 4.A.1b) and 2 (Figure 4.A.1c) for Round and Square bank, respectively. For high risk we use bank types 0 (Figure 4.A.1a) and 1 (Figure 4.A.1b) for Round and Square bank, respectively.

- The numbers in the paragraph 'Let's start with Round Bank...' change in high risk. The maximum earnings of 200 becomes 225, but the threshold fraction decreases from 0.2 to 0.1 (thus 1 out of 10 depositors).

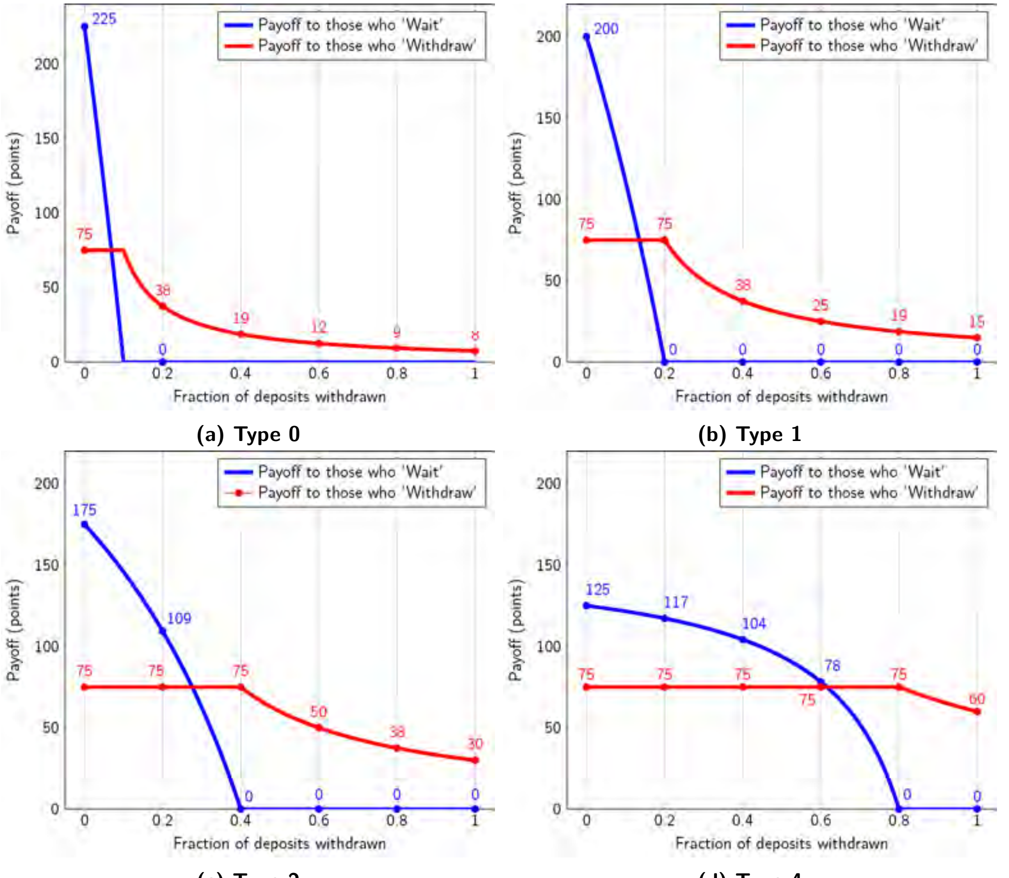
- The numbers in the paragraph 'In Square Bank' changes for both other risk levels. The maximum earnings are 175 and 200 points in medium, and high risk, respectively. The example fraction of depositors in the second sentence matches the threshold for the Round Bank, thus changes to 0.1 in high risk from 0.2. The payoff corresponding to this fraction is 109 in medium risk, and 111 in high risk. The threshold fraction of withdrawals of 0.8 (4 out of 5 depositors) changes to 0.4 (2 out of 5 depositors) in medium risk and to 0.2 (2 out of 10 depositors) in high risk.
- The correct answer to Understanding question nr. 3 changes from '117' to '109' in medium risk, and to '0' in high risk.
- The correct answer to Understanding question nr. 4 changes from '38' to '19' in high risk.

Different information: In the treatments with full information there are the following differences:

- Under 'Information' two sentences, starting by 'It shows the fraction...' change to 'It shows the fraction of depositors withdrawing in your bank by indicating the number of withdrawals and the number of depositors in the bank (e.g. 2/5 means that 2 out of 5 depositors withdrew their money from the bank). This information will be given for both banks, also the one in which you did not deposit in that particular round.'
- Under 'Summary' the sentence starting with 'During the experiment,...' changes to 'During the experiment, you will have access to the performance of both banks in previous rounds (number of depositors, and fraction of depositors deciding to withdraw).'
- The correct answer to Understanding question nr. 5 ('Do you receive information...?') changes from 'No' to 'Yes'.

4.A.3 Bank types

Figure 4.A.1 shows the payoffs of the different actions in the different bank types as the function of fraction of withdrawals.



(a) Type 0 (b) Type 1 (c) Type 2 (d) Type 4

Figure 4.A.1: Bank types used in the experiment

4.A.4 Instructions for the loss aversion task

In this subsection we reproduce the instructions for the loss aversion task. This instruction was the same after all treatments. The only difference in location was the conversion rate, denoted by italics in brackets below. In the table below radio buttons were presented for subjects to make their decisions.

Additional task

Below you find a series of 6 lotteries. In each of them there is a 50% chance to lose points and a 50% chance to gain points. In the end, one of these lotteries will be randomly selected (with equal probabilities). You can indicate for each lottery if you would like to play this lottery if it is selected, or not. If you chose to play a lottery and it is selected, the lottery is played and you will gain or lose points. If you chose not to play that particular lottery, nothing will happen. As a reminder, the conversion rate is [*450 points for 1 dollar / 675 points for 1 euro*].

50%	50%	Accept to play?
-150	1350	Yes / No
-450	1350	Yes / No
-750	1350	Yes / No
-1050	1350	Yes / No
-1350	1350	Yes / No
-1650	1350	Yes / No

Appendix 4.B Simulation results for different levels of experimentation

This Appendix presents further simulation results with experimentation rates $\rho = 0.01$ and $\rho = 0.10$.

Appendix 4.C Data per session

In this Appendix we provide plots of average strategies over rounds for each individual session. Figure 4.C.1 shows these plots for the treatments with full information and Figure 4.C.2 contains the plots for the partial info treatments. The four strategies are again represented by different colors: red for depositing in the risky bank and waiting, green for depositing in the safe bank and waiting, blue for depositing in the safe bank and withdrawing, and black for depositing in the risky bank and withdrawing.

Fraction of withdrawals: >90% 50-90% 10-50% <10%

$\rho = 0.01$

Full info

Initialization $f_r = 0.5,\ f_s = 0.5$

	0	1	2	3	4	5
0	1	2	2	9	12	12
1		2	3	7	12	12
2			2	7	11	12
3				5	12	12
4					5	12
5						6

Initialization $f_r = 0.1,\ f_s = 0.5$

	0	1	2	3	4	5
0	5	7	10	11	12	12
1		7	11	12	12	12
2			8	12	12	12
3				8	12	12
4					11	12
5						8

Partial info Sophisticated

Initialization $f_r = 0.5,\ f_s = 0.5$

	0	1	2	3	4	5
0	11	5	7	7	7	7
1		11	6	6	7	6
2			10	6	7	6
3				6	6	7
4					6	10
5						6

Initialization $f_r = 0.1,\ f_s = 0.5$

	0	1	2	3	4	5
0	11	7	8	9	9	10
1		10	9	10	9	9
2			10	11	11	12
3				10	12	12
4					11	12
5						10

Partial info Naive-lastknown

Initialization $f_r = 0.5,\ f_s = 0.5$

	0	1	2	3	4	5
0	6	0	0	0	0	0
1		6	0	0	0	0
2			6	0	0	0
3				6	1	1
4					5	8
5						5

Initialization $f_r = 0.1,\ f_s = 0.5$

	0	1	2	3	4	5
0	5	0	0	0	1	1
1		10	7	8	8	8
2			11	11	11	11
3				12	12	12
4					11	12
5						11

Partial info Naive-neutral

Initialization $f_r = 0.5,\ f_s = 0.5$

	0	1	2	3	4	5
0	6	7	7	6	1	0
1		6	7	6	1	0
2			6	5	2	0
3				5	2	1
4					5	4
5						6

Initialization $f_r = 0.1,\ f_s = 0.5$

	0	1	2	3	4	5
0	8	8	8	7	4	3
1		10	10	9	5	5
2			11	10	8	8
3				11	9	8
4					9	8
5						8

Figure 4.B.1: Simulation results with $\rho = 0.01$. Each table shows information about the average strategies in rounds 26 to 50 for all combinations of the 6 bank types defined in Table 4.1. The color represents the average fraction of withdrawals from both banks and the number represents how many of the 12 agents choose to deposit in the risky bank.

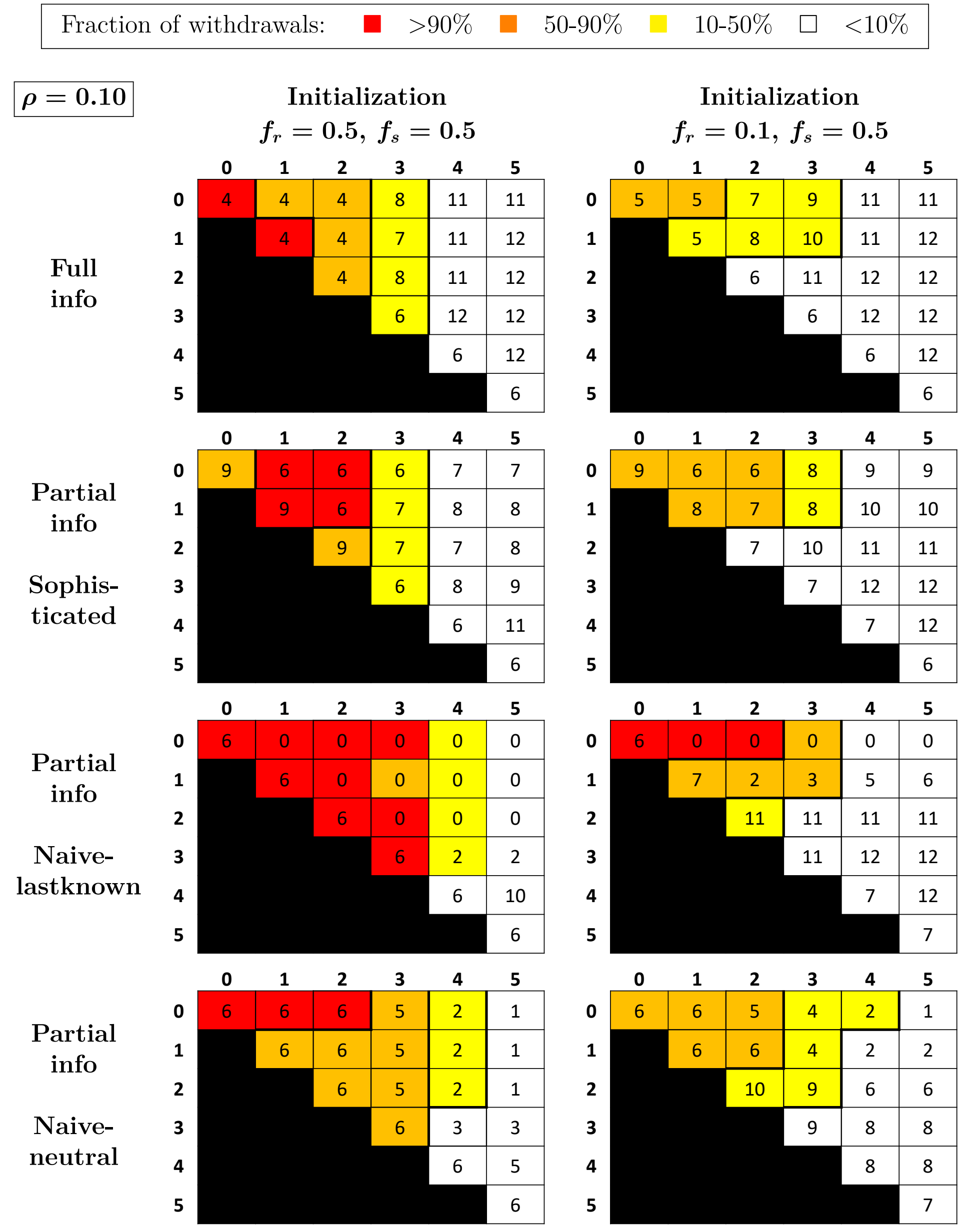


Figure 4.B.2: Simulation results with $\rho = 0.10$. Each table shows information about the average strategies in rounds 26 to 50 for all combinations of the 6 bank types defined in Table 4.1. The color represents the average fraction of withdrawals from both banks and the number represents how many of the 12 agents choose to deposit in the risky bank.

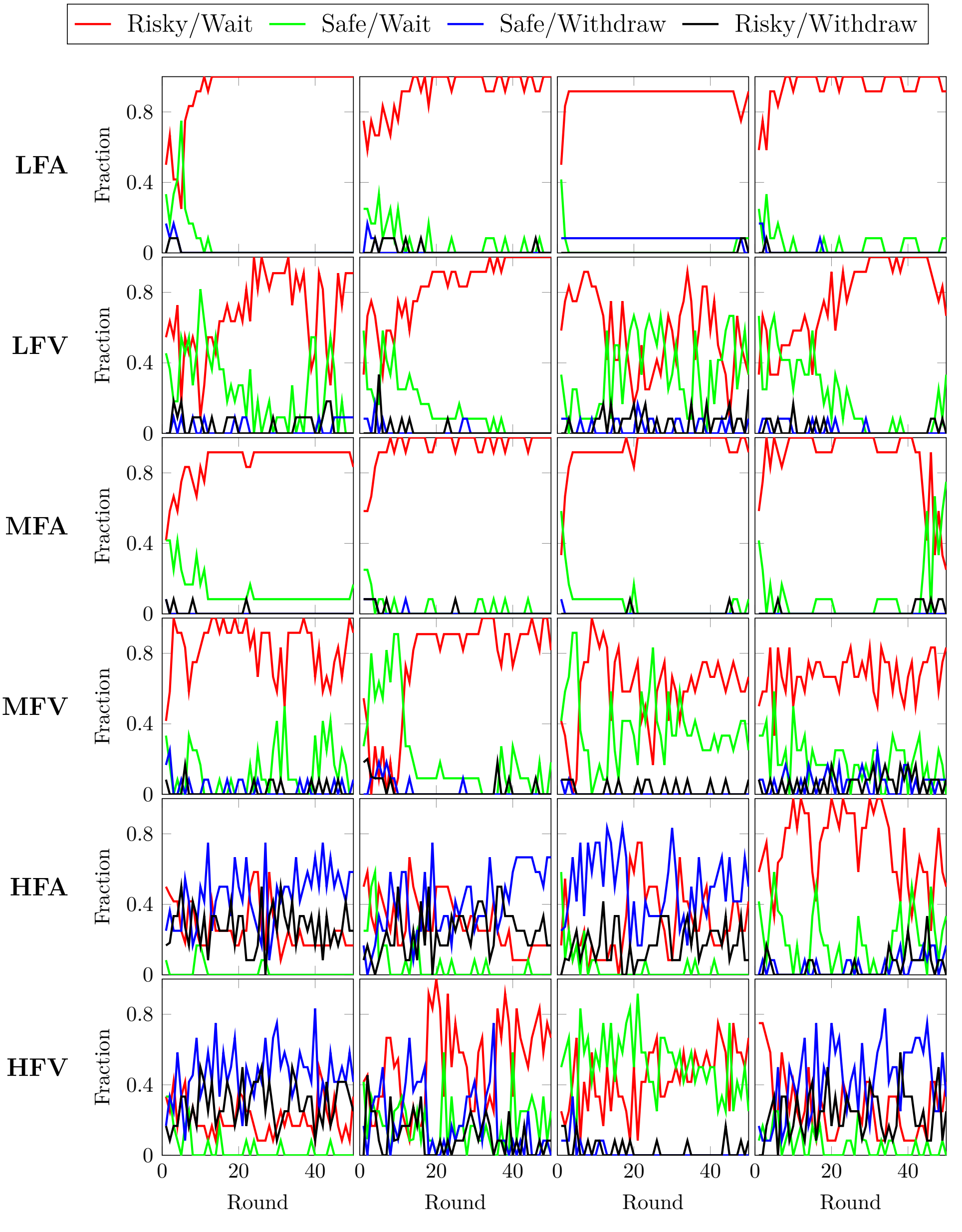


Figure 4.C.1: Strategies per group under full information. The first letter, L, M, or H, indicates whether the combination of banks was low risk, medium risk, or high risk and the last letter, A or V, is used to distinguish Amsterdam and Vancouver sessions. All treatments in this figure are full information treatments (hence the middle letter F).

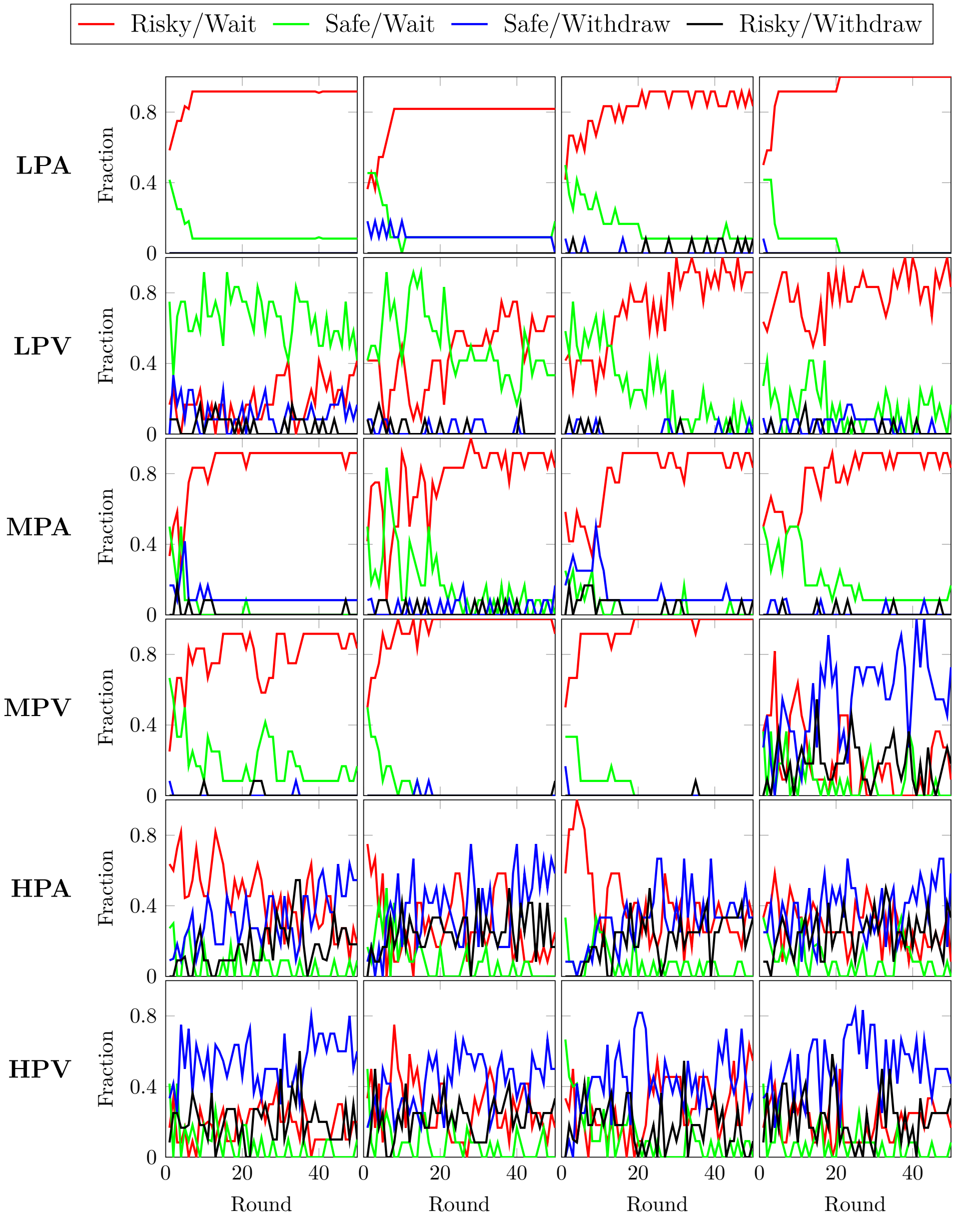


Figure 4.C.2: Strategies per group under partial information. The first letter, L, M, or H, indicates whether the combination of banks was low risk, medium risk, or high risk and the last letter, A or V, is used to distinguish Amsterdam and Vancouver sessions. All treatments in this figure are partial information treatments (hence the middle letter P).

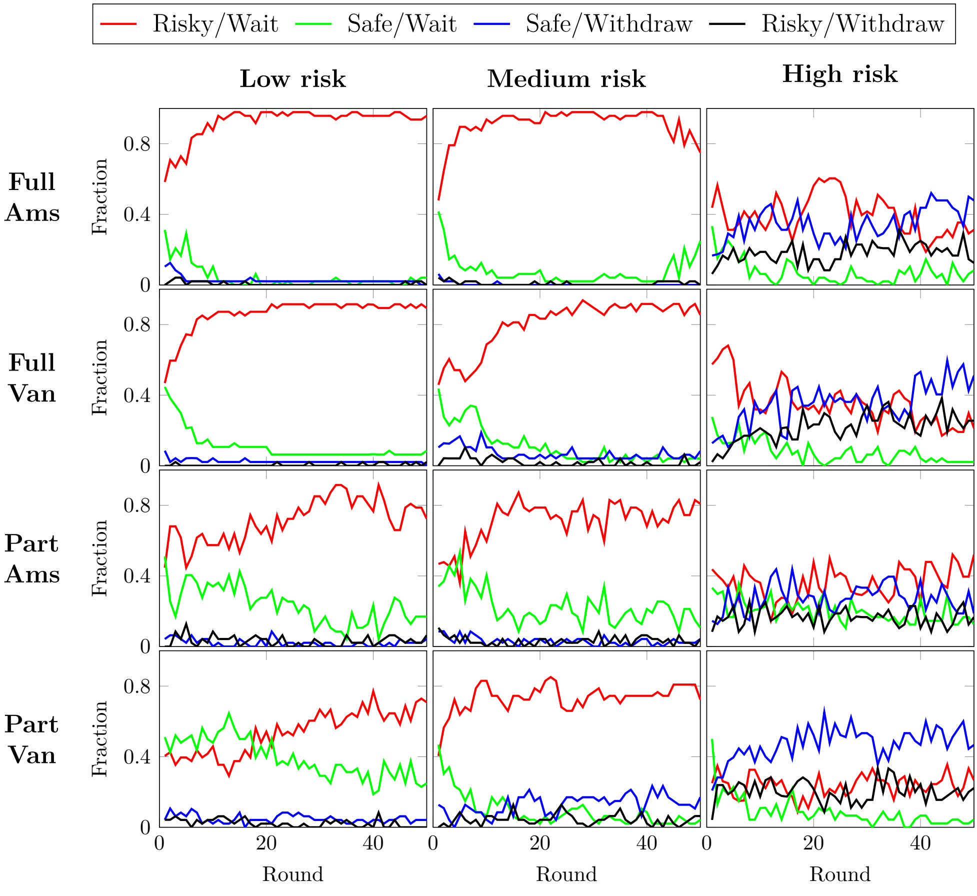


Figure 4.D.1: Strategies in the experiment in Amsterdam and Vancouver. The first two rows correspond to treatments with full, and the third and forth row correspond to treatments with partial information.

Appendix 4.D Location effect

In this Appendix we discuss the data in the two locations, Amsterdam and Vancouver. First, Figure 4.D.1 gives an overview over the aggregated data per treatment and location. Table 4.8 presents averages about bankchoices and withdrawal rates depending on the chosen bank per location and treatment. From the figures we can see that coordination seems to be quicker in Amsterdam than in Vancouver, but the qualitative results are the same. Given that we are more interested in the aggregated treatment effects (our hypotheses compare treatments) we pooled the data from the two locations for the main analyses. In this appendix we discuss the differences in the locations.

As we can see from Figure 4.D.1 and Table 4.8 comparing full information and partial information within a location does not show very different behavior for most of the cases. Partial information leads to a bit lower coordination on the Nash equilibrium in low and medium risk for both locations. We see the highest difference between low-risk full and partial information treatments in Vancouver, where in both treatments subjects learn to wait, but under full information they wait more often in the risky bank. Looking across riskiness levels, we find no substantial differences between low and medium risk for three out of the 4 cases.[18] Under partial information the low-risk and medium risk treatments seem to differ more in Vancouver than in Amsterdam. However, comparing low and medium risk to high risk, we always see the same relationship: subjects withdraw more often under high risk irrespective of the information structure and the location.

Appendix 4.E Regression results

Table 4.9 shows different specification for the pooled logit regressions for bank choice and withdrawal decisions over the course of the experiment. Table 4.12 shows robustness of the results of the first round logit regressions for bank choice and withdrawal decisions.

[18]Note that withdrawal rates in the safe bank are based on a lower number of observations, especially in Amsterdam, than for the risky bank. This is due to the fact that in the low and medium risk treatments the majority of the subjects decided to choose the risky bank.

Table 4.8: Average bank choices and withdrawal rates for the whole experiment in the two locations

	Amsterdam			Vancouver		
	low	medium	high	low	medium	high
Panel A: Bank choice decision - risky bank						
partial info	0.87 (0.34)	0.82 (0.38)	0.57 (0.49)	0.56 (0.5)	0.78 (0.42)	0.44 (0.5)
full info	0.93 (0.26)	0.92 (0.27)	0.58 (0.49)	0.75 (0.44)	0.74 (0.44)	0.53 (0.5)
Panel B: Withdrawal rate in the safer bank						
partial info	0.18 (0.39)	0.39 (0.49)	0.82 (0.38)	0.11 (0.31)	0.59 (0.49)	0.85 (0.36)
full info	0.37 (0.48)	0.04 (0.19)	0.83 (0.38)	0.08 (0.28)	0.12 (0.33)	0.58 (0.49)
Panel C: Withdrawal rate in the riskier bank						
partial info	0.00 (0.07)	0.02 (0.15)	0.38 (0.49)	0.04 (0.2)	0.06 (0.23)	0.46 (0.5)
full info	0.01 (0.08)	0.01 (0.09)	0.31 (0.46)	0.04 (0.2)	0.04 (0.2)	0.31 (0.46)

Averages and standard deviations (in brackets) calculated on the individual level.

Table 4.9: Logit regressions for all decisions

Dependent variable:	Deposit in risky bank		Withdrawal decision	
	(1)	(2)	(3)	(4)
Withdrawing fraction$_{t-1}$		-2.599^{***}		3.656^{***}
		(0.058)		(0.074)
Deposit in risky bank$_t$			-2.035^{***}	-1.550^{***}
			(0.039)	(0.046)
Full information	0.361^{***}	0.566^{***}	-0.666^{***}	0.207
	(0.027)	(0.056)	(0.038)	(0.110)
High risk	-1.140^{***}	0.632^{***}	3.289^{***}	1.716^{***}
	(0.032)	(0.058)	(0.057)	(0.088)
Medium risk	0.259^{***}	0.696^{***}	0.832^{***}	0.676^{***}
	(0.036)	(0.056)	(0.064)	(0.097)
Full info * high		-0.684^{***}		-0.296^{*}
		(0.073)		(0.123)
Full info * medium		-0.650^{***}		-0.813^{***}
		(0.084)		(0.155)
Round	0.015^{***}	0.016^{***}	0.015^{***}	0.008^{***}
	(0.001)	(0.001)	(0.001)	(0.002)
Age		-0.019^{***}		-0.070^{***}
		(0.004)		(0.006)
Male		0.225^{***}		-0.200^{***}
		(0.031)		(0.045)
Amsterdam		0.726^{***}		-0.002
		(0.031)		(0.045)
Constant	0.693^{***}	0.592^{***}	-1.962^{***}	-1.060^{***}
	(0.036)	(0.096)	(0.062)	(0.152)
Observations	28,399	23,669	28,399	23,669
Log Likelihood	−15,875.17	−12,892.87	−9,235.0.87	−6,990.219

Notes: ***: significant on 0.1%-level, **: significant on 1%-level, *: significant on 5%-level. The first two columns show the results of of pooled panel logit regressions with the bank choice decision as dependent variable (1 = risky bank, 0 = safe bank). Columns 3-4 show the results of pooled panel logit regressions for the withdrawal decisions as dependent variable (1 = withdraw, 0 = wait). Deposit in risky bank is 1 for choosing the risky bank in the first round, 0 otherwise. Full information is 1 for the full info treatments, 0 otherwise. High risk is 1 for the high risk treatments, 0 otherwise. Medium risk is 1 for the medium risk treatments, 0 otherwise. Full info * high and full info * medium are interaction terms between the above-mentioned variables. Age is the subject's age, Male is 1 for males, and 0 otherwise. Amsterdam is 1 for individuals participating in Amsterdam, 0 otherwise. Lagged variable for withdrawing fractions in the chosen bank is included. Standard errors are clustered on the session level, and are in brackets.

Table 4.10: Logit regressions for separately for the full information treatments

Dependent variable:	Deposit in risky bank		Withdrawal decision	
	(1)	(2)	(3)	(4)
Withdrawing fraction$_{t-1}$		-2.036^{***}		4.270^{***}
		(0.081)		(0.115)
Deposit in risky bank$_t$			-1.678^{***}	-1.277^{***}
			(0.055)	(0.068)
High risk	-1.451^{***}	-0.215^{**}	2.785^{***}	1.128^{***}
	(0.049)	(0.065)	(0.080)	(0.102)
Medium risk	-0.044	0.043	-0.187	-0.177
	(0.056)	(0.062)	(0.107)	(0.126)
Round	0.015^{***}	0.010^{***}	0.007^{***}	0.002
	(0.001)	(0.002)	(0.002)	(0.002)
Constant	1.277^{***}	1.182^{***}	-2.104^{***}	-2.530^{***}
	(0.051)	(0.055)	(0.090)	(0.104)
Observations	14,283	10,870	14,283	10,870
Log Likelihood	−7,478.418	−6,046.538	−4,402.24	−3,022.953

Notes: ***: significant on 0.1%-level, **: significant on 1%-level, *: significant on 5%-level. The first two columns show the results of of pooled panel logit regressions with the bank choice decision as dependent variable (1 = risky bank, 0 = safe bank). Columns 3-4 show the results of pooled panel logit regressions for the withdrawal decisions as dependent variable (1 = withdraw, 0 = wait). Deposit in risky bank is 1 for choosing the risky bank in the first round, 0 otherwise. High risk is 1 for the high risk treatments, 0 otherwise. Medium risk is 1 for the medium risk treatments, 0 otherwise. Lagged variable for withdrawing fractions in the chosen bank is included. Standard errors are clustered on the session level, and are in brackets.

Table 4.11: Logit regressions for the two highest risk treatments separately

Treatment:	Medium risk				High risk			
Dependent variable:	Deposit in risky bank		Withdrawal decision		Deposit in risky bank		Withdrawal decision	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Withdrawing fraction$_{t-1}$		−3.667***		5.235***		−1.980***		3.287***
		(0.130)		(0.189)		(0.070)		(0.087)
Deposit in risky bank$_t$			−2.809***	−1.585***			−1.809***	−1.537***
			(0.089)	(0.119)			(0.047)	(0.054)
Full info	0.217***	−0.427***	−1.493***	−0.313*	0.183***	−0.071	−0.600***	−0.221***
	(0.054)	(0.067)	(0.096)	(0.127)	(0.041)	(0.045)	(0.046)	(0.054)
Round	0.026***	0.019***	0.013***	0.003	−0.002	0.007***	0.021***	0.007***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.001)	(0.002)	(0.002)	(0.002)
Constant	0.764***	1.537***	−0.466***	−2.400***	0.068	1.082***	0.988***	−0.698***
	(0.056)	(0.071)	(0.086)	(0.140)	(0.047)	(0.062)	(0.058)	(0.080)
Observations	9,493	7,009	9,493	7,009	9,411	9,017	9,411	9,017
Log Likelihood	−4,417.322	−3,125.094	−2,009.512	−1,152.823	−6,495.775	−5,784.733	−5,486.0.87	−4,377.335

Notes: ***: significant on 0.1%-level, **: significant on 1%-level, *: significant on 5%-level. The first four columns show the results of of pooled panel logit regressions only using data from the medium risk treatments. Columns 5-8 use data from the high risk treatments. The first two columns for both subsamples show results with the bank choice decision as dependent variable (1 = risky bank, 0 = safe bank). The second two columns show the results of pooled panel logit regressions for the withdrawal decisions as dependent variable (1 = withdraw, 0 = wait). Deposit in risky bank is 1 for choosing the risky bank in the first round, 0 otherwise. Full information is 1 for the full info treatments, 0 otherwise. Lagged variable for withdrawing fractions in the chosen bank is included. Standard errors are clustered on the session level, and are in brackets.

Table 4.12: Logit regressions for the first round decisions

	Dependent variable:					
	Deposit in risky bank			Withdrawal decision		
	(1)	(2)	(3)	(4)	(5)	(6)
Deposit in risky bank				-1.336^{***}	-1.349^{***}	-1.355^{***}
				(0.282)	(0.285)	(0.285)
Full information	0.234	0.309	0.228	-0.090	0.275	-0.105
	(0.292)	(0.170)	(0.293)	(0.546)	(0.253)	(0.547)
High risk	-0.062	-0.002	0.0004	1.010^{*}	1.216^{***}	0.993^{*}
	(0.292)	(0.209)	(0.296)	(0.458)	(0.331)	(0.464)
Medium risk	-0.105	0.024	-0.099	0.322	0.620	0.339
	(0.293)	(0.208)	(0.294)	(0.496)	(0.351)	(0.498)
Full info * high	0.040		-0.005	0.364		0.438
	(0.412)		(0.416)	(0.657)		(0.663)
Full info * medium	0.232		0.246	0.525		0.546
	(0.413)		(0.415)	(0.702)		(0.704)
Age		-0.032	-0.032		-0.051	-0.052
		(0.024)	(0.024)		(0.038)	(0.038)
Male		0.242	0.243		0.276	0.278
		(0.171)	(0.172)		(0.253)	(0.253)
Amsterdam		0.302	0.302		-0.109	-0.114
		(0.170)	(0.170)		(0.253)	(0.253)
Constant	-0.171	0.246	0.281	-1.936^{***}	-1.066	-0.858
	(0.207)	(0.551)	(0.569)	(0.379)	(0.887)	(0.925)
Observations	570	566	566	570	566	566
Log Likelihood	-392.727	-387.090	-386.852	-212.413	-208.888	-208.563

Notes: ***: significant on 0.1%-level, **: significant on 1%-level, *: significant on 5%-level. The first three columns show the results of logit regressions with the bank choice decision as dependent variable (1 = risky bank, 0 = safe bank). Columns 4-6 show the results of logit regressions for the withdrawal decisions as dependent variable (1 = withdraw, 0 = wait). Deposit in risky bank is 1 for choosing the risky bank in the first round, 0 otherwise. Full information is 1 for the full info treatments, 0 otherwise. High risk is 1 for the high risk treatments, 0 otherwise. Medium risk is 1 for the medium risk treatments, 0 otherwise. Full info * high and full info * medium are interaction terms between the above-mentioned variables. Age is the subject's age, Male is 1 for males, and 0 otherwise. Amsterdam is 1 for individuals participating in Amsterdam, 0 otherwise. Heteroskedasticity-robust standard errors are in brackets.

Summary

Expectations and beliefs play an important role in economics. The default choice in most economic models is to assume that people's expectations and beliefs are rational, meaning they are correct in expectation. In this thesis I study situations in which this assumption is not sufficient and different or extra assumptions about expectations are needed to explain phenomena that we observe empirically. Deviating from rational expectations or adding assumptions to it can be done in many ways and it is often difficult to find out which one is most in accordance with reality. Each chapter includes an experiment designed to solve this problem in a particular context.

Chapter 2 is a contribution to an old and unresolved question in financial economics: do futures markets help to reduce the volatility of commodity prices, or do they contribute to it? Almost all theoretical models predict that futures markets help to stabilize prices, but that is with the crucial assumption that people form expectations that are, on average, accurate. This conflicts with the inconclusive evidence from many empirical studies using data from real markets. We used a lab experiment in which we let participants provide price forecasts for an unspecified commodity. When we use these forecasts in a stylized model with a commodity futures market, we find that futures markets have a stabilizing effect when storage is rather expensive, but a destabilizing effect when storage is cheap. In the first case storage helps to move some of the commodity from times when it is abundant to times when it is scarce. However, when storage becomes too cheap, the commodity basically becomes an asset, making it more vulnerable to uninformed speculation.

In Chapter 3 I look at how the decision to deposit at a certain bank affects subsequent decisions to withdraw money or not. In the experiment participants can choose between two banks. In the typical scenario one of the banks offers a higher interest rate, but is

more vulnerable to bankruptcy when depositors start to withdraw. In theory the 'risky' bank with the high interest rate should be perfectly safe, because the 'safe' bank is a better alternative for participants who intend to withdraw. This is also what I see in the experiment. However, despite the 'safeness' of the 'risky' bank, about half the participants still chose to deposit in the other bank in which they earned less. This finding is quite robust to variations in the level of riskiness of the two banks.

Chapter 4 presents a study of a repeated version of the bank choice game. Its aim is to see if people learn to deposit in the risky bank over time. In our experiment we vary both the relative riskiness of the banks (high-risk, medium-risk, and low-risk) and the information environment (seeing outcomes in own bank only or seeing outcomes in both banks). In most low- and medium-risk sessions we find that participants converge to coordinating on the single pure strategy Nash equilibrium of the stage game: depositing in the risky bank and choosing to not withdraw. By contrast, in the high-risk treatments none of the groups show stable coordination on any action. Next to the experiment we also simulate learning in this game using an Individual Evolutionary Learning (IEL) algorithm. To make it work with the different information environments, we extended the algorithm with beliefs. Here we find that our simulations are only similar to our experimental results if we let the agents use very sophisticated belief-updating.

Samenvatting

Verwachtingen en overtuigingen spelen een belangrijke rol in economie. The standaard keuze in de meeste economische modellen is om aan te nemen dat de verwachtingen en overtuigingen van mensen rationeel zijn. Dat wil zeggen dat de verwachtingswaarde overeenkomt met de werkelijkheid. In dit proefschrift bestudeer ik situaties waarin deze aanname niet toereikend is en extra aannames ten aanzien van verwachtingen nodig zijn om de verschijnselen die wij in de wereld om ons heen zien, te verklaren. Het afwijken van rationele verwachtingen of het toevoegen van aannames kan op veel manieren en het is vaak moeilijk om erachter te komen welke het beste aansluit bij de realiteit. Elk hoofdstuk bevat een experiment dat is ontworpen om dit probleem in een specifieke context op te lossen.

Hoofdstuk 2 is een bijdrage aan een oude en onopgeloste vraag in de financiële economie: helpen futures markten om de volatiliteit van grondstoffenprijzen te verminderen, of zorgen ze juist voor extra volatiliteit? Bijna alle theoretische modellen voorspellen dat futures markten helpen om prijzen te stabiliseren, maar dat is met de cruciale aanname dat mensen verwachtingen vormen die, gemiddeld gezien, nauwkeurig zijn. Dit staat in schril contrast met de uitkomsten van empirische studies die gebruik maken van gegevens uit echte markten. Deze studies laten namelijk geen eenduidig beeld zien. Wij hebben een lab experiment gebruikt waarin we deelnemers prijzen van een ongespecificeerde grondstof hebben laten voorspellen. Wanneer we deze voorspellingen gebruiken in een gestileerd model met een futures markt voor grondstoffen, vinden we dat futures markten een stabiliserend effect hebben als opslag vrij duur is, maar een destabiliserend effect in het geval dat opslag goedkoop is. In het eerste geval helpt opslag om een deel van de grondstof uit de markt te halen op momenten dat er veel van de grondstof beschikbaar is en het weer in de markt te brengen als de grondstof schaars is. Echter, wanneer opslag te goedkoop wordt, gaat een grondstof zich gedragen als een asset en daarmee wordt het kwetsbaar voor ongeïnformeerde speculatie.

In Hoofdstuk 3 kijk ik naar hoe de beslissing om geld aan een bepaalde bank toe te vertrouwen, invloed heeft op latere beslissingen om geld op te nemen of niet. In het experiment kunnen deelnemers kiezen tussen twee banken. In het typische scenario biedt één van de banken een hogere rente, maar is deze wel kwetsbaarder om failliet te gaan als rekeninghouders geld gaan opnemen. In theorie is de 'risicovolle' bank die de hoge rente biedt zeer veilig, omdat de 'veilige' bank een beter alternatief is voor deelnemers die van plan zijn hun geld op te nemen. Dit is ook wat ik zie in het experiment. Echter, ondanks de 'veiligheid' van de 'risicovolle' bank koos ongeveer de helft van de deelnemers er toch voor om hun geld te stallen bij de andere bank waar ze minder verdienden. Deze uitkomst is vrij robuust ten aanzien van variaties in het risiconiveau van de twee banken.

Hoofstuk 4 is een studie naar een versie van het bankkeuze-spel waarin deelnemers het spel herhaald spelen. Het doel is om erachter te komen of mensen in de loop van de tijd leren om hun geld aan de risicovolle bank toe te vertrouwen. In ons experiment variëren we zowel het relative risiconiveau van beide banken (hoog risico, gemiddeld risico, laag risico) als de informatie die de deelnemers krijgen (alleen de uitkomsten van de eigen bank of uitkomsten van beide banken). In de meeste sessies met laag en gemiddeld risico vinden we dat de deelnemers uiteindelijk coördineren op het enige Nash evenwicht in pure strategieën: ze zetten hun geld op de risicovolle bank en kiezen ervoor het niet op te nemen. In de hoog-risico sessies was er daarentegen in geen enkele groep coördinatie op één van de acties. Naast het experiment hebben we het leren in dit spel gesimuleerd met behulp van een Individueel Evolutionair Leren (IEL) algoritme. Om dat te laten werken in omgevingen met verschillende hoeveelheden informatie, hebben we het algoritme uitgebreid met overtuigingen. Onze bevinding hier is dat onze simulaties de experimentele resultaten alleen benaderen als we de agenten hun overtuigingen op een heel geraffineerde manier laten updaten.

Bibliography

Adam, K., A. Marcet, and J. Beutel (2017): "Stock price booms and expected capital gains," *American Economic Review*, 107, 2352–2408.

Algieri, B. (2016): "Conditional price volatility, speculation, and excessive speculation in commodity markets: sheep or shepherd behaviour?" *International Review of Applied Economics*, 30, 210–237.

Amihud, Y., H. Mendelson, and L. H. Pedersen (2006): "Liquidity and asset prices," *Foundations and Trends® in Finance*, 1, 269–364.

Amromin, G. and S. A. Sharpe (2014): "From the horse's mouth: Economic conditions and investor expectations of risk and return," *Management Science*, 60, 845–866.

Anufriev, M. and C. Hommes (2012a): "Evolution of market heuristics," *The Knowledge Engineering Review*, 27, 255–271.

——— (2012b): "Evolutionary selection of individual expectations and aggregate outcomes in asset pricing experiments," *American Economic Journal: Microeconomics*, 4, 35–64.

Arifovic, J. (2019): "Evolution of sunspot like behavior in the agent based economies of bank runs," *Journal of Evolutionary Economics*, 29, 365–389.

Arifovic, J., C. Hommes, A. Kopányi-Peuker, and I. Salle (2023): "Ten isn't large! Group size and coordination in a large-scale experiment," *American Economic Journal: Microeconomics*, 15, 580–617.

Arifovic, J. and J. H. Jiang (2019): "Strategic uncertainty and the power of extrinsic signals–evidence from an experimental study of bank runs," *Journal of Economic Behavior & Organization*, 167, 1–17.

Arifovic, J., J. H. Jiang, and Y. Xu (2013): "Experimental evidence of bank runs as pure coordination failures," *Journal of Economic Dynamics and Control*, 37, 2446–2465.

Arifovic, J. and J. Ledyard (2007): "Call market book information and efficiency," *Journal of Economic Dynamics and Control*, 31, 1971–2000.

——— (2011): "A behavioral model for mechanism design: Individual evolutionary learning," *Journal of Economic Behavior & Organization*, 78, 374–395.

Bao, T. and C. Hommes (2019): "When speculators meet constructors: Positive and negative feedback in experimental housing markets," *Journal of Economic Dynamics and Control*, 107, 103730.

Bao, T., C. Hommes, and J. Pei (2021): "Expectation formation in finance and macroeconomics: A review of new experimental evidence," *Journal of Behavioral and Experimental Finance*, 32, 100591.

Bao, T., C. Hommes, J. Sonnemans, and J. Tuinstra (2012): "Individual expectations, limited rationality and aggregate outcomes," *Journal of Economic Dynamics and Control*, 36, 1101–1120.

Barberis, N., R. Greenwood, L. Jin, and A. Shleifer (2018): "Extrapolation and bubbles," *Journal of Financial Economics*, 129, 203–227.

Bernanke, B. S. (1983): "Nonmonetary effects of the financial crisis in the propagation of the great depression," *The American Economic Review*, 73, 257–276.

Bohl, M. T. and P. M. Stephan (2013): "Does futures speculation destabilize spot prices? New evidence for commodity markets," *Journal of Agricultural and Applied Economics*, 45, 595–616.

Brock, W. A. and C. H. Hommes (1998): "Heterogeneous beliefs and routes to chaos in a simple asset pricing model," *Journal of Economic Dynamics and Control*, 22, 1235–1274.

Brown, M., S. T. Trautmann, and R. Vlahu (2017): "Understanding bank-run contagion," *Management Science*, 63, 2272–2282.

Brunetti, C., B. Büyükşahin, and J. H. Harris (2016): "Speculators, prices, and market volatility," *Journal of Financial and Quantitative Analysis*, 51, 1545–1574.

Büyükşahin, B. and J. H. Harris (2011): "Do speculators drive crude oil futures prices?" *The Energy Journal*, 32, 167–202.

Chakravarty, S., M. A. Fonseca, and T. R. Kaplan (2014): "An experiment on the causes of bank run contagions," *European Economic Review*, 72, 39–51.

Chen, D. L., M. Schonger, and C. Wickens (2016): "oTree—An open-source platform for laboratory, online, and field experiments," *Journal of Behavioral and Experimental Finance*, 9, 88 – 97.

Cheng, I.-H. and W. Xiong (2014): "Financialization of commodity markets," *Annu. Rev. Financ. Econ.*, 6, 419–441.

Cooper, R., D. V. De Jong, R. Forsythe, and T. W. Ross (1992): "Forward induction in coordination games," *Economics Letters*, 40, 167–172.

Crosetto, P. and A. Filippin (2013): "The "bomb" risk elicitation task," *Journal of Risk and Uncertainty*, 47, 31–65.

Davis, D. D. and R. J. Reilly (2016): "On freezing depositor funds at financially distressed banks: An experimental analysis," *Journal of Money, Credit and Banking*, 48, 989–1017.

Diamond, D. W. and P. H. Dybvig (1983): "Bank runs, deposit insurance, and liquidity," *Journal of Political Economy*, 91, 401–419.

Du, X., C. L. Yu, and D. J. Hayes (2011): "Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis," *Energy Economics*, 33, 497–503.

Duffy, J., A. Karadimitropoulou, and M. Parravano (2019): "Financial contagion in the laboratory: Does network structure matter?" *Journal of Money, Credit and Banking*, 51, 1097–1136.

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

Dvir, E. and K. S. Rogoff (2009): "Three epochs of oil," National Bureau of Economic Research Working Paper.

Forsythe, R., T. R. Palfrey, and C. R. Plott (1982): "Asset valuation in an experimental market," *Econometrica*, 50, 537–567.

——— (1984): "Futures markets and informational efficiency: A laboratory examination," *The Journal of Finance*, 39, 955–981.

Friedman, D., G. W. Harrison, and J. W. Salmon (1984): "The informational efficiency of experimental asset markets," *Journal of Political Economy*, 92, 349–408.

Friedman, M. (1953): *Essays in positive economics*, University of Chicago Press.

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

Goldstein, I. and L. Yang (2021): "Commodity financialization and information transmission," Working Paper.

Goodwin, R. M. (1947): "Dynamical coupling with especial reference to markets having production lags," *Econometrica, Journal of the Econometric Society*, 181–204.

Gray, R. W. (1963): "Onions revisited," *Journal of Farm Economics*, 45, 273–276.

Greenwood, R. and A. Shleifer (2014): "Expectations of returns and expected returns," *The Review of Financial Studies*, 27, 714–746.

Hart, O. D. and D. M. Kreps (1986): "Price destabilizing speculation," *Journal of Political Economy*, 94, 927–952.

Heemeijer, P., C. Hommes, J. Sonnemans, and J. Tuinstra (2009): "Price stability and volatility in markets with positive and negative expectations feedback: An experimental investigation," *Journal of Economic Dynamics and Control*, 33, 1052–1072.

Holt, C. A. and S. K. Laury (2002): "Risk aversion and incentive effects," *American Economic Review*, 92, 1644–1655.

Holzmeister, F. (2017): "oTree: Ready-made apps for risk preference elicitation methods," *Journal of Behavioral and Experimental Finance*, 16, 33–38.

Holzmeister, F. and A. Pfurtscheller (2016): "oTree: The "bomb" risk elicitation task," *Journal of Behavioral and Experimental Finance*, 10, 105–108.

Hommes, C., J. Sonnemans, J. Tuinstra, and H. Van de Velden (2005): "Coordination of expectations in asset pricing experiments," *The Review of Financial Studies*, 18, 955–980.

Hommes, C., J. Sonnemans, J. Tuinstra, and H. Van De Velden (2007): "Learning in cobweb experiments," *Macroeconomic Dynamics*, 11, 8–33.

Hommes, C., J. Sonnemans, J. Tuinstra, and H. Van de Velden (2008): "Expectations and bubbles in asset pricing experiments," *Journal of Economic Behavior & Organization*, 67, 116–133.

Hommes, C. H. (1994): "Dynamics of the cobweb model with adaptive expectations and nonlinear supply and demand," *Journal of Economic Behavior & Organization*, 24, 315–335.

——— (1998): "On the consistency of backward-looking expectations: The case of the cobweb," *Journal of Economic Behavior & Organization*, 33, 333–362.

Kaldor, N. (1939): "Speculation and economic stability," *The Review of Economic Studies*, 7, 1–27.

Kawai, M. (1983): "Price volatility of storable commodities under rational expectations in spot and futures markets," *International Economic Review*, 24, 435–459.

Kennedy, Joseph P., II. (2012, April 11): "The high cost of gambling on oil," *The New York Times*, A23.

Keynes, J. M. (1936): *The general theory of employment, interest and money*, McMillan.

Kiss, H. J., I. Rodriguez-Lara, and A. Rosa-García (2012): "On the effects of deposit insurance and observability on bank runs: an experimental study," *Journal of Money, Credit and Banking*, 44, 1651–1665.

——— (2014): "Do women panic more than men? An experimental study of financial decisions," *Journal of Behavioral and Experimental Economics*, 52, 40–51.

——— (2016): "Think twice before running! Bank runs and cognitive abilities," *Journal of Behavioral and Experimental Economics*, 64, 12–19.

——— (2018): "Panic bank runs," *Economics Letters*, 162, 146–149.

Kiss, H. J., I. Rodriguez-Lara, and A. Rosa-Garcia (2022a): "Experimental bank runs," *Handbook of Experimental Finance*, 347.

——— (2022b): "Who withdraws first? Line formation during bank runs," *Journal of Banking & Finance*, 140, 106491.

Madies, P. (2006): "An experimental exploration of self-fulfilling banking panics: Their occurrence, persistence, and prevention," *The Journal of Business*, 79, 1831–1866.

Masters, M. W. and A. K. White (2008): "The accidental Hunt brothers: How institutional investors are driving up food and energy prices," Accessed July 2017, Available at https://www.bettermarkets.com/michael-w-masters.

McPhail, L. L., X. Du, and A. Muhammad (2012): "Disentangling corn price volatility: The role of global demand, speculation, and energy," *Journal of agricultural and applied economics*, 44, 401–410.

Morgan, C. W. (1999): "Futures markets and spot price volatility: a case study," *Journal of Agricultural Economics*, 50, 247–257.

Muth, J. F. (1961): "Rational expectations and the theory of price movements," *Econometrica*, 29, 315–335.

Nagel, R. (1995): "Unraveling in guessing games: An experimental study," *The American Economic Review*, 85, 1313–1326.

Nerlove, M. (1958): "Adaptive expectations and cobweb phenomena," *The Quarterly Journal of Economics*, 72, 227–240.

Netz, J. S. (1995): "The effect of futures markets and corners on storage and spot price variability," *American Journal of Agricultural Economics*, 77, 182–193.

Newbery, D. M. (1987): "When do futures destabilize spot prices?" *International Economic Review*, 28, 291–297.

Noussair, C. and S. Tucker (2006): "Futures markets and bubble formation in experimental asset markets," *Pacific Economic Review*, 11, 167–184.

Noussair, C. N., S. Tucker, and Y. Xu (2016): "Futures markets, cognitive ability, and mispricing in experimental asset markets," *Journal of Economic Behavior & Organization*, 130, 166–179.

Palan, S. (2010): "Digital options and efficiency in experimental asset markets," *Journal of Economic Behavior & Organization*, 75, 506 – 522.

Peck, J. and K. Shell (2003): "Equilibrium bank runs," *Journal of Political Economy*, 111, 103–123.

Pindyck, R. S. and J. J. Rotemberg (1990): "The excess co-movement of commodity prices," *The Economic Journal*, 100, 1173–1189.

Porter, D. P. and V. L. Smith (1995): "Futures contracting and dividend uncertainty in experimental asset markets," *Journal of Business*, 68, 509–541.

Powers, M. J. (1970): "Does futures trading reduce price fluctuations in the cash markets?" *American Economic Review*, 60, 460–64.

Ricci, U. (1930): "Die „synthetische Ökonomie "von Henry Ludwell Moore," *Zeitschrift für Nationalökonomie*, 1, 649–668.

Roll, R. (1984): "Orange juice and weather," *The American Economic Review*, 74, 861–880.

Sargent, T. J. (1987): *Macroeconomic Theory*, Academic Press, 2nd ed.

Sarris, A. H. (1984): "Speculative storage, futures markets, and the stability of commodity prices," *Economic Inquiry*, 22, 80–97.

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

Schultz, H. (1930): *Der Sinn der statistischen nachfragekurven*, Schroeder.

Shakina, E. (2019): "Bank runs as a coordination problem within a two-bank set-up: Who will survive?" *Economics Letters*, 177, 85–88.

Shakina, E. and M. Angerer (2018): "Coordination and communication during bank runs," *Journal of Behavioral and Experimental Finance*, 20, 115–130.

Sims, C. A. (1980): "Macroeconomics and reality," *Econometrica*, 48, 1–48.

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

Sockin, M. and W. Xiong (2015): "Informational frictions and commodity markets," *The Journal of Finance*, 70, 2063–2098.

Sonnemans, J. and J. Tuinstra (2010): "Positive expectations feedback experiments and number guessing games as models of financial markets," *Journal of Economic Psychology*, 31, 964–984.

Stein, J. C. (1987): "Informational externalities and welfare-reducing speculation," *Journal of Political Economy*, 95, 1123–1145.

Taylor, G. S. and R. M. Leuthold (1974): "The influence of futures trading on cash cattle price variations," *Food Research Institute Studies*, 13, 29–35.

Tinbergen, J. (1930): "Bestimmung und Deutung von Angebotskurven, Ein Beispiel," *Zeitschrift für Nazionalökonomie*, 1, 669.

Trautmann, S. T. and R. Vlahu (2013): "Strategic loan defaults and coordination: An experimental analysis," *Journal of Banking & Finance*, 37, 747–760.

Van Damme, E. (1994): "Banking: A survey of recent microeconomic theory," *Oxford Review of Economic Policy*, 10, 14–33.

van der Cruijsen, C. and M. Diepstraten (2017): "Banking products: you can take them with you, so why don't you?" *Journal of Financial Services Research*, 52, 123–154.

Working, H. (1960): "Price effects of futures trading," *Food Research Institute Studies*, 1, 3–31.

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Expectations and beliefs play a crucial role in many economic models. The common approach, in which it is assumed that people are on average correct about the future and about the actions of others, is not always sufficient to properly predict empirically observed phenomena. This thesis explores examples in both stylized market and stylized banking environments in which it is useful to deviate from rational expectations and make other or additional assumptions.

Johan de Jong completed an MSc in physics at Leiden University, a PhD in physics at Radboud University Nijmegen, and an MPhil in economics at the Tinbergen Institute before joining the Department of Quantitative Economics at the University of Amsterdam in 2017. This thesis is the result of the work he did there as a PhD candidate. He currently works as a postdoctoral researcher at Erasmus University Rotterdam.