

**UNIVERSITY OF LJUBLJANA
FACULTY OF ECONOMICS**

Matjaž Steinbacher

**SIMULATING PORTFOLIOS BY USING
MODELS OF SOCIAL NETWORKS**

Doctoral Dissertation

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Committee Chair: MARKO PAHOR, PhD
Supervisor: HARRY M. MARKOWITZ, PhD
Member: VLADIMIR BATAGELJ, PhD

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Author's signature: _____

SIMULIRANJE PORTFELJEV Z UPORABO OMREŽNIH MODELOV

Matjaž Steinbacher

POVZETEK

Vprašanje, s katerim se na finančnih trgih srečujejo investitorji in ga tudi rešujejo, je, kako na učinkovit način upravljati s premoženjem. V tem procesu pomeni izbor portfelja izbiro med mnogimi stohastičnimi alternativami, ki so posameznim agentom na voljo v času. Disertacija je ilustracija vedenjske dinamične igre sočasnih potez igralcev v negotovem svetu trgov kapitala. Model predstavlja aplikacijo socialnih omrežij v ekonomiji in vsebuje agente in njihove preference, vrednostne funkcije, povezave med agenti in nabor akcij za posameznega agenta. V modelu se vedenjske finance nanašajo na psihologijo izbora agentov. V igrah uporabim tako zaupljive, kot tudi nezaupljive agente. Temeljna metodološka značilnost disertacije je ta, da interakcija med agenti privede do kompleksnega vedenja celotne skupine, ki ga brez uporabe pristopa, ki vključuje interakcijo med agenti, ni mogoče pojasniti.

V prvem delu (poglavje 5) pokažem, na kakšen način donosi in raven tveganja posameznih portfeljev vplivajo na njihov izbor v preprosti igri z dvema vrednostnima papirjema. Simulacije izvedem v dveh različnih okoliščinah: najprej z netveganim in tveganim vrednostnim papirjem, nato še z dvema tveganimi vrednostnima papirjema. Rezultati pokažejo, pod katerimi okoliščinami se agenti odločijo za mešane portfelje tvegane in netvegane vrednostnega papirja. Simulacije še pokažejo, da je za nemoten potek izbora nujno potrebno zagotavljanje likvidnosti. Vključitev šoka v proces izbora pokaže, da v kolikor jakost šoka ni premočna, je njegov učinek zgolj kratkoročen.

V drugem delu (poglavja 6-8) razširim osnovni okvir in se lotim iger z mnogoterimi alternativami. Četudi imajo agenti v modelu omejeno vedenje o donosih vrednostnih papirjev, svoje portfelje pa izbirajo na podlagi realiziranih donosov, pa so portfelje kljub temu sposobni izbrati skladno s hipotezo učinkovite meje. Nekoliko bolj razpršeni izbor nezaupljivih agentov je posledica njihove nezmožnosti igranja načela "zmagovalec pobere vse," četudi so sposobni identificirati iste "zmagovalce" kot zaupljivi agenti. Omenjena ugotovitev je podprta tako v bikovskem kot tudi medvedjem trendu, četudi v bikovskem trendu agenti prevzemajo več tveganja, kar je skladno s teoretičnimi predvidevanji. Agenti ne preferirajo preveč razpršenih portfeljev, ampak portfelje dveh vrednostnih papirjev, ki so zgrajeni okrog najbolj zaželenega posamičnega vrednostnega papirja. Testi konsistentnosti, opravljeni s pomočjo koficienta variacije in metode Monte Carlo, pokažejo, da so najbolj konsistentno izbrani bodisi najbolj bodisi najmanj zaželeni portfelji. Ti testi še pokažejo, da so zaupljivi agenti bolj konsistentni pri svojih odločitvah kot nezaupljivi agenti. Simulacije z novicami so navrgle dve skupini zmagovalnih portfeljev: portfelje iz učinkovite meje oz. iz njene okolice, in diverzificirane portfelje, katerih izbor je pozitivno koreliran s številom objavljenih nenegativnih novic.

Ključne besede: večperiodni izbor portfelja, navidezni finančni trgi, družbena omrežja, razvojne omrežne igre, informacije in vedenje, komuniciranje, zaupljivost, ocenjevano učenje.

SIMULATING PORTFOLIOS BY USING MODELS OF SOCIAL NETWORKS

Matjaž Steinbacher

SUMMARY

The problem that financial agents address and solve is how to manage assets efficiently. This involves choosing from different types of stochastic alternatives that are available over time. The dissertation is an application of a dynamic behavioral-based and a simultaneous-move game in a stochastic environment that is run on a network. The model includes agents and their preferences, value functions, relations among agents and the set of actions for each agent. The notion of behavioral finance is on the psychology of agents' decision-making. In the games, I use unsuspecting and suspicious agents. A fundamental methodological premise of the dissertation is that interaction and information sharing lead to complex collective behavior associated with non-linear dynamics, which can only be explained with an interaction-based approach.

In the first part of the simulation games (Chapter 5), I demonstrate how returns and risk affect portfolio selection in a very simple two-asset game. Games are simulated under two different environments: with riskless and risky asset, and in the environment of two risky assets. I present the conditions, under which agents select mixed portfolios. Games of this part also demonstrated that preserving liquidity is essential for the selection process to work smoothly. It has been demonstrated that one-time shocks affect the selection process in the short run but not over the longer run unless the magnitude is very large.

In the second part of Chapters 6-8, I extend the basic framework and consider multiple-asset games. Here, I examine the selections in the context of the efficient frontier theory. Although agents follow only the returns of the portfolios they have and make decisions based on realized returns, it has been demonstrated that they are capable of investing according to the efficient frontier hypothesis. The slightly more dispersed selection by suspicious agents is a consequence of their slight failure to conduct a "winner takes all" principle, even though they identify the same "winners" as unsuspecting agents do. This conclusion is supported in both bull and bear markets, except that agents take on more risk in the former, which is consistent with the theory. Agents do not prefer excessively diversified portfolios, but two-asset portfolios with the most desired individual stock in the center. Consistency tests, tested by the coefficient of variability and Monte Carlo simulations, demonstrate that agents behave the most consistently on the most desired or the least desired choices. In addition, unsuspecting agents were more consistent in their selections than suspicious agents were. In the presence of news and returns, two groups of portfolios seemed to be the winners. As before, the first group consisted from the efficient frontier portfolios, or portfolios from its closest neighborhood. The second group of selected portfolios was stimulated by the number of non-negative news and included highly diversified portfolios.

Keywords: multiperiod portfolio selection, stochastic finance, artificial markets, social networks, evolutionary games on networks, information and knowledge, communication, suspiciousness, reinforcement learning.

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In writing this dissertation, I tried to follow the words of Polonius that brevity is the soul of wit.

I alone, and none of the individuals mentioned above take any responsibility for the results.

DISCLAIMER:

Past performance does not guarantee future results. This dissertation provides no business or financial advice on how to manage the assets. Nothing herein should be construed as an offer or solicitation to buy or sell any security. The author does not take any responsibility for the losses someone would make if using the conclusions of the dissertation, neither is he entitled to any compensation for the profits someone would make on that basis.

Ljubljana, October 2012

Matjaž Steinbacher

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Chapter I

Introduction

1.1 Research motivation

The dissertation examines portfolio selection and relates it to the games on networks. The main interest of the research has been to understand portfolio choices of interacting agents under a variety of circumstances when prices are uncertain. To examine these issues, I conduct a series of simulation-based games that are based on simple behavioral rules and local interaction.

Financial markets are inherently occupied with issues that involve time and uncertainty.¹ Securities are traded at date zero, which is certain, and their payoffs are realized at date 1. Because any state can occur at date 1, it is uncertain (Arrow 1963, Mandelbrot 1963, Campbell et al. 1998).^{2,3} Much of this uncertainty is related to the informational inefficiency that exists even in well-functioning capital markets, and even informationally perfectly efficient markets might be expectationally inefficient as agents build different expectations (Grossman and Stiglitz 1980, see also Ben-Porath 1997).⁴ Expectational inefficiency utilizes the maxima that cognitive impairments limit investors' ability to process information, which makes human cognition a scarce resource. In practice this means that although three investors all observe the same earnings announcement, they may be still induced to trade with one another.

The existence of uncertainty is essential to portfolio selection and among the main reasons for making a portfolio of different assets, preferably with uncorrelated returns. A portfolio rule is an old ideal. In about the fourth century, Rabbi Issac bar Aha proposed the rule, according to which "One should always divide his wealth into three parts: a third in land, a third in merchandise, and a third ready at hand." Benartzi and Thaler (2001) examined investment patterns of investors when choosing between many social security funds, and found that some investors follow such naïve $1/n$ strategy and divide their contributions evenly across the funds offered in the plan. In 1952, Harry Markowitz (1952a) published a seminal paper on portfolio selection in which he dealt with questions regarding the relationship between risk and return and the selection process, and derived an optimal rule according to which agents ought to select portfolios in relation to their risk. Since the early contribution of Markowitz, portfolio selection has become an object of immense interest for researchers in various sciences. Its first extensions were the capital asset pricing model (Sharpe 1964, Lintner 1965a, b), and the arbitrage pricing theory (Ross 1976), which take into account the assets' relation to market risk.

¹ I use the terms *risk* and *uncertainty* interchangeably, although uncertainty relates to the state in which outcomes and related probabilities are not known, while risk relates to the state in which all outcomes and their probabilities are known (Knight 1921). Knight suggests that people dislike uncertainty more than risk.

² Hamilton (1994) is a good reference on time series analysis, while financial time series is given in Cochrane (2005), Duffie (2001), and LeRoy and Werner (2001).

³ Variability in prices is required for the market to function at all (Milgrom and Stokey 1982).

⁴ Random walk theory is used for testing the efficient market hypothesis, in which stock prices reflect all information that is publicly known (Fama 1965, Malkiel 1973, 2003). See Stigler (1961), McCall (1970), Akerlof (1970), Spence (1973), Shiller (2002), and Hayek (1937, 1945) on the role of information in the economy.

Merton (1969, 1971), Brennan, Schwartz and Lagnado (1997), Barberis (2000), Liu (2007) considered portfolio selection as a multiperiod choice problem in an uncertain world. Barberis found that when stock prices are predictable, agents allocate more assets in stocks the longer their horizon. Wachter (2003) demonstrated that as risk aversion approaches infinity, the optimal portfolio would consist only of long-term bonds. Constantinides (1986) and Lo et al. (2004) considered the portfolio selection process in relation to transaction costs and demonstrated that agents accommodate large transaction costs by reducing the frequency and volume of trade. Xia (2001) demonstrated that agents who ignore the opportunity of market timing could incur very large opportunity costs, so that return predictability, even if quite uncertain, is economically valuable. Cocco (2005) examined the housing effects on portfolio choice and argued that investments in housing limit financial capabilities of people to invest in other assets. Campbell (2000) surveyed the field of asset pricing until the millenium.

Along with a substantial literature on the equilibrium-based portfolio selection problem, many different computational techniques have been used for solving these optimization problems. Some of the more recent literature includes Fernandez and Gomez (2007), who applied a method based on neural networks. Crama and Schyns (2003) used a simulated annealing algorithm. Chang et al. (2000) compared the results of alternative methods: tabu search, genetic algorithm and simulated annealing. Cura (2009) used particle swarm optimization approach to portfolio optimization. Doerner et al. (2004) applied an ant colony optimization method for solving the portfolio selection problem. Although these equilibrium-based models reduced the sensitivity of the portfolio selection to the parameter estimates, while being also intuitive and computationally very complex, LeRoy and Werner (2001) called them “the placid financial models [that] bear little resemblance to the turbulent markets one reads about in the Wall Street Journal.” The chief objection against these models is that they do not consider the financial world a complex adaptive system, although it is characterized by large number of micro agents who exhibit a non-standard behavior and are repeatedly engaged in local interactions thereby producing global consequences (Sornette 2004). In the dissertation, the notion of such consequences relates to the proportion of agents per portfolio. As outlined by Tesfatsion (2006), the only way to model and analyze such systems is to let them evolve over time. Once the initial conditions of the system have been specified and the behavioral methods (procedures) defined, the model develops over time without further intervention from the modeler. Finally, equilibrium-based models regularly exclude extremes, or outcomes that seem outliers, in order to obtain reliable statistical estimations, in spite of all the effects they produce. In reality, stock markets repeatedly switch between periods of relative calm and periods of relative turmoil.

Behavioral approach to finance, or ACE (*Agent-Based Computational Economics*) finance, includes a great part of this micro-structure that was missing in previous models. Rabin (1998), Hirshleifer (2001), Barberis and Thaler (2003) and DellaVigna (2009) contain extensive surveys of behavioral finance. As argued by DellaVigna, individuals deviate from the standard model in three respects: nonstandard preferences, nonstandard beliefs, and nonstandard decision making. ACE has evolved in two directions that are intertwined to some extent: strictly behavioral and interaction-based. As pointed out by Simon (1955) and Kahneman and Tversky (1979) and the subsequent literature on agents’ behavior under uncertainty, even minor variations in the framing of a problem may dramatically affect agents’ behavior. Another part of the literature focuses on the communication related part, dealing with agents and the ways of how they gather and use information. In ACE, agents have incomplete and asymmetric information, they belong to social networks and communicate with others, they learn and imitate; sometimes they make good judgements,

sometimes poor. Following von Neumann and Morgenstern (1953), we distinguish between games with complete information and games with incomplete information. In addition, communicating investors share news to each other, leading to herding. Herding is one of the unavoidable consequences of imitation and is probably the most significant feature of the ACE models. Herding in financial markets may be the most generally recognized observation that has been highlighted by many (Bikhchandani et al. 1992, Banerjee 1992, Lux 1995, Shiller 1995, 2002, Scharfstein and Stein 1990).⁵

Applications of ACE models are abundant. One of the first was a segregation model of Schelling (1971). Considering many different classes of networks, Schelling's model was later generalized by Fagiolo et al. (2007). ACE models of financial markets start with Zeeman (1974) and Garman (1976). Epstein and Axtell (1996) study a number of different social behavior phenomena. Many other ACE models have been proposed: Arifovic (1996), Brock and Hommes (1998), Brock and LeBaron (1996), Cont and Bouchaud (2000), Raberto et al. (2001), Stauffer and Sornette (1999), Lux and Marchesi (1999), Palmer et al. (1994), Johnson (2002), Caldarelli et al. (1997), Sharpe (2007), Kim and Markowitz (1989), Jacobs et al. (2004), Frijns et al. (2008), Dieci and Westerhoff (2010). Preis et al. (2006) propose a multi-agent-based order book model of financial markets where agents post offers to buy and sell stock. Rosu (2009) presents a model of an order-driven market where fully strategic, symmetrically informed traders dynamically choose between limit and market orders, trading off execution price and waiting costs. Samanidou et al. (2007) provide an overview of some agent-based models of financial markets. These models are mostly focused on portfolio selection in relation to modeling asset pricing. Nagurney and Siokos (1997) present a financial equilibrium model in a network structure and provide the equilibrium conditions for the optimal portfolio selection.

Based on these developments from different fields, the dissertation is an application of a dynamic behavioral-based and a simultaneous-move game in a stochastic environment that is run on a network. It includes agents along with their preferences, value functions, relations among agents and the set of actions for each agent. In the games, agents are price-taking individuals who make decisions autonomously. A number of games on networks have been proposed so far, and they can be found in a variety of disciplines. Pastor-Satorras and Vespignani (2001) and Chakrabarti et al. (2008) use a network approach to study the spread of diseases. Calvo-Armengol and Jackson (2004) applied the network approach into the labor market. Allen and Gale (2000) used financial networks to study contagion in financial markets that leads to financial crises. Leitner (2005) constructed a contagion model where the success of an agent's investment in a project depends on the investments of other agents an agent is linked to. Cohen et al. (2008) used social networks to identify information transfer in security markets. Bramoulle and Kranton (2007) analyzed networks in relation to public goods. Close to the intuition of my work are Jackson and Yariv (2007) and Galeotti et al. (2010), who considered a game where players have to choose in partial ignorance of what their neighbors will do or who their neighbors will be. Szabo and Fath (2007) and Jackson (2010) provide a review of some of the evolutionary games on networks.

The network I use is similar to that proposed by Watts and Strogatz (1998). In such network agents do not interact with all other agents, but only to those to whom they trust. This is a

⁵ Herding has been observed in the behavior of interacting ants. Kirman (1993) provides a simple stochastic formalization of information transmission inspired by macroscopic patterns emerging from experiments with ant colonies that have two identical sources of food at their disposal near their nest. In his experiment, a majority of the ant population concentrated on exploiting one particular food source, but they switched to the other source after a period.

realistic assumption for multi-agent systems. Agents use the network as an infrastructure to communicate with their peers. Information diffuses over the network by the word-of-mouth, as emphasized by Ellison and Fudenberg (1995) and Shiller (2002), and tested by Hong et al. (2004, 2005). Information-sharing means that agents base their decisions also on the experience of others. Such second-hand recommendations or opinions have always been an important piece of information for most of the people in their decision-making process. Individual agents are interacting decision makers with incomplete and asymmetric information regarding asset returns, portfolios of other agents with whom they do not communicate and the network structure. Agents have knowledge only of portfolios they possess or are possessed by adjacent agents with whom they communicate. Then, action is viewed as a mapping of agents' knowledge to a decision. Agents make decisions without knowing what others have selected. Agents do neither know what those with whom they have exchanged information regarding portfolios have selected. Thus, although agents interact with each other and share information to each other, it might be said that they make decisions in isolation. The objective of agents in the model is to select a portfolio in every time period so as to increase their wealth. Because agents in the model possess limited computational resources and information on which to base their decisions, a reasonable principle for decision making is that of satisficing and not optimizing. Therefore, their decisions might seem to be suboptimal decisions. I should acknowledge that agents do not play against each other.

The basic intuition for the selection process comes from Markowitz (1952a). He defined portfolio selection as a two-step procedure of the information gathering and expectations building, ending in a portfolio formation. Building on the Markowitz framework, the selection process in this dissertation is broken down into four stages: the observation of returns, the choice of an adjacent agent, the comparison of the two portfolios, and the choice. Agents are assumed to base their decisions upon past realizations of their actions and the past actions of agents with whom they are cooperating. This makes the learning mechanism similar to reinforcement learning in that agents tend to adopt portfolios that have yielded high returns in the past, either their own or those of agents with whom they are interacting (Ellison 1993, Roth and Erev 1995, Erev and Roth 1998, Camerer and Ho 1999, Bala and Goyal 1998). Similarly, Barber and Odean (2008) argue that investors are likely to buy stocks that catch their attention. Grinblatt et al. (1995) demonstrated that hedge funds behave in such a way, which DeLong et al. (1990a) defined as a "positive-feedback" strategy. Agents continually modify their selections, unless they are liquidity agents. Liquidity agents do not change their initial alternative. The introduction of liquidity agents into the model follows the idea that there is a small fraction of passive investors among the participants on the markets. Similarly, Cohen (2009) built a loyalty-based portfolio choice model to explain the large portion of employee pension wealth invested in one's own company stock.

Finally, agents' decision making as applied in the dissertation is subject to behaviorism. This is modeled through the level of agents' suspiciousness. The salient characteristic of suspicious agents is that they might depart from adopting the seemingly most promising alternatives. An agent is said to be suspicious if there is a positive probability that to his detriment he would deviate from an action that stems from information provided to him by his adjacent link. Some reasons for such deviant behavior might be distrust among interacting agents at a personal level, or suspiciousness of the data, while agents may intentionally choose such a deviant alternative. In addition, it may also depict the presence of various types of "errors" in the decision-making process (Selten 1975, Tversky and Kahneman 1974). Errors in selection might also be induced by confusion (DellaVigna 2009). Whatever its reasons, the introduction of suspiciousness becomes highly significant and also

relevant when the difference in the values of two portfolios is very small. Its stochastic nature also makes the course of the selection process over time unpredictable. With the uncertainty in asset pricing and the uncertainty in the selection itself, portfolio selection, although very simple at first, is considered a complex adaptive process.

The remainder of the dissertation is organized as follows. Chapter 2 brings a discussion on the portfolio selection and the developments in finance over time. Chapter 3 brings an essay on social networks. The basic model is developed in Chapter 4. Chapter 5 provides simulations and results of the simple games under different circumstances. Chapters 6-8 represent a multiple-asset framework under different circumstances. Here, the average-game selections and the endgame selections are examined. The dissertation concludes with a final discussion and direction for further work.

1.2 Objectives and goals

I consider portfolio selection a complex adaptive system in an uncertain financial world, in which many individual interacting agents produce the aggregate dynamics. Two features are important in building such complexity. First, autonomous agents have incomplete and asymmetric information and communicate to each other, which imply herding (Hayek 1937, 1945, Keynes 1936, Banerjee 1992, 1993, Lux 1995, Scharfstein and Stein 1990, Bikhchandani et al. 1992, 1998, Cont and Bouchaud 2000, Shiller 1995, 2002).⁶ Collective behavior in social systems such as ours is not limited by the nearest-neighbor interactions, because local imitation might propagate spontaneously into a convergent social behavior with large macro effects. The second is induced by the behavioral aspect in agents' behavior, which is modeled through the level of suspiciousness. This makes the behavior of agents sluggish and close to heuristic when the difference in the two uncertain alternatives is not large (Kahneman and Tversky 1979, Rubinstein 1998, Heath and Tversky 1991, Hirshleifer 2001). The level of suspiciousness thus affects the magnitude of herding, which makes it significant for the behavior of individual agents and the system.

A fundamental methodological premise of the dissertation is that interaction and information sharing lead to complex collective behavior that goes far beyond equilibrium closed-form solutions of non-interacting or representative agents (Simon 1955, Aumann and Myerson 1988, Schelling 1978, Smith 1976, Axelrod 1984, 1997, Epstein and Axtell 1996, Tesfatsion 2006, Hommes 2006, LeBaron 2006, Duffy 2006, Camerer et al. 2005). Specifically, I address the following questions.

Q1: How do agents select between risky and riskless portfolios? (Chapter 5)

The simulation part begins with a simple setting in which a market consists of two types of securities: a riskless asset and a risky asset, while agents can also select a combination of the two. This is the application of the very basic idea that was explicitly presented by Tobin (1958), Arrow (1965) and Pratt (1964), who were the first to consider the portfolio choice problem with a single risky security. In fact, in most of the papers that examine portfolio choice in a mathematical or computational way as an equilibrium-based problem, the economic environment is reduced to one risky and one riskless asset. The general conclusion

⁶ Smith and Sorensen (2000) note that information cascade occurs when a sequence of individuals ignore their private information when making a decision, while herding occurs when a sequence of individuals make an identical decision, not necessarily ignoring their private information. In information cascade an idea or action becomes widely adopted due to the influence of others, usually neighbors in the network. I do not make such distinctions.

from this research is that an agent's willingness to invest in a risky security depends, among other things, on its return and risk. Generally, this is also a conclusion of behavioral economists who argue that agents prefer returns, but are susceptible to losses (Kahneman and Tversky 1979). Benartzi and Thaler (1995) analyzed the static portfolio problem of a loss-averse investor. They conclude that an investor who is trying to allocate his wealth between treasury bills and the stock market, is reluctant to allocate much to stocks, even if the expected return on the stock market is set equal to its high historical value.

In games of this part, I am interested in how the mean return and risk influence portfolio selection patterns. In particular, I investigate how agents' decisions are influenced by perturbations of both parameters throughout both definition spaces. Each game is run for 10.000 periods and is repeated 20 times. Endgame decisions are then averaged over these repetitions and displayed on heat-map visualizations.

I demonstrate that when both returns and variance are high, agents choose mixed portfolios. I also demonstrate that agents also opt for mixed portfolios when the returns of risky securities lie in the neighborhood of riskless returns. On the other side, although agents try to avoid negative returns if they can choose a riskless alternative with zero return, the variance of a risky security gives them the opportunity to earn non-zero returns. In these circumstances mixed portfolios were considered a fair choice between risk and return. Agents choose riskless portfolios when the mean returns of risky securities are negative (bearish market), irrespective of variance. Obviously, variance is considered a negative factor. Unsuspicious and suspicious agents demonstrate pretty similar selection patterns. Finally, initial proportion of agents with different types of portfolios affects the agents' final decisions in the extreme cases.

Q2: How do agents select between two risky alternatives? (Chapter 5)

Next, I extend the basic framework and consider the case with two risky stocks of two financial institutions, Credit Suisse (CS) and Citigroup (C), while, as before, agents can also select a combination of the two. In this part, I use real data and explore the evolution of agents' selections over time, not just their endgame selections, as before. This allows me to accurately see how agents react to the changing returns over time.

These games very illustratively reveal a very distinctive feature of interaction-based games - herding, which leads to synchronization in the very early stages of the games. This conclusion is very intuitive and was proven by Bala and Goyal (1998). Herding proved to be fast in the environment of unsuspicious agents who perfectly rebalance their portfolios. Consequently, selections of unsuspicious agents were highly consistent as the games were repeated. In contrast, suspicious agents do not end in a unanimous decision, while suspicious agents are highly inconsistent in their selections. In these games, consistency in selections is measured through the correlation coefficients of individual games to the average game.

I demonstrate that when the initial proportion of agents with unfavorable portfolios is larger, developments in selections are significantly different from the case when this proportion is smaller. Under new circumstances, the agents also do not end in a unanimous decision, as they did before.

Q3: What is the effect of a one-time shock on portfolio selection? (Chapter 5)

In the last part of Chapter 5, I include a one-time shock into the portfolio selection process. One of the most remarkable emergent properties of natural and social sciences is that they

are punctuated by rare large events, which often lead to huge losses (Sornette 2009). Shocks are highly relevant for the economy and common to financial world and might be characterized as sudden and substantial moves in prices in any direction that are likely to change the environment in which agents make decisions. Shocks are very relevant for portfolio selection (Merton 1969, 1971). De Bondt and Thaler (1985) showed that investors tend to overreact to unexpected and dramatic news events. The question I ask here is how sensitive are agents' selection patterns to a one-time shock of different magnitude over different time horizons and under different circumstances. These games included liquidity agents.

As argued by Binmore and Samuelson (1994), Binmore et al. (1995), and Kandori et al. (1993), so did also the games demonstrate that the short run effects of a shock can not be avoided, with the short run of a strong enough shock being especially critical. In the games, a shock resulted in the move from a portfolio that was hit by a negative shock into other portfolios, while these moves were positively correlated with the magnitude of the shock. In addition, these effects were much more intense in the environment of unsuspecting agents. This is an implication of overreaction, which is followed by the post-shock recovery processes. The effects of a shock on the ultra-long run depend on the extent to which a shock changes agents' behavior, the post-shock activities, and the extent of herding. In the games, the recovery was slow.

Q4: Are agents capable of selecting portfolios from the efficient frontier? (Chapters 6-8)

In the games of Chapters 6-8, I extend the basic framework and examine multiple-asset games. Two-asset games are too simplistic, although being very applicable. A multiple-choice environment increases the extent of an agent's problem, bringing it closer to reality. Specifically, investors are faced with formidable search problem when buying stocks on a huge market, because of their limited capabilities of gathering information, while not when selling them (Barber and Odean 2008). Merton (1987) argued that due to search and monitoring costs investors may limit the number of stocks in their portfolios.

In the multiple-asset games, I examine the selections in the context of the efficient frontier theory. The theory states that agents choose portfolios that maximize their return given the risk or minimize the risk for the given return (Markowitz 1952a, 1959). These games include liquidity agents. As was the case in all other games, agents have limited knowledge about asset returns, while means and variances of returns are used as my endpoints in the analysis. I use real data on returns.

My objective was not to argue whether agents prefer mean-variance portfolios, but rather to examine whether such portfolios can be attained by adaptive agents who interact with each other in an uncertain and a dynamic financial world. In addition, selection patterns also allow me to assess the level of agents' risk aversion.

Given the behavior of both types of agents, the results suggest that the riskier the portfolio, the more likely it is that agents will avoid it. Unsuspecting agents had much higher abilities of selecting winning and losing portfolios than suspicious, while also being much more consistent in their behavior. In both cases, under-diversified portfolios were more desired than diversified portfolios. Consistency in selection is tested by two different measures: coefficient of variation and Monte Carlo simulations. Unsuspecting agents were also much more synchronous in their selections than suspicious agents.

Q5: Do agents invest differently in “good” times than in “bad” times? (Chapter 7)

Following the intuition first provided by Kahneman and Tversky (1979), my next objective is to test whether agents behave differently when stocks rise than when they fall. The question goes beyond variance as a measure of risk, because in a bull market variance depicts variability in the uptrend, while in the bear market variability in the downtrend. Conclusions from the behavioral finance argue that agents’s value functions are convex for losses and concave for gains (Tversky and Kahneman 1991). Besides, Fama and Schwert (1977) argued that expected returns on risky securities are higher in bad times. Barberis et al. (2001) argued that agents are less prone to taking risk in a bear market, as they first start to recognize and then also evaluate it.

The simulation results were consistent with the theory, as agents were much more susceptible to variance in a bear than in a bull market. In addition, agents’ decisions were highly synchronized in a bear market, reflecting a very strict “winner takes all” scheme. In an uptrend, agents slightly departed from choosing efficient frontier portfolios, as higher-variance portfolios were not avoided so strictly for a given return. However, these portfolios lie in the closest neighborhood of the efficient frontier portfolios. Again, unsuspecting agents had much higher abilities of selecting winning and losing portfolios than suspicious, while also being much more consistent in their behavior. Unsuspecting agents were also much more synchronous in their selections than suspicious agents.

Q6: How do news events affect a portfolio selection process? (Chapter 8)

In the last part of the dissertation, I examine how news events that are related to individual stocks affect the portfolio selection process. In the previous chapters agents decided upon realized returns, which means that significant news events were considered indirectly through market responses, i.e. usually with a time lag of one period.

Chen et al. (1986) argued that stock returns are exposed to systematic economic news. Kandel and Pearson (1995) found that public announcements induce shifts in stock returns and the volumes. Similarly, Fair (2002) found that most large moves in high-frequency Standard and Poor’s (S&P) 500 returns are identified with U.S. macroeconomic news announcements. Bernanke et al. (2005) analyzed the impact of unanticipated changes in the Federal funds target on equity prices and found that on average over the May 1989 to December 2001 sample, a “typical” unanticipated 25 basis point rate cut has been associated with a 1.3 percent increase in the S&P 500 composite index. Boyd et al. (2005) examined the stock market’s short-run reaction to unemployment news. Andersen et al. (2007) characterized the response of U.S., German and British stock, bond and foreign exchange markets to real-time U.S. macroeconomic news, and find that equity markets react differently to news depending on the stage of the business cycle. Barber and Odean (2008) argued that attention-grabbing news events significantly affect the buying behavior of investors. They find that individual investors are net buyers of attention-grabbing stocks, e.g., stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one day returns.

To an agent, news events that come in irregular intervals appear as multiple shocks. They can be positive, neutral or negative. News events provoke a shift into portfolios that are subject to positive news and away from those that are subject to negative news. Because agents react not only to news but also to the returns that follow the news, negative returns that follow positive news may turn agents away from such portfolios, while positive returns that follow negative news may make such portfolios more desirable. This means that price

reactions to news events are crucial for the behavior of market participants with over- and underreaction spurring movements in the opposite direction.

I use real data on both returns and news events. News events are evaluated by a simple and intuitive rule. It is assumed that significant news should be followed by shifts in trading volumes and also in prices; this same rule was also used by Barber and Odean.

In the presence of news and returns, two groups of portfolios seemed to be the winners. As before, the first group consisted from the efficient frontier portfolios, or portfolios from its closest neighborhood. The second group was stimulated by the number of non-negative news and was comprised of highly diversified portfolios.

1.3 Research contribution

The main contribution of the dissertation is methodological; the dissertation is deeply rooted in methodological individualism. The complex system approach is applied, which studies portfolio selection from the perspective of individual agents and their interaction, and also includes a behavioral aspect. Such technique has not been applied, yet. In fact, applications of financial games on social networks are extremely rare, although financial markets are particularly appealing applications for such an approach (Bonabeau 2002). An agent-based approach allows me to examine selection patterns over time under many different circumstances and for a broader range of parameter values. Moreover, repetitions of the games allow me to assess consistency in agents' selections as the games repeat. Namely, because learning processes do not follow a strictly determined procedure, repetitions of the games do not duplicate their history, despite an unchanged learning algorithm (Vriend 2000). The dissertation thus provides a unique approach not only to portfolio selection but also to modeling finance.

New to the agent-based finance research are inclusions of suspicious agents and liquidity agents. By using suspicious agents, I introduce a psychological aspect into agents' decision making bringing them closer to reality. By using two types of agents, I am also able to compare the behavior of suspicious agents with that of the unsuspicious, both in terms of selections and consistency in selections. Liquidity agents are highly significant for the selection process, as they prevent the dominated alternatives to die off, even though they are dominated only occasionally for some short consecutive time periods. Liquidity agents may resemble highly conservative investors or investors who are extremely loyal to the portfolio they have.

The games of simulated data are run on the Levy returns, which incarnates the notion that extreme events are not exceptional events (Mandelbrot 1963, Fama 1965, Sornette 2009). Real data is used in the multiple-asset games, which means that in these parts the dissertation contains all the specifics regarding the asset pricing, including over- and underreaction, time lags of switching processes, correlation and cointegration between assets, etc.

Chapter II

Portfolio selection and financial market models

2.1 A portfolio

A portfolio is a set of investments. Units of assets might capture savings accounts, equities, bonds and other securities, debt and loans, options and derivatives, ETFs, currencies, real estate, precious metals and other commodities, etc. These holdings might be positive (long position), zero or negative (short position). The set of all possible portfolios from the available assets is denoted a portfolio space. Let me first define a portfolio and a mixed portfolio.

Let $J = \{1, 2, \dots, n\}$ represents a finite set of units of assets, then portfolio P is composed of the holdings of these n units of assets. If the number of non-zero holdings is larger than 1, the portfolio is called a mixed portfolio.

The return of a portfolio R_t^P equals the weighted average return of its units of wealth in time t . It is defined as $R_t^P = \sum_{i=1}^n q_t^i R_t^i$, with R_t^i representing the return of i -th unit of wealth in time t , and q_t^i the proportion of i -th unit in the portfolio in time t . Cumulative proportion of all units of wealth of a portfolio should always sum to unity, therefore $\sum_{i=1}^n q_t^i = 1$. Throughout I will be working with returns. The variance of a portfolio is a measure of portfolio risk.

THEOREM 2.1: If P_t^1 and P_t^2 are two portfolios with variances $\sigma_{P,1}^2$ and $\sigma_{P,2}^2$, respectively, then P_t^1 is strictly riskier than P_t^2 , iff $\sigma_{P,1}^2 > \sigma_{P,2}^2$.

THEOREM 2.2: If agents possess all information regarding asset prices, for which the prices are common knowledge, and all these assets have different returns, a mixed portfolio is never the optimal solution.

Proof:

Assume there are n different assets with returns R_t^i . Then the return of a portfolio equals to the weighted return of assets from the portfolio $R_t^P = \sum_{i=1}^n q_t^i R_t^i$, in which q_t^i denotes the proportion of i -th assets in the portfolio. Then we have $q_t^i \geq 0$ and $\sum_{i=1}^n q_t^i = 1$. When maximizing the return of a portfolio, the solution is $q_t^i = 1$ for the asset with the highest return and $q_t^i = 0$ for all the rest. If more than one asset has the same return, for which R_l , $l = (1, 2, \dots, L)$, then any allocation among them for which $\sum_{l=1}^L q_l R_l = 1$ is the solution to the maximization problem, which maximizes R_t^P . **Q. E. D.**

2.2 Historical developments of the portfolio theory

The early stage

Although the diversification of investments was well-established practice well before 1952, portfolio theory starts with the Markowitz's (1952a) seminal paper *Portfolio selection*. In the paper, Markowitz derived the optimal rule for allocating wealth across risky assets. His portfolio selection process is the first mathematical formalization of the diversification idea in an uncertain world. In order to reduce risk, Markowitz argued that agents ought to follow portfolios in relation to their risk. He introduced the concept of the mean-variance efficient portfolio, which represents one of the fundamental concepts of finance.

DEFINITION 2.1: If $R_t^{P,1}$ and $R_t^{P,2}$ denote returns of portfolios P_t^1 and P_t^2 and $\sigma_t^{P,1}$ and $\sigma_t^{P,2}$ their variances, then a portfolio P_t^1 is mean-variance efficient iff there is no other portfolio P_t^2 with the same variance and higher return, thus $R_t^{P,2} > R_t^{P,1}$ and $\sigma_t^{P,2} = \sigma_t^{P,1}$, or with the same return and lower variance, thus $R_t^{P,2} = R_t^{P,1}$ and $\sigma_t^{P,2} < \sigma_t^{P,1}$.

The definition suggests that to find a mean-variance efficient portfolio, one needs to fix either the mean return or the variance, and then choose a portfolio so as to minimize the variance or maximize the return. The idea is very straightforward and intuitive, and was awarded a Nobel Prize in 1990. It yields two important economic insights. First, it illustrates the effect of diversification. Imperfectly correlated assets can be combined into portfolios with preferred expected return-risk characteristics. Second, it demonstrates that, once a portfolio is fully diversified, higher expected returns can only be achieved by taking on more risk. Roy's (1952) notion is different from that of Markowitz in that Markowitz let an investor to choose where on the frontier he would like to be, while Roy put the safety first criterion.

The mean-variance concept and the efficient frontier hypothesis have had a profound impact on the modeling in finance. Sharpe (1964) and Lintner (1965a, b) developed the capital asset pricing model (CAPM), and Ross (1976) developed the arbitrage pricing theory (APT). CAPM and APT link the portfolio selection to the relation between the stocks' (or a portfolio) risk and market risk. Campbell and Vuolteenaho (2004) proposed a version of the CAPM, in which investors care more about permanent cash-flow-driven movements (bad beta) than about temporary discount-rate-driven movements (good beta) in the aggregate stock market. Jorion (2007) proposed a Value-at-Risk method to portfolio selection, which is focused on the worst expected loss of a portfolio over target period within a given confidence interval. The method is highly used in the banking sector.

A multiperiod perspective of the portfolio problem under uncertainty was provided by Merton (1969, 1971). Merton derived the condition under which optimal portfolio decisions of long-term investors would not be different from those of short-term investors, which occurs when the investment opportunity set remains constant over time, which implies that excess returns are not predictable. The second assumption was later omitted by Liu (2007); she considered the case with multiple risky assets and predictable returns. Brennan, Schwartz and Lagnado (1997) were the first to make the empirical work on portfolio choice in the presence of time-varying mean returns. When stock prices are predictable, agents allocate more assets in stocks the longer their horizon (Barberis 2000). In addition to this conclusion, Wachter (2003) demonstrated that as risk aversion approaches infinity, the

optimal portfolio would consist only of long-term bonds. Constantinides (1986) and Lo et al. (2004) considered the portfolio selection process in relation to transaction costs, and demonstrated that agents accommodate large transaction costs by reducing the frequency and volume of trade. Transaction costs thus broaden the area of no transaction towards riskless securities and determine the number of securities in a portfolio. These papers all build on the Merton model and provide some new closed-form solutions to it. Another extension of the Merton model was provided by Bodie et al. (1992), who examined the effect of the labor-leisure choice on portfolio decisions over an individual's life cycle. They show that labor and investment choices are intimately related. Specifically, they showed that exogenous, riskless labor income is equivalent to an implicit holding of riskless assets. The ability to vary labor supply *ex post* induces the individual to assume greater risks in his investment portfolio *ex ante*. Cocco (2005) examined the effects of housing on portfolio choice patterns and found that investments in housing limit financial capabilities of people to invest in other assets.

Along with different models of portfolio selection, many different computational techniques have been used for solving the optimization problems (Judd (1998) provides an overview of different computational techniques). Fernandez and Gomez (2007) applied a heuristic method based on artificial neural networks in order to trace out the efficient frontier associated to the portfolio selection problem. They considered a generalization of the standard Markowitz mean-variance model which includes cardinality and bounding constraints. These constraints ensure the investment in a given number of different assets and limit the amount of capital to be invested in each asset. Crama and Schyns (2003) used a simulated annealing algorithm. Chang et al. (2000) considered a problem of finding the efficient frontier of data set of up to 225 assets, and examined the solution results of three techniques: tabu search, genetic algorithm, and simulated annealing. Cura (2009) applied a particle swarm optimization technique to the portfolio optimization problem. Doerner et al. (2004) applied an ant colony optimization method, where investors first determine the solution space of all efficient portfolios and then interactively explore that space.

Behavioral aspect

Dissatisfied with the inability of representative agent models to explain empirical facts, behavioral economists pioneered a new approach towards modeling financial markets. Behavioral finance is the study of how psychology affects financial decision making and financial markets. It suggests that individuals deviate from the standard model in three respects: nonstandard preferences, nonstandard beliefs, and nonstandard decision making (Rabin 1998, Hirshleifer 2001, Barberis and Thaler 2003, DellaVigna 2009).

Economists have traditionally assumed that agents have stable and coherent preferences, and that they rationally maximize those preferences. Kahneman and Tversky (1979) argued that agents have non-standard preferences, for which their decisions under uncertainty tend to systematically violate the axioms of expected utility theory (see also Kahneman and Tversky 1982, Tversky and Kahneman 1991, Camerer et al. 2005). Experimental studies have demonstrated that indifference curves of individuals are not independent of the current state, but are kinked, and that value functions of individuals are convex for losses and concave for gains. This means that a loss is subject to a much bigger decline in satisfaction than gains contribute to it. It has been argued that when evaluating gambles, individuals consider the cost of the gamble and the possible reward (Kahneman and Tversky 1979), and that gambles are valued higher if a small investment can lead to a large reward (Lichtenstein

and Slovic 1971, and Tversky et al. 1990). They also found that wealthy individuals consider games only in terms of the potential gain and do so without regard to the probability of a loss, although individuals tend to avoid even a small probability of suffering huge losses, and usually also to avoid uncertain events, that is, those whose probabilities of any particular outcome are unknown (Allais 1953, Heath and Tversky 1991). Analogically, individuals are much more active on the capital markets they know best (Cooper and Kaplanis 1994, Coval and Moskowitz 1999, and Grinblatt and Keloharju 2001). Benartzi and Thaler (1995) included a behavioral aspect to the static portfolio problem. They found that a loss-averse investor, who is trying to allocate his wealth between treasury bills and the stock market, is reluctant to allocate much to stocks, even if the expected return on the stock market is set equal to its high historical value. In addition, they (Benartzi and Thaler 2001) also found that some investors follow a naïve $1/n$ rule when choosing between social security funds, and evenly distribute their contributions across all funds offered to them.

The next class of a critique relates to the selection part, in particular, to a tradeoff between the efficiency and the complexity of alternatives. As argued by Rubinstein (1998), individuals prefer alternatives that are as efficient as possible, while also being simple. Agents do not only use alternative criteria in their decision making, but, at times, also conflicting. When faced with an uncertain decision, agents value those goods that can be lost or given up more highly than when the same goods are evaluated as a potential gain (Thaler 1980). Tversky and Kahneman (1992) also argue that most people would refuse a gamble with even chances of winning or losing, unless the potential gain is twice as much as the potential loss. Ellsberg (1961) and Elster (1991) set out the role of emotions in decision making, while Campbell and Cochrane (1999) the role of customs and habits. Shefrin and Statman (1985) argue that agents might suffer a disposition effect, i.e. the preference for selling winners and holding losers.

The two another behavioral characteristics of agents' behavior and probably the most robust findings in the psychology of judgment are overconfidence about the precision of private information and biased self-attribution (Weinstein 1980, Lichtenstein et al. 1982, Griffin and Tversky 1992, Odean 1998a, b, Daniel et al. 1998). The combination of them both cause asymmetric shifts in agents' confidence as a function of the efficiency of their past investment performance (Thaler and Johnson 1990, Barberis et al. 2001).⁷ Agents who have achieved some consecutive positive results are much more inclined to make risky decisions than those who have not. Lakonishok et al. (1994) argued that many times, individuals unreasonably and naïvely extrapolate their opinions from past decisions, thus estimating too large a prospect for such securities that had experienced large returns in the past. Attribution theory states that individuals too greatly attribute to their ability events that confirm the validity of their actions, while attributing to external noise the events that disconfirm their actions (Bem 1972). In Scheinkman and Xiong (2003), overconfidence leads to heterogeneous beliefs, while the resulting fluctuations in the differences of beliefs induce trading, which can even be infinite and also produce bubbles.⁸ Empirical studies found that agents who overestimate their abilities and trade very aggressively usually end with losses (Odean 1999, Barber and Odean 2000, 2002). Barber and Odean (2001) analyzed gender differences in trading, and found that because men are more overconfident than women, they trade much more than women and, consequently, by trading more they reduce their returns much more than women do. Odean (1998a) pointed out that overconfident investors hold riskier portfolios than other investors with the same degree of risk aversion do. In addition, Daniel

⁷ An experimental study of Fischhoff et al. (1977) found that events that individuals consider as certain happen in about 80 percent of cases, while those that are considered as impossible happen in some 20 percent of cases.

⁸ Akerlof (1997) argued that there exist subgroups that behave differently than the majority of the population.

et al. (1998) demonstrated that the effects of overconfidence are more severe in less liquid securities and assets, because such markets are subject to substantial stochastic jumps in prices.

Shefrin and Statman (2000) included a behavioral aspect into the Roy's safety-first criterion and developed a model, in which investors choose portfolios by considering expected wealth, desire for securities and potential, aspiration levels, and probabilities of achieving aspiration levels. BPT thus suggests that investors have variety of motivations in making their portfolios. Their model is an optimization-based model, which does not consider the selection process as a complex system of interacting agents. Black and Litterman (1992) provided an alternative method for incorporating beliefs into portfolio theory. In their model, an investor is allowed to combine his views about the outlook for global equities, bonds and currencies with the risk premiums generated by the CAPM equilibrium. Pastor (2000) proposed a portfolio selection model in which investor's prior beliefs are centered around an asset pricing model. As the degree of skepticism about the model grows, the resulting optimal allocation moves away from a combination of benchmark portfolios toward the allocation obtained in the data-based approach. Garlappi et al. (2007) extended the mean-variance portfolio model to explicitly account for uncertainty about the estimated expected returns. In contrast to the Bayesian approach to estimation error, where there is only a single prior and the investor is neutral to uncertainty, they allow for multiple priors and aversion to uncertainty.

Interaction-based approach

In addition to the behavioral approach to portfolio theory, the application of networks and the network theory provide formalism for modeling financial markets as complex systems in terms of their interdependencies, i.e. when the movement of an entity over space and time is critical. "A central property of a complex system is the possible occurrence of coherent large-scale collective behaviors with a very rich structure, resulting from the repeated nonlinear interactions among its constituents," as is argued by Sornette (2004). Interaction helps agents accumulate knowledge that is dispersed among many (Hayek 1937, 1945), while in a connection with the behavioral aspect it makes a system complex.

Interacting economic agents are thus able to continually adjust their market moves, buying decisions, prices and forecasts to the situation these moves, or decisions, or prices, or forecasts together create (Arthur 2006). Dynamic systems exist and change in accordance with the environment in which they exist. Behavior creates pattern; and pattern in turn influences behavior. New opportunities that occur regularly prevent the system to be in optimum or global equilibrium. A significant feature of interacting agents who are able to imitate is herding, which is highly significant for financial markets (Bikhchandani et al. 1992, Banerjee 1992, Lux 1995, Shiller 1995, Scharfstein and Stein 1990).⁹ The ability to imitate is people's inborn capacity, which allows them to exploit information possessed by others. Keynes (1936) claimed that herding is implied when people do not trust their own knowledge and experiences, but rather rely on some external authority. It is not that those who herd believe that the "experts" are capable of overcoming the uncertain future, but rather that due to their experiences and knowledge they are far more capable of avoiding

⁹ Herding might induce large macro effects, even stock bubbles and crashes (Lux 1995, Harrison and Kreps 1978, Scheinkman and Xiong 2003, Abreu and Brunnermeier 2003, Santos and Woodford 1997, and Kindleberger and Aliber 2011).

losses. Welch (2000) and Graham (1999) found herding to be very significant among analysts and among investment newsletters. Herding might also be provoked by rumors, which link herding to interaction and communication. Hong et al. (2004, 2005) explored the effects of word-of-mouth information on individuals' stock market participation and found that local networks of "friends" affect their decisions. They argue that investors, who live near each other, pass information between themselves by word-of-mouth communication.

In addition, Coval and Moskowitz (1999) argued that geographical proximity influences investors' portfolio choices. Feng and Seasholes (2004) found that in the Chinese stock market trades are positively correlated for geographically close investors but negatively for distant investors. Colla and Mele (2010) found that for close traders the information sharing effect induced by the traders' linkages dominates the negative correlation effect related to each trader standing on the opposite side of the market as a whole. Cohen et al. (2008) used social interaction to study the relationship between the portfolio choices of individuals in relation to some observable characteristic, such as educational background. They also tried to identify information transfer in security markets. Pastor-Satorras and Vespignani (2001) and Chakrabarti et al. (2008) used a network approach to study the spread of diseases. Calvo-Armengol and Jackson (2004) applied the network approach into the labor market. Allen and Gale (2000) used financial networks to study contagion in financial markets and the emergence of financial crises. Leitner (2005) constructed a model where the success of an agent's investment in a project depends on the investments of other agents this agent is linked to. Bramouille and Kranton (2007) analyzed networks in relation to public goods. Close to the intuition of my work are Jackson and Yariv (2007) and Galeotti et al. (2010), who considered a game where players have to choose in partial ignorance of what their neighbors will do, or who their neighbors will be.¹⁰

These behavioral and social features make financial system a complex system, which is populated with many dispersed agents who have incomplete and asymmetric information, assess situations individually, communicate with each other, make decisions based upon a set of rules, and use rule-of-thumb strategies. Individuals deviate from the standard theory in each step of the decision making process (DellaVigna 2009). Such system is said to be computationally irreducible; an interaction-based approach is not only indispensable for studying such system, as it allows us to see how the aggregate outcome is built in the context of micro motives, but, on many occasions, the only way to analyze it. ACE modeling can easily incorporate all sorts of nonlinear effects and can proceed even if equilibria are computationally intractable or non-existent (Teshfatsion 2006).

ACE is similar to laboratory experiments. Gode and Sunder (1993) and LeBaron et al. (1999) argued that ACE is capable of isolating and monitoring the effects of individuals' various preferences, such as risk aversion, learning abilities, trust, habits, and similar factors, while this is nearly impossible in laboratory experiments. Even though the experimenter controls the procedure in laboratory experiments, those who take part in it are aware that they are participating in a fictitious circumstance, and are likely to adapt their responses accordingly. Such experiments do not necessarily reflect what individuals would do under the same circumstances in reality.

¹⁰ Szabo and Fath (2007), and Jackson (2010) provide a review of some of the evolutionary games on networks. Allen and Babus (2008) review some models of financial networks.

2.3 Agents in ACE models

Interaction-based approach is grounded on methodological individualism with agents in the center of the model. Macal and North (2010) argued that it is always beneficial to think in terms of agents when:

- there is a natural representation as agents,
- there are decisions and behaviors that can be defined discretely (with boundaries),
- it is important that agents adapt and change their behaviors,
- it is important that agents learn and engage in dynamic strategic behaviors,
- it is important that agents have dynamic relationships with other agents and that agent relationships form and dissolve,
- it is important that agents form organizations and learning being important at the organization level,
- it is important that agents have a spatial component to their behaviors and interactions,
- the past is no predictor of the future; when scaling-up to arbitrary levels is important,
- structural change in a process is a result of the model rather than a model input.

An agent is a simplified and abstract version of a human being – an investor, while a multiagent system is a system that contains multiple agents interacting with each other and/or with their environments over time. An agent is a target-oriented being who is privately oriented and is capable of information gathering, reasoning, adaptation, learning and decision making. It is a software agent, who is repeatedly engaged in local interaction.

DEFINITION 2.2: An agent is defined as anything that can perceive its environment through sensors and act upon that environment through effectors. (Russell and Norvig 1995)

DEFINITION 2.3: An autonomous agent is a system situated within and as part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future. (Franklin 1997)

In the dissertation, agents make decisions simultaneously and autonomously in every time period. Each agent is endowed with simple preferences and adaptive learning rules, is a part of a social network and has a set of possible actions. In an artificial world, the goal of an agent is to solve a given problem. In the present dissertation, the problem relates to portfolio selection and agents solve their problem by searching for information and dealing with several constraints. The first constraint relates to bounded knowledge. Agents know neither the future stock prices, nor all the other agents in the network, nor the value functions of those agents whom they do know. They are capable of neither solving large nor complicated mathematical equations. Instead, they learn from their past decisions and also by actions of other adjacent agents. Adaptation takes place at the individual level. In addition to unsuspicious agents, I also introduce suspicious agents.

DEFINITION 2.4: An agent is said to be suspicious if there is a non-negative probability that he will depart from adopting the most promising alternative of the two being compared.

The formation of agent's beliefs

The rule which agents pursue when faced with a selection problem is very simple: an agent may either proceed with the alternative he had before or switch to any other alternative. This

simple rule is standard in dynamic games. In learning games, agents start with some initial belief regarding the relevant data, and after observing the actions of others and the change in data, they update their beliefs and behave accordingly in the next period. Such agents learn in two ways: by observing their own past actions or by communicating with others. Agents then choose such actions that represent their best responses or best actions to the given circumstances. They use matching rules such that their perceptions are challenged in relation to their expectations (Kahneman and Tversky 1982). The better (worse) the results of individual actions or strategies, the higher (smaller) is the probability that such actions and strategies will also be used in the future. Such agents, who learn from the past, behave as if past decisions are important for the future. Lettau (1997) found that flows to individual hedge funds are positively correlated with their past returns.

Different situations spur different learning processes, so there is no single universal learning model. There are many ways in which learning processes can be structured, pertinent to a different situation (Fudenberg and Levine 1998, Hart and Mas-Colell 2000, Hart 2005, Brenner 2006).

However, an agent who observes the actions of others may choose such an action that would maximize his utility according to what others have played in the past (Blume 1993, 1995), or may simply copy the past decisions of others (Bala and Goyal 1998). In the latter case, agents choose the actions and strategies that produced “good” results in the past, while the actions and strategies that produced poor results vanish over time. If actions have distinct payoffs and agents in the connected network have the same preferences, learning upon information sharing converges to a consensus decision in the long run in which all agents end up choosing the same action and achieve the same payoff (Levine and Pesendorfer 2007). If learning processes do not follow a strictly determined procedure, repetitions of the games never duplicate their history exactly, despite an unchanged learning algorithm, and always end up with different outcomes (Vriend 2000). Such learning changes the environment in which agents gather information, which in turn affects their actions. Below are presented those models that have received the most attention in the professional community.

Belief-based models

In the belief-based models, agents prefer the alternatives and actions that they assume represent the best response to the actions of others. One widely used model of learning is that of fictitious play and its variants. In this process, agents behave as if they think they are facing a stationary, but unknown, distribution of opponents’ strategies and in every period select the best response to the expected actions of their opponents (Fudenberg and Levine 1995, 1998). The process of fictitious play presupposes that players do not try to influence the future play of their opponents. To assess the expected actions of others more easily, agents might reduce the sample or weight future periods with some probabilities.

Experience weighted attraction – EWA

In experience-weighted attraction learning, proposed by Camerer and Ho (1999), strategies have attractions that reflect initial predispositions, are updated based on payoff experience, and determine choice probabilities according to some rule. The key feature is a parameter that weights the strength of the hypothetical reinforcement of strategies that were not chosen according to the payoff they would have yielded, relative to the reinforcement of chosen strategies according to received payoffs. The other key features are two parameters, the first being a discount factor of previous attractions and the second experience weight.

Regret-matching

Regret-matching is defined by the following rule (Hart and Mas-Colell 2000): next period switch to a different action with a probability that is proportional to the regret for that action, where regret is defined as the increase in payoff had such a change always been made in the past. Regret is the pain an agent feels when he realizes that he would be better off if he had not taken a certain action in the past. For an agent who chose a winning alternative in the previous period, the value of the regret is zero, thus, such an agent continues with the same alternative. When agents follow a regret-matching rule, their actions are simple and dynamic over time, while they directly relate to the development of the game.

Reinforcement learning

The basic assumption behind reinforcement learning is that actions that lead to rewards occur with a higher frequency in the future than actions that cause punishment. According to the reinforcement learning method, agents do not form special sorts of beliefs upon which to make decisions, but simply copy those past actions that yielded the highest payoffs (Roth and Erev 1995, Erev and Roth 1998). Reinforcement learning is not strictly a learning model. These models have been used highly successfully in the research of biological evolutionary processes, especially in understanding animal behavior. They have also been extensively used in the “cheap-talk” or “asking around” communication games of social learning to describe the result of some types of “emulation” by economic agents. In these games, agents do not learn only from their own experience, but can obtain information and learn from other agents. An example of such a dynamic is that of emulation, in which an agent asks another what strategy he used and how well it did. Such agents “satisfy” rather than “optimize” their payoffs. This learning method is applied in the dissertation, which is an illustration of a “cheap talk” model in an uncertain financial world of satisficing and not agents.

2.4 Artificial market models

Let me conclude this section with some ACE applications in finance. With some early models being developed during the 1970s (Zeeman 1974 and Garman 1976), ACE modeling has developed further at an impressive pace since the 1990s. Arifovic (1996) used a method of genetic algorithm for studying the dynamics of exchange rates. Later on, Brock and Hommes (1998) and Brock and LeBaron (1996) extended Arifovic’s model by introducing social interaction and the principle of learning from other agents. More sophisticated asset pricing models include Kim and Markowitz (1989), Hakansson et al. (1990), Gode and Sunder (1993), Tay and Linn (2001), Cont and Bouchaud (2000), Stauffer and Sornette (1999), Lux and Marchesi (1999), Palmer et al. (1994), Arthur et al. (1997), Johnson (2002), Caldarelli et al. (1997), Levy et al. (2000), Jacobs et al. (2004), Sharpe (2007), Raberto et al. (2001), Hommes (2006), Preis et al. (2006), Rosu (2009). A short review of agent-based models of financial markets is provided in Samanidou et al. (2007). I will outline some models below.

JLMSim (Jacobs et al. 2004)

The JLMSim simulator is a tool that allows its users to model a market by supplying certain components. Its core elements are traders with their wealth, different securities and their prices, and the request and demand offers of the traders. It is either a general equilibrium model in which “mean-variance” agents gradually approach their optimal portfolios from the efficient frontier, or an asynchronous dynamic simulator. The simulator allows the

modeler to use different types of agents, who differ in their risk aversion, wealth, reoptimization frequency, and time at which they reoptimize. In general, the preferences of individual agents along with their trading specifics are defined through many exogenous variables.

An important factor of the simulator is price, which is set endogeneously according to the following procedure. Traders put in their request and demand offers in every time period. When placing an offer, they fix the price cap at which they are willing to buy a share. As long as market prices are lower than the caps, they buy at the market prices. When all the demands and requests are reported to the auctioneer, he ranks the orders from the lowest to the highest price, while requested offers are ranged from the highest to the lowest price. Thus, every security has its own set of request and demand prices, upon which the trades are done. For example, if there is an insufficient supply of stocks at the proposed price, agents wait for some time, i.e. day, week, month, and then lift the requested price. The trading mechanism lasts until all of the agents reach their efficient frontier portfolios. It is determined as the maximum difference between the expected return of a portfolio and the variance that is adjusted for an agent's risk aversion.

APSIM (Sharpe 2007)

APSIM (*Asset Price and Portfolio Choice Simulator*) is a discrete-state, discrete-time equilibrium portfolio simulator under complete market hypothesis. Agents in the model trade in order to maximize their marginal utility. The salient characteristic of the model is a trade-off between consumption and investment.

The model introduces probabilities of different events, upon which agents build a "price-per-chance" coefficient that measures the relation between the stock price and the probability of an event. In the model, agents prefer states with low values of the coefficient, designating a preference for low cost per investment. Agents in the model develop their expectations upon the CAPM model, while the stock prices are determined through the trading mechanisms, which proceed in two stages. First, agents report to an auctioneer their reservation prices at which they are willing to trade stocks. The market price is then proposed at the point in which there are adequate demand and supply per each individual stock. In the second stage, the auctioneer reports the proposed market prices to the agents, who then need to make their final offers. The solution of this stage determines the market-clearing price. If the supply (demand) of stocks exceeds the demand (supply), then all the sellers (buyers) sell (buy) the demanded stocks, while the received quantities of stocks of the buyers (sellers) are proportional to the demanded (supplied) stocks of individual agents compared to the entirety of demanded (supplied) stocks. By their activities, agents determine the price dynamics, while they slowly approach their optimum portfolios and equilibrium. When equilibrium is reached and all possess the requested portfolios, agents stop trading.

ASM (Palmer et al. 1994, LeBaron et al. 1999, LeBaron 2002, Johnson 2002)

The ASM simulator (*Artificial Stock Market*) is an artificial stock market simulator that was developed at the Santa Fe Institute. The stock market consists of an auctioneer along with an arbitrary number of traders. Traders are identical except that each of them individually forms his expectations of stock prices over time through an inductive learning process. Traders do not have precise knowledge of the fundamental value of the stocks, because the

dividends are defined as an AR(1) process with Gaussian white noise. There exists a riskless asset in infinite supply and many risky stocks, which are divisible.

At the beginning of each time period, each trader selects a portfolio to maximize his expected utility in the next period. Each trader is an inductive learner, for which new rules are continually being introduced as to the market conditions. In each time period, each trader decides how much of his wealth to invest in the risky stock and how much to invest in the riskless asset. Traders do this by generating a (net) demand for a stock as a function of their current expectations for the stock's price and dividend in the next period and the yet-to-be-determined price of the stock in period t . This demand function is reported to the auctioneer, who in turn determines the market-clearing price for the stock and communicates this price back to each of the traders. Given this market-clearing price, each trader then goes ahead and purchases his corresponding demand. The asset market has a reflexive nature in that prices are generated by agents' expectations as based on their anticipation of the expectations of others.

When in interaction with others, traders constantly update their knowledge and use it in future decisions (Arthur 1991, 1992, 1994). This is a two-step procedure in which, based upon their experience, knowledge, and interaction, agents first form a number of potential alternatives, which are then tested as to how well they solve the agent's decision-making problem. The selected alternative is the best solution to the problem. Traders modify their forecasting rules, by which they drive out the worst-performing rules and replace them with new "offspring" rules that are formed as variants of the retained rules. Traders construct new rules using a genetic algorithm, succeeded later by the method of swarms. Tay and Linn (2001) introduced a fuzzy logic principle into the learning mechanism of the ASM agents.

Order book models

Order book models are models of price formation, and represent the alternative to call auctions, in which all participants either have to wait or trade ahead of their desired time, or dealer markets, which provide immediacy to all at the same price. Market participants can post two types of buy/sell orders. A limit order is an order to trade a certain amount of a security at a given price. Limit orders are price-contingent orders to buy (sell) if the price falls below (rises above) a prespecified price. The lowest offer is called the ask price, or simply ask, and the highest bid is called the bid price, or simply bid. A market order is an order to buy/sell a certain quantity of the asset at the best available price in the limit order book. When a market order arrives it is matched with the best available price in the limit order book, and a trade occurs. A limit order book allows investors to demand immediacy, or supply it, according to their choice. Limit and market orders constitute the core of any order-driven continuous trading system.

Preis et al. (2006) developed an order book model that aimed to resemble the order book at a real exchange. Their market consisted of one asset. In their model, market participants can enter limit orders, which are executed at the assigned limit or some better price. If market orders have no limit price, these orders are matched immediately at the best available market price; at best ask and best bid, respectively. Their matching algorithm for the orders provides a price time priority which is usually found for most assets in real markets. The model can reproduce some important features of real markets, such as fat tails.

Rosu (2009) presented a model of an order-driven market where fully strategic, symmetrically informed market participants dynamically choose between limit and market orders, trading off execution price and waiting costs. Rosu demonstrated that: higher trading activity and higher trading competition cause smaller spreads; market orders lead to a temporary price overshooting; buy and sell orders can cluster away from the bid-ask spread; bid and ask prices display a comovement effect – after a sell market order moves the bid price down, the ask price also falls, by a smaller amount, so the bid-ask spread widens; and that when the order book is full, traders may submit quick, or fleeting, limit orders.

In the model of Foucault et al. (2005), a market is populated by strategic traders of varying impatience. In equilibrium, patient traders tend to submit limit orders, whereas impatient traders submit market orders. The authors offer several testable implications for various market quality measures such as spread, trading frequency, market resiliency, and time to execution for limit orders.

Bloomfield et al. (2005) proposed a model of informed traders who have superior information and liquidity traders who face both large and small liquidity needs. They found that liquidity provision changes dramatically over time due to the behavior of the informed traders. When trading begins, informed traders are much more likely to take liquidity, hitting existing orders so as to profit from their private information. As prices move toward true values, the informed traders shift to submitting limit orders. This shift is so pronounced that towards the end of the trading period informed traders on average trade more often with limit orders than do liquidity traders. Informed traders change their strategies depending on the value of their private information. Liquidity traders who need to buy or sell a large number of shares tend to use more limit orders early on, but switch to market orders in order to meet their targets as the end of the trading period approaches.

Other simulators

Zeeman (1974) proposed a heterogeneous-agent model to explain the dynamics between bull and bear markets. The model contains two types of traders: fundamentalists, who “know” the true value of stocks and buy (sell) them when the prices are below (above) it, and chartists who react to market circumstances, following the trend. Zeeman argues that in a bull market the proportion of chartists who follow the trend increases, which pushes the prices even higher. The uptrend continues until fundamentalists perceive the prices too high and start selling. This in turn leads to price drops (bear market), which then reduces the proportion of chartists. The downtrend provokes fundamentalists to start buying the stocks, which again turns the trend.

DeLong et al. (1990b) proposed a two-asset model with noise traders (naive traders) and sophisticated traders. The behavior of noise traders depends on the relative success of their past strategies. Noise traders incorrectly believe that they have special information about the future price of risky assets. Thus, they use signals from technical analysts, incorrectly believe that these signals carry the right information, and then select their portfolios based upon these incorrect beliefs. Sophisticated traders exploit the noise traders’ misperceptions and buy (sell) when noise traders depress (push up) prices. This contrarian trading strategy pushes prices in the direction of the fundamental value but not completely. As demonstrated, the proportion of noise traders will oust fundamentalists when the expected return of the error term is positive, as is the case of a bull market. In the model, the return of a risky asset equals that of a riskless one enlarged by Gaussian error.

GASM (*Genoa Artificial Stock Market*) of Raberto et al. (2001) is an artificial stock exchange model for asset pricing with heterogeneous agents who issue buy and sell orders in every iteration. The orders follow their preferences and wealth as well as past volatility in prices. GASM runs numerous simulations in which agents endowed with a limited amount of cash are divided into subpopulations, adopting either chartist, fundamentalist, or random trading strategies. The clearing price is set at the intersection of the demand and supply curves.

Lux (1995) and Lux and Marchesi (1999) proposed an asset pricing model that is based on social interaction. They use two types of agents, chartists and fundamentalists. The latter sell when prices are high and buy when prices are low. The chartists use a combination of imitating strategies mixed with that of trend following. Chartists are split in two groups, with pessimists (anticipate bear market) and optimists (anticipate bull market). They sell (buy) when prices are high (low). Based on common belief and the sensitivity of an agent to the changes in common belief chartists traverse among pessimists and optimists. Prices in their model are determined through the excess demand for an individual asset and the speed of adjustment to it. In the model, chartists buy (sell) when they are optimistic (pessimistic), while fundamentalists buy (sell) when the prices are below (above) their fundamental value. A market maker sets a price based upon the requests of all.

Chapter III

Social networks

3.1 General graph theoretical concepts

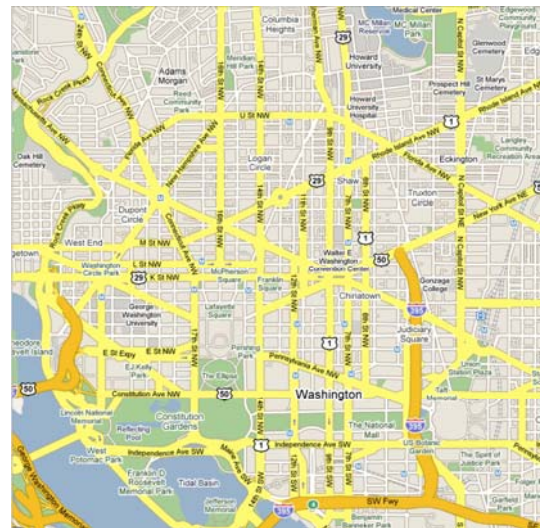
In the dissertation, a network represents a system of interactions among investors and symbolizes daily relations and information sharing among them. It depicts an infrastructure that is used for information sharing.

Apart from such communication networks, the world around us is full of some other types of networks such as the internet, networks of e-mail messages, genome and other biological networks, networks of chemical reactions, catalytic networks, networks of metabolic processes, protein networks, neural networks, transportation networks, networks of streets and villages, social networks and networks of colleagues and friendships, networks of rivers and water flows, networks of contacts, networks of viruses, and many other networks.¹¹ Newman (2003) distinguished four groups of networks: social networks, information (or knowledge) networks, technological networks and biological networks. Two representations of a network are exhibited in Figure 3.1.

Figure 3.1: Representations of a network



(a) protein network



(b) road map, Washington DC

Source: Barabasi and Oltvai (2004), maps.google.com.

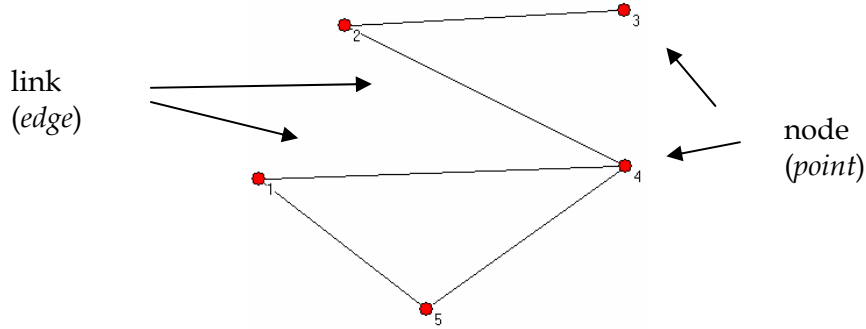
This chapter aims to provide some insights into the area of social networks. An extensive review of network models is given in Wasserman and Faust (1998), Chakrabarti and Faloutsos (2006), Jackson (2008). The introductory subsection reviews some basic concepts and properties of social networks, while the rest of the chapter presents some network types.

¹¹ Marriage networks have been used to explain the rise of the Medici family in medieval Florence (Padgett and Ansell 1993).

Graph and subgraph

A graph g consists of two sets (V, E) , where $V = \{v_1, v_2, \dots, v_n\}$ is the set of nodes (or vertex, point), and $E = \{e_1, e_2, \dots, e_n\}$ is the set of links (or line) among pairs of nodes (Figure 3.2).

Figure 3.2: A graph



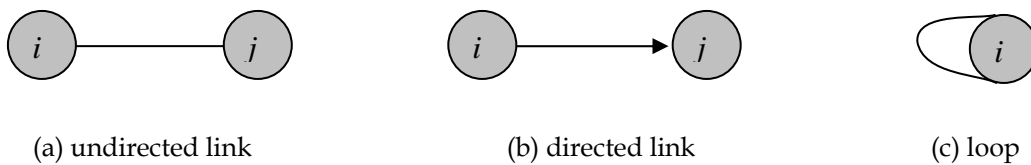
Each link links two nodes, let's denote them i and j . There are two possibilities:

- The order of the nodes is not important – we have an undirected link or edge. We denote it by ij . It holds $ij = ji$.
- The order of the nodes is important – we have a directed link or arc. We denote it by (i, j) . If $i \neq j$ then $(i, j) \neq (j, i)$.

The edge ij allows us to move from i to j and also from j to i ; while the arc (i, j) allows us to move only from i to j .

In the case when $i = j$ the link is called a loop (Figure 3.3).

Figure 3.3: Undirected and directed link and a loop



- Finite graph is a graph in which the set of links E and the set of nodes V are finite.
- Complete graph is a graph in which all nodes are linked with each other.
- Empty graph is a graph with a non-empty set of vertices V and an empty set of links $E = \{ \}$.
- Simple graph is a graph without loops and multiple links.
- Undirected graph is a graph with only undirected links.
- Directed graph is a graph with only directed links.
- Mixed graph is a graph with both undirected and directed.
- The graph with only one node and no edges is called the trivial graph.
- With e we denote the number of links (size of the graph), and with n the number of nodes (order of the graph).

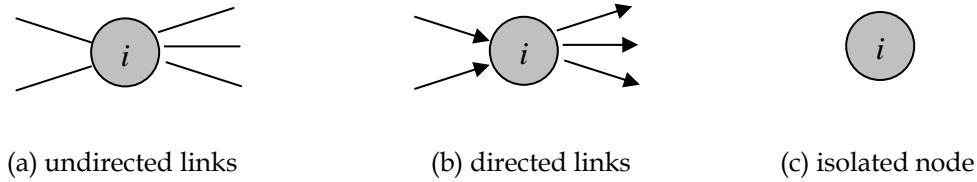
A graph describes the structure of a network. To get a network we have to provide additional information about the properties of nodes and links. The properties of nodes are usually called attributes (label, gender, age, ...), and the properties of links are usually called weights (frequency of interaction, amount of transfer, ...).

The degree $k(i)$ of a node i in the network is equal to the number of links that link it to other nodes in the network.

In a network, the degree of an individual node counts the number of links each node has (Figure 3.4). Its in-degree, $k_{in}(i)$, counts the number of links that enter the node, and out-degree, $k_{out}(i)$, counts the number of links leaving the node.

In undirected networks, the incoming link is also an outgoing link, therefore $k_{in}(i) = k_{out}(i) = k(i)$. In a graph a node is an isolated node if it is not linked to any other node. A graph in which all nodes have the same degree r is called a r -regular graph.

Figure 3.4: Node degree



In simple undirected graphs, a node degree belongs to the interval $0 \leq k(i) \leq (n-1)$; at one extreme the node is linked to every other node in the graph, at the other it is linked to none.

The average node degree in an undirected graph equals $\bar{k} = \frac{2e}{n}$; in a directed graph, the average node in/out-degree equals $\bar{k} = \frac{e}{n}$.

In the sequel we shall limit our attention to simple graphs - without loops and multiple links, if not explicitly stated differently.

Because a link in an undirected network connects two nodes, the order of the graph is two-times its size. The maximum size of an undirected graph of order n is $e = \binom{n}{2} = \frac{n(n-1)}{2}$, and the minimum size is zero. The maximum size of a directed graph is $e = n(n-1)$. A graph with order $n = 1$ is both complete and empty.

A convenient way to represent a network is using adjacency matrix \mathbf{A} . For a pair of nodes in the graph i and j , we write $\mathbf{A}(i, j) = 1$ if i is linked to j , and $\mathbf{A}(i, j) = 0$ otherwise.

A structure $g_S = (V_S, E_S)$ is a subgraph of graph $g = (V, E)$ if $V_S \subseteq V$ and $E_S \subseteq E$ and for each link from E_S both its endnodes belong to V_S .

Some additional concepts on graphs:

- A walk is a sequence of nodes and links, starting and ending with nodes, in which each node is incident with the links following and preceding it in the sequence.
- A path is a walk in the graph from a node i to j in which all nodes are distinct.
- A trail is a walk in the graph from a node i to j in which all links are distinct.
- A graph is connected if for every pair of nodes in the graph (i, j) there exists a walk from node i to node j .
- Maximal connected sub-graphs of a graph are called components.
- A graph is biconnected if it remains connected after the elimination of any single link.

Degree distribution

In a graph $g = (V, E)$, $\Pr(k)$ denotes the probability that a random node in the network is of degree k . The following distributions are usually used to describe the degree distribution (Dorogovtsev and Mendes 2003):

- Poisson distribution (random graphs),
- Exponential distribution (growing random graphs),
- Power law distribution (accelerated growth, preferential attachment),
- Multifractal distribution (copying models),
- Discrete distribution described with a table.

Distance, eccentricity and diameter

- The distance $L(i, j)$ from node i to node j is equal to the length of the shortest path (also known as geodesic) from i to j . If there is no path from i to j then $L(i, j) = \infty$. The average distance in the graph \bar{L} represents the mean of the distances between the nodes in the graph, $\bar{L} = \frac{1}{n} \sum_{i=1}^n L(i, j)$.
- The eccentricity of a node is the largest geodesic distance between the node and any other node in the graph, i. e. $E_k = \max_i L(i, j)$. Minimum eccentricity of any node is 1, and maximum is $(n - 1)$.
- A graph has a diameter D if every node in the graph can be reached by the maximum geodesic distance of a length D . Diameter is the largest eccentricity, $D = \max_{i,j} L(i, j)$. A graph with at least two components has infinite diameter.
- The effective diameter D' (Tauro et al. 2001) is equal to the shortest distance to reach at least 90 percent of the pairs of nodes in the graph.
- The neighborhood of a node i consists of the set of nodes that are linked with i .
- The k -neighborhood of a node i consists of the set of nodes that can be reached from the node i using a geodesics of length k .

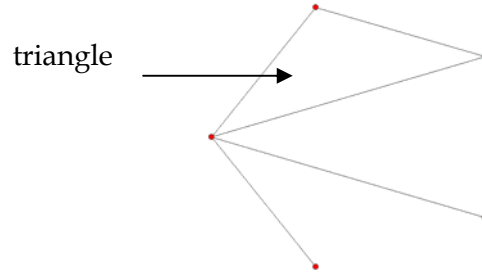
The term “degree of separation” is usually used in the context of diameter (Milgram 1967, Travers and Milgram 1969). Social networks usually have small diameters.

Cohesive subgroups

Cohesive subgroups within the graphs are subsets of nodes and their links.

A clique is the maximal complete subgraph of three or more nodes of the graph.

Figure 3.5: A clique



A clique represents a homogenous group of nodes in a graph. The easiest way to demonstrate a clique is to use triangles (Figure 3.5). Because cliques may overlap, individual nodes might belong to more than one clique, while some might belong to none. By definition, there cannot be a clique inside a clique, which would mean that the smaller clique was not of maximal size. Thus, the value of a clique, or a clique number, is defined as the largest order of a clique.

- L -clique defines the largest subgraph of a graph in which the largest geodesic distance between the two arbitrary nodes is at most L .
- L -clan defines the largest L -clique in which the geodesic distance between the two random nodes is no larger than L .
- L -club is the largest subgraph of a graph in which the distance between the two random nodes is at most L .
- k -plex is a maximal subgraph with n_s nodes in which a node is adjacent to no fewer than $n_s - k$ nodes in the subgraph.
- k -core is the largest subgraph in which every node is adjacent to at least k nodes.

Clustering coefficient

The density of a graph refers to the number of nodes in the graph and links between them. Density in a graph is equal to the ratio between the number of links of the graph and the maximum possible number of links in the graph (see Watts and Strogatz 1998, Wasserman and Faust 1998).

If in the graph of order n , e_i denotes the number of links linking the neighbors of node i , then the clustering coefficient of node i is defined as $C_i = \frac{2e_i}{k(k-1)}$. Conventionally, the clustering coefficient of a node i is a ratio between the total number e_i of the edges connecting its nearest neighbors and the total number of all $\frac{k(k-1)}{2}$ possible edges between all these nearest neighbors of a node i (Watts and Strogatz 1998).

The clustering coefficient of a graph is defined as the average clustering coefficients of the nodes, $C = \frac{1}{n} \sum_{i=1}^n C_i$. The clustering coefficient of fully connected network is equal to 1.

The clustering coefficient is based on transitivity, and it represents the expected probability that a node i in the graph is linked to node k , if node i is linked to j and node j to node k . Loosely speaking, the clustering coefficient tells us whether friends of some subgroup within the group are also friends themselves, and how feasible it is that individuals within the groups will cooperate among themselves. The value of the coefficient thus represents the probability that two members of the group will also be friends with each other.

Centrality and prestige

On the micro-level, the behavior of a network depends on the role, influence, and importance of single members of larger communities. These factors have been examined through the concepts of centrality and prestige¹² (Bavelas 1950, Bonacich 1987). Both ideas follow the assumption that larger groups have some sort of representatives or leaders who are “in charge” of the group and influence the behavior of its members.

Generally, the centrality of nodes is measured as to their reachability, while prestige distinguishes among the in-degrees and out-degrees of a node, with in-degree of a node representing its prestige. As such, the concept of prestige requires a directed graph, since in an undirected graph in-degree, out-degree and degree are equal.

Closeness centrality (C_C) focuses on how close a node is to all other nodes in a network. The shorter the paths, the more central in the network is the node, and the faster and more efficiently it communicates with other nodes (Sabidussi 1966).

Degree centrality (C_D) indicates the number of links each node in the graph has relative to the number of links other nodes in the graph have (Nieminen 1974).

Betweenness centrality (C_B) determines the importance of individual nodes within a network by considering the number of geodesics that pass through individual nodes (Freeman 1977). A node that lies on the path between two nodes controls the communication between the two nodes. Betweenness indicates the number of all the shortest paths in the network that pass among individual nodes and is denoted $\sigma(m)$. It was first introduced in sociology as a measure of the importance of individuals in a society. The more the shortest paths pass through an individual node in the network, the bigger the importance of the node. The betweenness coefficient of individual nodes can be used in assessing the flexibility of a network, for it denotes the number of shortest paths that will increase if one or more of the most important nodes is eliminated from the network (Albert et al. 2000, Newman 2001). The minimum value of an index is zero and indicates an isolated node that is not present in any shortest path between two nodes in the network. The maximum value of an index of $\frac{(n-1)(n-2)}{2}$ indicates the node that is present in every shortest path between any pair of the two nodes in the network.

¹² Some other expressions are used to designate prestige: popularity, status, respect (Wasserman and Faust 1998).

Graph connectivity and percolation theory

The connectivity of a graph is related to the question whether individual nodes can be reached. An unconnected graph is split into connected subgraphs, also known as components.

- A bridge is a link in a graph such that its elimination increases the number of components in a graph.
- An articulation node is a node in a graph such that its elimination increases the number of components in a graph.
- A node-connectivity of a graph, $\psi(g)$, is equal to the minimal number of nodes of the graph that need to be eliminated to disconnect the graph, or to produce a trivial graph.
- A link-connectivity of a graph, $\xi(g)$, is equal the minimal number of links of the graph, ξ , that need to be eliminated to disconnect the graph, or to leave a trivial graph.

Percolation theory analyzes connectivity in graphs. It presents the critical probability at which the two nodes in the graph are still linked to each other. Generally, we distinguish between the site percolation (from the point of nodes) and the bond percolation (from the point of links). An implication of the theory is that only intentional attacks focused on the elimination of some of the most important nodes or links within the network can destroy the network (Callaway et al. 2000, Albert et al. 2000).

Network stability and Nash equilibrium networks

Social networks bring economic value to the members; benefits on the one side and costs on the other (Jackson and Wolinsky 1996). The benefits and costs depend on whether agents are directly linked to others or not. Direct links usually bring higher benefits than indirect, whose benefits depend on the distance between the nodes in the network, but the costs of maintaining them are usually higher. As long as the benefits of indirect connections are higher than costs of maintaining direct links, agents have an incentive for using them. Although the larger number of direct links usually brings higher utility, having too many friends might reduce the utility of an agent due to diminishing returns.

If $u_i(g)$ and $u_j(g)$ denote the utility of individuals i and j in the network g , then a network g is pairwise stable iff:

- a) for all $ij \in g, u_i(g) \geq u_i(g - ij)$ then $u_j(g) \geq u_j(g - ij)$ and
- b) for all $ij \notin g, u_i(g + ij) > u_i(g)$ then $u_j(g + ij) < u_j(g)$.

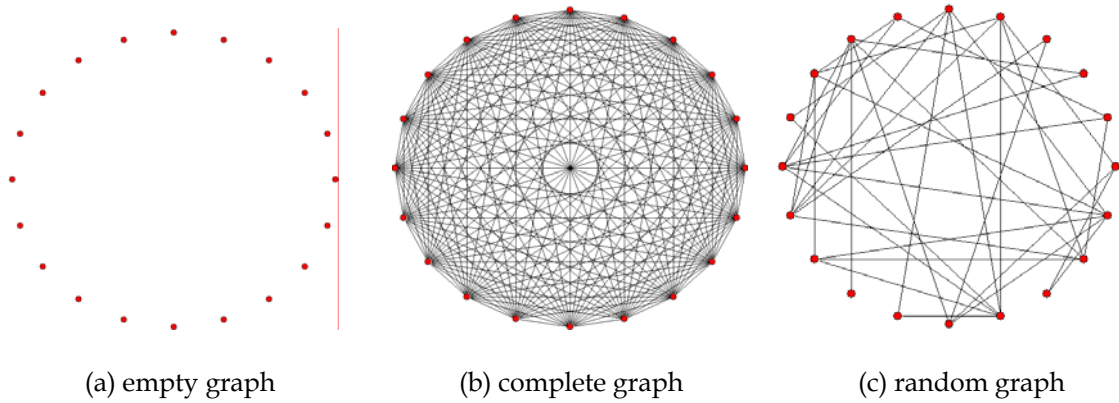
If $g + ij$ ($g - ij$) denote the graph obtained by adding (deleting) a link ij to (from) the existing graph, then the definition implies that in a pairwise stable network no individual has an incentive to form or to sever any of the existing links. If a link between two individuals is present, then it cannot be that either individual would strictly benefit from deleting that link. On the other side, if a link between two individuals is absent, then it cannot be that both individuals would benefit from forming that link.

The last notion relates to the quality (or strength) of the ties. Granovetter defines strong ties as direct friendships and weak ties as casual acquaintances. Because individuals with strong ties are homogenous, the flow of new information into such a group is bounded. Because distant friends and acquaintances are likely not to be known by other members of a clustered group, such weak ties prove to be of the greatest significance for the propagation of new information into such clustered groups. Weak ties also link different sub-networks of networks (Granovetter 1973, Montgomery 1992).

3.2 Random graphs (Erdos and Renyi)

A random graph of Erdos-Renyi type consists of a set of nodes V and the set links E in which a link (i,j) is included with the probability p (Erdos and Renyi 1959).

Figure 3.6: Graphs at different values of p



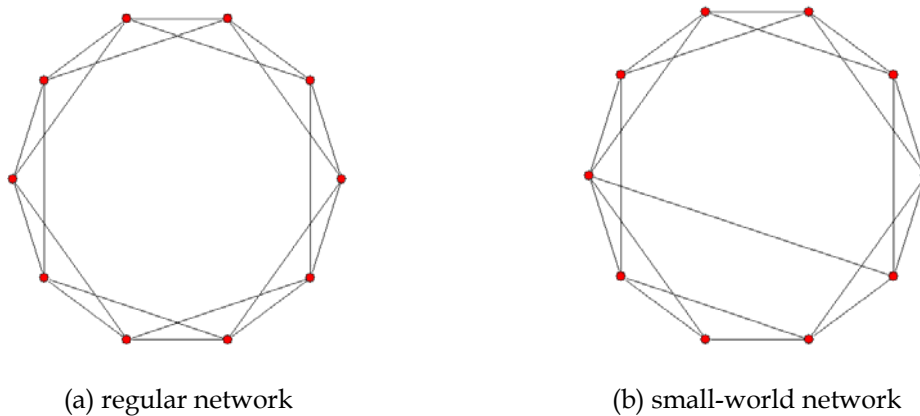
An undirected graph with $V = (1, 2, \dots, n)$ nodes and the probability of a link p has $\frac{p(n-1)n}{2}$ (expected number) random links (Figure 3.6). For $p = 0$, there is an empty graph of isolated nodes. For $p = 1$, there is a complete graph with $\frac{(n-1)n}{2}$ links, in which every single node is linked with each of the rest. For $0 < p < 1$, we have a family of random graphs with the non-zero probability that nodes are linked with each other. For low probabilities of p , a graph is low in homogeneity and density.

Since links in a random graph are completely independent, the clustering coefficient depicts the probability that two random nodes are linked, therefore $C = \frac{k}{n} = p$. As a graph approaches infinity in size, the probability that two random nodes are linked tends towards zero. When all nodes are linked with each other, the clustering coefficient approaches unity, therefore $C = \frac{k}{n} = \frac{(n-1)}{n} \doteq 1$. Because the nodes in a random graph are linked with each other at random with the probability of a link well below unity, a random graph usually has more than one component.

3.3 Small world networks (Watts and Strogatz)

Real-world networks are not random in the sense of Erdos and Renyi but rather locally clustered (Watts and Strogatz 1998). Small-world networks combine characteristics of regular and random graphs, with the former providing local clustering and the latter the effect of a small world due to a small number of random “shortcut” links. The shortcut links reflect the idea of global friendships among people, while they drastically reduce geodesic paths (Milgram 1967, Travers and Milgram 1969). The experiment indicates that not only do the shortest paths between individuals exist, but also that individuals are able to find and use them (Newman 2003, Kleinberg 2000).

Figure 3.7: Regular network and a small-world network



The formation of a small-world network is a two-step process (Figure 3.7):

- **The formation of a regular network:** proceed with a regular circle network of a size n . Every node in the regular network has k edges to their closest neighbors; half of them symmetrical on each side.
- **Rewiring:** in such a regular network with the probability p , each node is rewired to a randomly selected node from the network. In the rewiring process, loops and multiple links are not allowed. Thus, we insert long-range shortcut links into the network and get a small-world effect (Watts and Strogatz 1998).

Instead of rewiring, Newman and Watts (1999) begin with a regular lattice to which they add random shortcuts, thereby reducing the diameter and retaining local homogeneity.

The introduction of long-range links heavily increases the average connectivity of nodes in the graph, while a drastic decrease in the average distance is induced by the probability that each randomly rewired link will directly connect some very distant nodes and nodes of their immediate neighbors. It has been demonstrated that a small number of such long-range links is enough to produce a small-world effect, meaning that the rewiring process does not significantly reduce local homogeneity of a network. Watts and Strogatz (1998) and Barrat and Weigt (2000) demonstrated that the small-world effect is induced when the rewiring probability lies in the neighborhood of $p = 0.1$.

The average degree in a graph is of order k , while after the process of rewiring, the network remains connected. A small-world network keeps a high level of homogeneity, a high clustering (local property), and has a small diameter (global property). As only one edge of

the link between the two nodes is rewired with the probability p , we get a graph with $\frac{pkn}{2}$ long-range links also after the rewiring. With the probability of rewiring approaching unity, the network gets less regular and more random. At the limit, as $p \rightarrow 1$, the network is random, even though each node still has at least $\frac{k}{2}$ links. Since such a network retains connectivity, it differs from the Erdos-Renyi type of random graph.

A clustering coefficient is generally defined as $C(p) = C(0)(1-p)^3 = \frac{3(k-1)}{2(2k-1)}(1-p)^3$, and approaches $\frac{3}{4}$ as $k \rightarrow \infty$ and $C(0) = \frac{3(k-1)}{2(2k-1)}$ for $p=0$ (Barrat and Weigt 2000). For $p > 0$, the two neighboring nodes of i that were linked for $p=0$ are still linked with the probability $(1-p)^3$. At small probabilities of rewiring, the clustering coefficient is still in the neighborhood of $\frac{3}{4}$. This indicates that the network retains all the characteristics of a locally homogenous network. When $p \rightarrow 1$, the clustering coefficient approaches zero. Such a network retains its connectivity but has no local homogeneity.

Networks pose a problem of navigation (Kleinberg 1999). In the Milgram experiment, people were faced with the task of delivering a letter to a particular person. The question was whether individuals were able to use their links in order to find the shortest paths, and the experiment proved that they are able. In addition, Watts et al. (2002) claimed that agents solve navigation problems by looking for some common characteristics among their friends, such as occupation, place of living, hobbies. Stephenson and Zelen (1989) added that agents choose friends with the highest degrees.

3.4 Scale-free networks

In Erdos-Renyi and small-world networks, nodes with degrees significantly higher than others do not exist. Yet, some surveys have shown that there are nodes in the World Wide Web (WWW) network that are more attractive than others, resulting in them having higher degrees (Albert et al. 1999, Broder et al. 2000, Kleinberg et al. 1999).

If x represents a random variable and λ is a positive constant, then the distribution of a random variable follows a power law iff it has a probability density function of the form $f(x) \propto x^{-\lambda}$.

Acknowledge that $\lambda > 1$ if the “rich get richer” pattern is to be met. The distribution of a random variable is said to follow a power law if the frequency of an event decreases to the inverse of some exponential degree as the size of the event increases, or when the amount one has increases with the amount one already has had (Lotka 1926). When examining the number of citations of scholars within Chemical Abstracts, Lotka demonstrated that the number of authors is inverse to the square of their published papers. The Pareto law of income distribution is another demonstration of a power law distribution. Vilfredo Pareto proposed a question as to the number of individuals in a society that have an income higher

than x and found that the probability of an event $X \geq x$ equals the inverse of x , that is $\Pr(X \geq x) \propto x^{-\lambda}$. This means that a small fraction of a population earns a very high income, while the vast majority has a modest one. Experimental studies have found the value of λ to be around 2 and 3. Barabasi and Albert (1999) showed that the degree distribution in a network follows the power law if it is growing following the “preferential attachment.” In the present dissertation, λ is used to demonstrate ranking of selected portfolios, thereby being an indicator of the level of synchronization in portfolio selections. For further details regarding the mathematical derivations of a scale-free distribution see Mitzenmaher (2004), and Newman (2005).

Preferential attachment

Barabasi and Albert (1999) posit a network growing process of preferential attachments in which newcoming nodes attach to the existing nodes with the probability proportional to the node’s degree, implying the “rich get richer” rule. In this process, the age of nodes is significant. Because older nodes have had more time to make a larger number of links than younger nodes, they are more attractive. Therefore, such process implies correlation in degrees, and also age-based homophily. Homophily refers to the state in which people prefer to maintain relationships with people who are similar to themselves (Jackson 2008). Barabasi and Albert assume that the probability that a new node will attach to node i in the network depends on its relative degree to other nodes.

The rich-get-richer principle neglects the fact that such “endless” link formation is confined by at least two factors: the aging of nodes and the cost of linking new nodes to nodes with higher degrees. Every individual has only a limited time to work and live, which makes aging and physical capabilities far more significant in social networks than in transportation or similar networks. Amaral et al. (2000) proposed a network of preferential attachment in which existing nodes do not have endless possibilities of accepting new nodes or are limited by aging. As nodes get older and have high degrees, the probability that such a node will become inactive increases. This represents a deviation from the “winner-takes-all” scheme. However, since the probability that an individual node will link to a random node i in the network depends on the age of the node and not just on their degree k_i , there is still a chance for such a link. In these circumstances, the probability for such a link follows a power law. Thereby, the older the node, the smaller the probability for such link formation.

Fitness models assume that every node in a network has some fitness η_i that determines its attraction to others (Bianconi and Barabasi 2001, Caldarelli et al. 2002). The fitness of a node depends not only on its degree but also on many other factors, with nodes of higher fitness being more attractive and having higher degrees.

Flaxman et al. (2004, 2007) proposed a geometric preferential attachment model in which nodes in a neighborhood prefer links with nodes from that neighborhood. Dorogovtsev, Mendes and Samukhin (2000) proposed a model in which there is a small non-negative probability that new nodes link to isolated nodes. Therefore, every node in the network has a non-negative probability to be found and to become linked. Pennock et al. (2002) find this principle within the sub-groups of the WWW.

Communities

A community is generally considered a set of nodes where each node is “closer” to the other nodes within the community than to the nodes outside it. There are numerous definitions of communities. The structure of communities often follows homophily and assortativity (Schelling 1969, Girvan and Newman 2002, McPherson et al. 2001, Newman and Girvan 2004, Jackson and Rogers 2005). Homophily is the principle that a contact between similar people occurs at a higher rate than that among dissimilar people as to gender, race, ethnicity, age, religion, wealth and social status, educational attainment, etc. One form of homophily is due solely to opportunity, while the other is due to choice, although the two possibilities are often intertwined. Assortativity relates to the state in which nodes with high degrees are more attractive to other nodes with high degrees.

Copying

Kleinberg et al. (1999) proposed a directed graph of copying models (see also Kumar et al. 2000 and Newman 2003). Copying refers to the process of incoming nodes replicating some links of existing nodes. Copying is a two-stage process in which an incoming node chooses a node from the network from which to copy links and then the links to be copied.

In each iteration a node is chosen with some number of k out-degree links. Then with a probability α , these k links are linked to nodes chosen randomly from the host node. With a probability $(1 - \alpha)$, links are copied from another node that is chosen randomly. The process continues until the links are adjacent. The coefficient α is called a copying factor. Copying models induce a power law distribution in accord with the principle “rich get richer”.

Krapivsky and Redner (2001) proposed a slightly modified copying model, in which an incoming node first chooses a random node, and then with some probability link to its neighbors thereby approaching its initial preference. Blum et al. (2006) proposed a random surfer model, in which an incoming node chooses a node from the network at random, and then randomly walks through the links of the host in the network and makes links to visited nodes with some probability.

Forest fire

Leskovec et al. (2005), Leskovec et al. (2007) and Leskovec (2008) proposed a forest fire network growing process. The model is based on the assumption that new nodes attach to a network by burning through existing edges in epidemic fashion.

The forest fire model is a three-stage process in which node v first chooses an ambassador node w at random and forms a link to it and starts to spread through it by using its links; selects x outlinks and y in-links of w incidents to nodes that were not yet visited; and finally, forms out-links to the visited links, and continues with the stage 2 recursively until the out-links are full (the fire dies out). Nodes in the network can only be visited once.

Forest fire models are preferential attachment models that have low diameters and preserve local homogeneity. They are capable of capturing the “rich-get-richer” principle but cannot

explain the phenomena of orphans. The model assumes that the fire can break out only from one core, even though there could have been many (Leskovec et al. 2007).

Similar to the forest fire models are random walk models, in which a node links to a random node in the network and then continues the walk by visiting its neighbors and links with each node it visits with some positive probability (Vazquez 2001).

Chapter IV

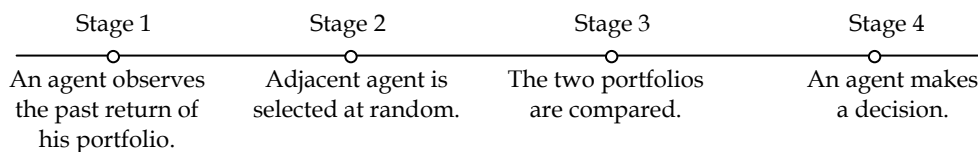
Portfolio simulator

4.1 Basic framework

I start this chapter with a short paragraph on the methodological aspect of network modeling in economics and finance in general. Building a network of connections and information flows in economics and finance is far different from studying information networks, or information flows on the internet, or networks of actors. In latter networks, every step someone makes is well documented. For example, it is easy to detect an IP address that hosts an internet site, or to find citations or the list of one's friends on Facebook, or the actors who appear in a movie. In all these cases the actions of individuals leave very good traces, but this is not the case when someone would like to capture conversation. It is difficult to capture communication between people, but even more so to detect the subject of their conversation – was it about the weather or financial issues? And, if it was about the latter, questions still remain as to whether they exchanged well-known data or private information. Stasser, Taylor and Hanna (1989) argue that agents do not reveal their private information to most of their professional colleagues, but rather discuss about the public news that is expected to be well known. I am thus aware that the efficiency of economic models is far from absolute, be they approximations or caricatures, for they hold true only within artificially produced circumstances (Gibbard and Varian 1978, Friedman 1953).

The model is discrete-time and discrete-state, is defined over time $t = \{1, 2, 3, \dots, T\}$, and consists of three critical pieces: agents, rules, and securities. Agents are connected in a social network and simultaneously and autonomously make decisions in every time period. They follow very simple, straightforward, and intuitive behavioral rules, which are implemented in four stages, as summarized in Figure 4.1. The model resembles a complex adaptive system.

Figure 4.1: Decision-making process



In the beginning of each period t agents observe $t - 1$ returns of assets they hold and hence the value of their portfolios. Stage 1 is then followed by stage 2 where agents randomly select one of their adjacent agents. After the selection is done, each agent compares the $t - 1$ value of his holdings to $t - 1$ value of the holdings of his selected counterpart. Finally, in the last stage, an agent decides whether to continue with his current portfolio or to switch to the portfolio of his counterpart. Following the decision, the system proceeds to the next period.

4.2 Agents and the network

4.2.1 Agents

At each time interval there is a constant number of n agents in the network labeled $i = 1, 2, 3, \dots, n$. There are $n = 1.000$ agents in the games of Chapter 5 and $n = 5.000$ agents in the games of Chapters 6-8. Agents in the model follow extremely simple rules; they accumulate wealth in time, and each of them faces the following problem (4.1):

$$\begin{aligned} \max_W (E_t(W_{t+1})), \text{ s. t.} \\ W_{t+1}(A_i) = W_t(A_i) \cdot [1 + R_t(\bullet)], W_0(A_i) = 1 \text{ and } q_t^i \geq 0 \end{aligned} \quad (4.1).$$

W_t and W_{t+1} represent the wealth of an agent i in time intervals t and $t+1$, and $R_t(\bullet)$ denotes the returns of the alternative (\bullet) used by an agent in t . Values of portfolios in $t = 0$ equal one. I do not allow short sales or borrowings for which $q_t^i \geq 0$.

Agents are randomly populated over the network, while an initial portfolio is randomly assigned to each of them. If not stated differently, games start with equally sized groups of agents. In the base case scenario games of chapter subsections 5.2 and 5.3, the proportion of agents that prefer riskless portfolios are denoted with u . For a given value of u , games always start with equally shared agents among the two subgroups. In chapter subsections 5.3 and 5.4, u denotes the fraction of agents that prefer Credit Suisse stocks (CS).

4.2.2 Learning mechanism and portfolio selection

Agents in the model are neither omniscient nor ideal; they tend to resemble human behavior. They have incomplete and asymmetric information about stock returns and portfolio holdings. Agents follow adaptive heuristic behavior that is simple, unsophisticated, simplistic, and myopic but that also leads to movement in seemingly “good” directions (Hart 2005). When choosing among portfolios, agents address the following questions (Rubinstein 1998): What is feasible? What is desirable? What is the best alternative according to the notion of desirability, given the feasibility constraints?

Another assumption of the model is that portfolios are feasible to agents iff agents possess them or are possessed by adjacent agents with whom they communicate. This implies the rule that only portfolios that are possessed by more than zero agents are kept.

Action is viewed as a mapping of agents’ knowledge to a decision. When solving (4.1), agents prefer high returns but face several constraints: incomplete information, the two portfolios that they compare in every time period, and the network of adjacent agents. After choosing one of the adjacent agents, an agent makes a decision about the portfolio formulation. Unless an agent is a liquidity agent, an agent either keeps his current portfolio or adopts a portfolio of an interacting agent. The initial portfolios are assigned at random to agents in $t = 0$ with equal probability.

Agents are price-takers and make decisions autonomously, which means that there is no central, or “top down,” control over individual behavior once the rules are specified and the game is run. Agents make their decisions simultaneously without knowing what other agents have selected, and they also do not know with whom others have communicated. They also do not know what those with whom they have exchanged information regarding portfolios have selected. Agents also do not play against each other. Decision making is a continuous activity, so are also trades. In every time period, agents adopt a decision by which they expect to increase the value of their wealth. In the dissertation, agents communicate portfolios and returns, while they tend to adopt portfolios that have performed well in the past (Roth and Erev 1995, Erev and Roth 1998, DeLong et al. 1990a).¹³ This is known as reinforcement learning. A behavioral aspect is included at this point. It is assumed that despite agents’ preference for more rather than less, they do not always choose the better portfolio. I denote this behavior by way of levels of suspiciousness. This notion is similar to Selten (1975), who argued that errors intervene between the decision to take a certain action and the action itself. Some additional arguments for using suspicious agents are provided in Chapter 4.4. The level of suspiciousness is given by an exogenous factor that denotes a non-negative probability that an agent will depart from adopting the most promising portfolio of the two being compared. I assume that the worse portfolio has some baseline probability of being selected. I capture this by defining the following function:

$$\wp = \left[1 + \exp\left(\left(W(A_i) - W(A_j)\right) / \kappa\right) \right]^{-1} \quad (4.2)$$

In every time period t , after choosing one of the adjacent agents j , an agent i compares his accumulated payoff $W(i)$ to the payoff of the adjacent agent $W(j)$. The coefficient $\kappa \in (0,1)$ depicts the level of suspiciousness in the agent’s decision-making process and alters the decision-making rule in the following way. If $ran > \wp$, an agent keeps his portfolio, otherwise an agent adopts the portfolio of adjacent agent. Parameter $ran \sim U(0,1)$ is a uniformly distributed IID random number.

Thus, decision making depends upon the expected benefit differential $(W(i) - W(j))$ and the suspiciousness parameter κ . The scheme relates to the preferential attachment model, in that agents have a preference to “attach” to popular, the most profitable, portfolios, but may fail to get them for different reasons. In general, the lower the κ the higher is probability that an agent adopts the most promising portfolio, and vice versa. This brings the selection process closer to reality. I invoke the following theorems.

THEOREM 4.1a: Unsuspicious agent shows absolute preference for portfolios with a higher expected return.

Proof:

Let $\wp: \mathbb{R} \rightarrow \mathbb{R}$ s.t. $\wp(A) = \left[1 + \exp\left[\left(A_i - A_j\right) \kappa^{-1}\right] \right]^{-1}$; $A_i, A_j \in \mathbb{R}; \kappa \in (0,1)$. Say f is the following continuous mapping on U and \wp :

¹³ Asset prices are exogenous by the assumption, irrespective of agents’ decisions, for which they cannot affect future prices.

$$f: \begin{cases} A_i & ; \quad U(0,1) > \wp \\ A_j & ; \quad U(0,1) < \wp \\ 0 & ; \quad U(0,1) = \wp \end{cases}$$

By definition, the fully unsuspicious agent has κ coefficient set to zero.

As $\kappa \downarrow 0$ and $(A_i > A_j)$ there exists $\lim_{\kappa \rightarrow 0}(\wp) = 0 = \inf(\wp)$. Say we pick $\varepsilon \in U$ s.t. $\varepsilon \leq \wp$. It follows that $\Pr(\varepsilon \leq \wp) = \int_0^{\wp} du = 0 \rightarrow \Pr(\varepsilon > \wp) = 1$ and $f(\varepsilon > \wp, \wp) = A_i$ for all $A_i > A_j$. In these circumstances an unsuspicious agent will always choose A_i .

As $\kappa \downarrow 0$ and $(A_i < A_j)$ there exists $\lim_{\kappa \rightarrow 0}(\wp) = 1 = \sup(\wp)$. However, we can always pick $\delta \in U$ s.t. $\delta \geq \wp$. It follows that $\Pr(\delta \geq \wp) = \int_0^{\wp} du = 0 \rightarrow \Pr(\delta < \wp) = 1$ and $f(\delta < \wp, \wp) = A_j$ for all $A_i < A_j$ and an unsuspicious agent will again choose the better alternative, which is A_j .

The level of suspiciousness κ has no influence over two equally profitable portfolios as the choice between the two is made at random: $\wp = 0.5$ for each $\kappa \in [0,1]$ and $(A_i = A_j)$. If we pick $\beta \in U$, s.t. $\beta = \wp$, it follows that $\Pr(\beta = \wp = 0.5) = \int_0^{0.5} du = 0.5$. The result shows up also in the close proximity of the two portfolios as $\lim_{A_j \rightarrow A_i}(\wp) = 0.5$. **Q.E.D.**

THEOREM 4.1b: Unsuspicious and suspicious agents randomly choose among portfolios with equal expected returns.

Proof:

See the last part of the prior proof.

THEOREM 4.2: A strictly suspicious agent shows a relative preference for portfolios with a higher expected return.

Proof:

I keep the setting from the last proof. By definition, a suspicious agent has κ coefficient set to unity.

As per the mapping f from the previous proof, a suspicious agent holding A_i will start showing a relative preference for changing to A_j once $\wp > 0.5$, which is in turn true for all $A_i < A_j$. Say we pick $\varepsilon \in U$ s.t. $\varepsilon < \wp$. The probability that a suspicious agent does switch to a better alternative is then $\Pr(\varepsilon > 0.5) = \int_0^{\wp} du = \wp > 0.5 \rightarrow \varepsilon \in (0.5, 1)$, true for all $A_i < A_j$. The

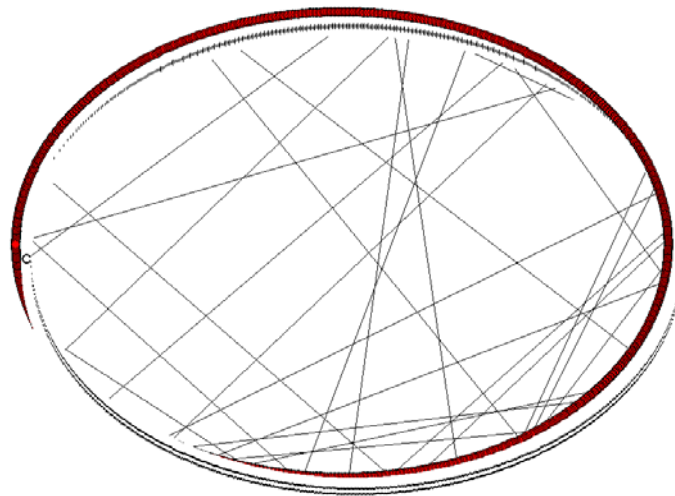
probability that he stays with A_i is $q = 1 - \text{Pr} \rightarrow q < \text{Pr}$, showing a relative preference for a better alternative.

For $A_i > A_j$, an agent shows a relative preference to keeping a better alternative once $\wp < 0.5$, which is in turn true for all $A_i > A_j$. Say we pick $\delta \in U$ s.t. $\delta > \wp$, the probability that a suspicious agent does stay with a better alternative is then $q(\delta > 0.5) = \int_0^{\delta > 0.5} du = \delta > 0.5 \rightarrow \delta \in (0.5, 1)$, true for all $A_i > A_j$. However, the probability that an agent adopts A_j is $\text{Pr} = 1 - q \rightarrow \text{Pr} < q$, showing again a relative preference for a better alternative. In both cases the agent's relative preference for a better alternative increases exponentially in the return differential of the two, which never falls below 0.5 and never reaches unity. **Q. E. D.**

4.2.3 Network

Agents are represented by nodes and their pairwise connections by links. They are interdependent; they are linked with each other in a static undirected network. Agents are able to gather information only from their own local environment. The actions of each agent influence the others, whether directly or indirectly.

Figure 4.2: Network of agents



The network is finite. I use the Watts and Strogatz (1998) procedure for building the network (Figure 4.2).¹⁴ It is an undirected network, which exhibits a short average path length and high clustering. This is in line with empirical research that found social networks to be highly transitive, i.e. people with common friends tend to be friends themselves. High clustering preserves group homogeneity. In Chapter 5, there are $n = 1.000$ agents in the network, each of them being initially adjacent to the six closest agents in a ring lattice, three on each side. $n = 5.000$ agents are present in the network throughout Chapters 6-8, each of them being initially adjacent to ten closest agents, five on each side. As proposed by Watts and Strogatz and Barrat and Weight (2000), I use the rewiring probability $p = 0.1$. This is

¹⁴ The network was displayed in Pajek 1.23, that is available at <http://vlado.fmf.uni-lj.si/pub/networks/pajek/>

within limits by which the network is highly clustered and has a low diameter. Loops and multiple links between agents are not allowed in the network. For node selection, I use a random number generator that draws uniformly from a pool of other nodes (Knuth 1981, Press et al. 2002). If a randomly selected node is already linked to a node, then the algorithm breaks the loop and repeats the link search for another node. The rewiring procedure ends when all nodes are considered. Once built, the network remains unchanged.

In every iteration agents are allowed to contact only one of the adjacent agents. I thus assume that agents fail to make more contacts on the ultra-short run. The selection process of an adjacent agent becomes random, drawing from a uniform distribution of adjacent nodes. I thus assume that no agent has any special ability by which he could be able to outperform the market perpetually, whereby he would be a desired link. That is why agents have no incentive to search for such individuals.¹⁵

4.3 Securities

Let $M = \{1, \dots, m\}$ be the set of different assets from which agents can build portfolios $P = \{P_1, \dots, P_n\}$ whose returns in time period t are exogenously given as R_t^1, \dots, R_t^m and are unknown to the agents until the end of stage four. Let R_t^j be the return of the asset j in time t , then $R_t^j \in \mathfrak{R}^B$ holds for all t and all j . \mathfrak{R}^B denotes the stochastic nature of returns as any of B returns can occur in every time period to any security. Let $q_t^j \geq 0$ ¹⁶ denote the holding of an asset j in time t , then the return of a portfolio is given as the weighted sum of assets that form a portfolio, $R_t^S = \sum_{j=1}^m q_t^j \cdot R_t^j$, with $\sum_{j=1}^m q_t^j = 1$.

Portfolios are valued in relative terms through returns. It is further assumed that all securities are infinitesimally divisible and liquid. The latter means that agents can buy or sell any quantity of stocks quickly with no price impacts. Many stocks, corporate and sovereign bonds, and other assets are relatively illiquid, so reliable transaction data for individual bonds are not readily available. Amihud (2002) finds that stock returns are negatively related over time to contemporaneous unexpected illiquidity, which more strongly affects small firm stocks. Acharya and Pedersen (2005) derive a liquidity-adjusted CAPM and argue that investors require a return premium for a security that is illiquid when the market as a whole is illiquid; that investors are willing to pay a premium for a security that has a high return when the market is illiquid; and investors are willing to pay a premium for a security that is liquid when the market is down. Both assumptions are required for agents to be able to modify their portfolios perpetually as desired. I assume that there are no additional transaction costs or any other trade-related costs that would reduce the returns of the portfolios. This assumption is limited by the effects such costs might have on the trading policy (Constantinides 1986, Lo et al. 2004). Keim and Madhavan (1998) argue that they might even exceed 4% of the portfolio's value when small quantities are traded.

In the games, agents have three sorts of securities: risk-free securities, such in a combination with simulated risky securities, and risky securities (real data). Only portfolios that are

¹⁵ The question is whether agents are able to identify the "quality" of their local network, and whether they are capable of forming such connections as to find the shortest path and benefit from it.

¹⁶ Agents are allowed to possess non-negative shares of different assets. Short sales are not allowed.

possessed by more than zero agents are kept. An important assumption of the dissertation is that agents have incomplete and asymmetric information regarding asset prices.

4.4 Discussion

Understanding the behavior of a complex system requires a model that includes behavioral and interaction-based aspects. “By incorporating a consideration of how agents interact into our models we not only make them more realistic but we also enrich the types of aggregate behavior that can occur. However, as soon as we introduce this sort of interaction the notion of equilibrium has to be reconsidered, and this is particularly true if we allow for stochastic interaction and study the ensuing dynamics.”¹⁷ In the dissertation, portfolio selection is constructed on an interaction-based basis, where markets are viewed as complex evolving systems populated with many bounded rational and autonomous agents who use simple rule-of-thumb strategies. It captures both behavioral and interaction-based features.

My motivation in building the model was similar to the idea presented in Markowitz’s 1952 article. Similar to Markowitz, so could also my model be considered a data-based model. By extending the selection process into four stages, my model gets closer to reality and also meets the conclusions that investors discuss their portfolios with their colleagues just before they execute the trades. In addition, studies also claim that investors do not reveal their private information to everyone, but rather discuss only public information with most of their colleagues. I also believe that a decision making process has to be structured in a way that resembles the non-linear behavior of agents. In the present case, perpetual (daily) portfolio rebalancing gives the model a dynamic and a stochastic component; the dynamic component is what ACE models require, while a stochastic one brings the model closer to reality.

My next objective was to build a simple interaction-based model with a behavioral aspect that would be as realistic as possible with as few parameters as possible. The complexity of the model (and the results) thus arises from the interactions among the bounded rational agents and not because of complex assumptions about individual behavior and the presence of many free parameters. According to Axelrod (1997), this should be the main behavioral principle of ACE models.

The network

A network provides an infrastructure that agents use to communicate with each other. A network approach is indispensable for studying the behavior of complex and adaptive systems. It provides a useful multidisciplinary tool for exploring models that are mathematically intractable. Examples of such issues are path dependency, the effects of adaptive versus rational behavior, the consequences of heterogeneity among agents, etc. The model is constructed in a way that allows the agents to communicate locally with adjacent agents. This makes the network a source of opportunities and constraints to them. Such local interactions have often been modeled in the form of interactions with nearest neighbors on a grid or lattice. Every agent is a node in the network, and two agents are linked if they share with each other their private information regarding their portfolios.

¹⁷ Kirman (1994).

By using an undirected, unweighted, and connected network, I assume that adjacent agents only know those to whom they are linked. Undirected links are indispensable, because by definition if two agents would like to communicate directly and share information with each other, especially information that relates to financial issues, they have to be linked with each other and be conscious of the link. This does not mean that interactions have to be “face-to-face”; they can also be executed via different telecommunication channels that work in an undirected fashion.¹⁸ I implicitly assume that investors do not discuss their financial issues with those they do not know, or on public domains. The distinction between directed and undirected networks is not a mere technicality. In particular, when links are necessarily reciprocal it will generally be the case that mutual consent is needed to establish and/or maintain the link. For example, in order to form a trading partnership, both partners need to agree. Most economic applications fall under the reciprocal-link (and mutual-consent) framework, and as such undirected networks are indispensable to my analysis. Directed networks would suffice, if agents were using public blogs, for example, and announcing their holdings regularly there, from which others would be able to obtain the information.

Trust lies at the core of all interactions between the entities that have to operate in uncertain and constantly changing environments. To make the copying process successful, agents must share genuine information to adjacent agents and not lead them astray. Granovetter (2005) argues that social interaction affects the flow and the quality of information. Because much information is subtle and is difficult to verify, individuals are more prone to believe those they know better. Individuals in social networks trust that their “friends” will accomplish a task, whatever it is, in the “right” way irrespective of any additional unrelated incentives their “friends” might have. Although there are occasions where it can be taken almost for granted that participants communicate honestly with each other, there are occasions where honesty is not so straightforward. Talking about financial issues is far different from giving an opinion about a restaurant or a movie. As argued by Stasser, Taylor and Hanna (1989), agents do not reveal their private information to most of their professional colleagues, with whom they rather more frequently discuss information that is public and expected to be well known. A “no-information-flow” network of linked agents in which agents would not share information with each other is irrelevant for my purposes.

Through the chains of links, agents can also receive information from the agents to which they are not directly linked. Such information is inevitable subject to the time lag, from the moment the information is “produced” to the moment it is received. Time lags make information-sharing less beneficial, with the more distant the connection, the less valuable the information.

Agents in the model have two sorts of links (or outputs), the one being agent-to-agent and the other broadcast-to-agent. I assume that agent-to-agent links are undirected, while the broadcast-to-agent link is strictly directed and goes from the broadcast to an agent. The first assumption of an agent-to-agent link is related to trust and in fact implies the second link of broadcast-to-agent. Trust (and social) networks are a sort of undirected network, in which a mutual agreement is required for the link formation. I assume that investors trust and communicate their private information only to a small number of their colleagues, not to everyone they might know, let alone a broad public. Therefore, agents in the model do have two outputs, a choice of portfolio and a recommendation to their friends. It is just that links

¹⁸ Twitter, for instance, does not meet this condition, because it represents a directed relationship between the users. Although Facebook requires mutual agreement on individual link formations, it allows the users to follow correspondence of their friends with their friends to whom they are not linked.

to friends relate to investors with whom they cherish trust. This does not mean that those who communicate with each other also share the same views or beliefs. We can imagine that investors trust their colleagues in the same firm and also have some friends from other firms to whom they trust private information. I should acknowledge that links in the network relate to trust, not to acquaintances, and for this reason are undirected.

As argued by Goyal et al. (2006), the notion of small world is a broad one and applies to a wide range of social and economic activities. The small-world network has been found among American CEOs of the Fortune 1000 companies (Davis et al. 2003), and investment bankers in Canada (Baum et al. 2003). It is a network where most of the agent's acquaintances are with his cluster of friends, with a few located elsewhere in a network. Hong et al. (2005) argued that communication processes are significant in financial markets, and they found local clustering in selected portfolios. They argued that a local mutual fund agent was more likely to buy or sell a particular stock if other agents in the same city were buying or selling it. In a number of papers (Cohen 2009, Cohen and Frazzini 2008, Cohen et al. 2008), Cohen examined the connection patterns of a business world, and they provide some additional arguments in favor of using a network with a small world property.

Data and the media

Good forecasts about the mean returns are critical to agents' selections. Agents in the model are opportunists and have limited information regarding the asset prices. Agents get information from different sources, but I implicitly assume that the great flux of information prevents them from being accurately informed about all economic and financial matters that affect to asset pricing. In that different investors read different financial and business newspapers, a question is how much these newspapers differ in providing firms' "standard" information, and how much they differ in delivering opinions and other complementary issues that do not directly affect decision-making. In addition, there is also a question of how to delineate and evaluate the effects of using different media. Due to such, I assume that stock returns and relevant news are accurately reported on all major portals, and additionally assume that investors have access to the relevant news of the stocks they have. It is further assumed that agents act as price takers. In this respect, it is not important whether or not prices follow any of the known processes until agents are unable to predict them.

The next question relates to variance. Two views are prevalent; the first being that variance is caused by trading itself and the second that it is caused by the arrival of new information. I avoid using variance directly for several reasons. It is time- and sample-dependant, with a very long time series of data being required to estimate expected returns precisely (Merton 1980). Different agents may end up choosing different lengths of history or memory in their rules for evaluation. Variance measures variation from the mean over time. In a bull market, it refers to the variation in returns on the upward sloping curve, which is much more appreciated than the variance on the downward sloping curve of a bear market. Extreme events such as market bubbles and crashes as well as political decisions might well undermine the power of such statistics.¹⁹ That the estimated parameters are dependent on the policy prevailing at some specific time and not on the entire time horizon is also the thrust of the Lucas critique (Lucas 1976). Its policy implications say that the behavior of agents is not invariant in the presence of changing market circumstances or policy changes.

¹⁹ Kindleberger and Aliber (2011) provide a thorough historical overview of how manias, panics and crashes have shaped financial world over time.

The latest financial crisis substantially increased variance and reduced mean returns, which, in contrast to predictions of conventional wisdom, many took to be smart buys. The crisis created some very attractive investment opportunities (see Barber and Odean (2008) on the attention-grabbing stocks). Generally, variance increases during an event period. By using monthly U.S. stock market data, Bloom (2009) finds that major shocks temporarily double (implied) volatility on average.

It might be objected that communication processes among agents who participate in the markets contribute to day-to-day or hour-to-hour price fluctuations (Shiller 2002). For instance, Campbell (1991) decomposed stock market movements into two components: one is the “news about future returns” component, and the other is the “news about future dividends” component. By using real data directly from the market, I do not endogenize the returns and do not go into the question of what pushes the prices but use variance indirectly. However, the assumption that agents only follow returns and not also variance does not restrict their attitude towards risk. They consider risk indirectly through realized returns of their alternatives over time.

I avoid using a mathematical calculation based on the distribution function of returns. The first reason is because the returns of different stocks do not follow an identical distribution over time. Second, even if returns would follow a particular distribution, agents cannot know the distribution in advance. Imagine periods zero and one, when only one realization is given. Agents cannot know which, if any, distribution will be reflected in the year ahead. Finally, even if the function is known, such does not explain daily movements in prices, while it also overlooks the possibility that many agents would probably not miss out on opportunities to capitalize on daily volatilities. In this way, I avoid proposing an asset-pricing model that would omit some significant variables involved in describing expected returns and stock prices, as well as (auto)correlations in asset returns. Implicitly, I assume a trade-related asset pricing, which to a certain extent follows the idea of Campbell et al. (1993); their model implies that a stock price decline on a high-volume day is more likely than a stock price decline on a low-volume day to be associated with an increase in the expected stock return. Even closer to my intuition are Lamoureux and Lastrapes (1990), who use daily volume as a proxy for information arrival time and find its significant explanatory power regarding the variance of daily returns. Because market prices are used, a market-clearing mechanism is implicitly considered.

Adjacent agent is chosen

In addition to the information that investors can collect from media, they often learn about investment opportunities from others. In the model, every investor is connected to a small number of other investors with whom he shares his private information, and the assumption is that only information-sharing causes a link. An agent with a given number of adjacent agents always faces the problem of deciding which of them to contact to reach the desired outcome. I assume that agents can only contact one of them in every time period. Following the random walk hypothesis,²⁰ I also assume that none is capable of beating the market systematically. Agents thus do not have special preferences as to whom to contact; rather they choose one of the adjacent agents at random. My next assumption is that individuals are not capable of knowing their entire networks of friends, though they might know and be

²⁰ A sequence of random variables follows a random walk if successive price changes are independent, and the price changes conform to some probability distribution (Fama 1965, Malkiel 1973).

linked to some friends' friends. In this respect, it is important that they are atomistic and being so cannot affect the market. This is required in order to support the assumption of random selection and, foremost, to assure the exogeneity of prices. Prices can be exogenous only as long as none of the agents have some relevant private information or some special ability to outperform the others consistently. If such were present, others would then have preference for whom to contact and to build a friendship. However, such agents would probably not tolerate such rent seeking regarding their skills. It is thus important that agents can neither foresee future returns nor know the mechanics according to which returns change over time. Because none of the agents is able to outperform the others, none has an incentive to search for such individuals but rather to choose an adjacent one at random. Thus, nodes and links are unweighted. Although agents exchange the value of their portfolios, implicitly they are also allowed to discuss the prospects of their alternatives.

Value function

The simplicity of the value function illustrates the apparent simplicity of the problem that agents face: to accumulate wealth. I avoid using the usual representation of consumption-based utility functions, as in Cochrane (2005), because I consider financial and consumption features as two separate issues. In addition, I assume that agents are not capable of solving large mathematical formulations in every period, not to mention multi-equation and multi-period dynamic problems; nor do they behave consistently in time, but accurately respond to daily market opportunities. I assume that the behavior of agents is nonlinear and can be characterized by thresholds, if-then rules, nonlinear coupling, memory, path-dependence, and hysteresis, non-markovian behavior, temporal correlations, including learning and adaptation. These assumptions are even more relevant given that information is very subjective, never (or extremely rarely) objective, and never available to everyone but is rather highly dispersed and dynamic.²¹ This is why portfolio selection cannot be explained through differential equations. In addition, at some high frequency level it is reasonable to expect consumption and return data to be de-linked. Yet, stock prices are at least affected by income, habits, macroeconomic data, sector specific data, firm specific data, etc. Portfolio selection is thus taken as a complex process on the macro level, but very simple on the micro level. In the model, individuals decide according to realized returns and the wealth they have acquired over time, and later also in the combination with news.

Reinforcement learning

There is a large literature on observational learning and reinforcement learning mechanisms in relation to asset management and portfolio selection (Shiller 2002, Hong et al. 2005, Roth and Erev 1995, Erev and Roth 1998). As argued by Duffy (2006), examples of varieties of reinforcement learning algorithms in agent-based models are commonplace. Agents in the model learn from past returns and communication with adjacent agents, tending to adopt those decisions that have worked in the past. To capture this idea, agents in the model are likely to copy portfolios of those adjacent agents whose portfolios have been previously successful. Although agents have intentions to copy the best-performing portfolios, they are constrained by their incomplete and asymmetric information and the specter of their links. An intuition here is simple, agents can only copy from those to whom they compare their

²¹ Many asset-pricing models and models of portfolio selection are built on the assumption that individual economic agents efficiently incorporate all information available at the time.

portfolios, and they can only compare their portfolios to those to whom they are adjacent. This is why the introduction of liquidity agents is so important.

The introduction of communicating agents does not suggest that such agents do not also receive information from traditional financial producers and aggregators such as Bloomberg, Reuters, Wall Street Journal, and others, each of which distribute information to millions of users. Still an open question is how to include blogs and other review-like sites into the decision-making process. Neither is this to say that I discount other institutions, educational for example, that are set up to communicate and transmit centuries of knowledge and experience. I implicitly assume that stock-market participants have some prior knowledge about the markets and the rules of the market. This is in line with Hong et al. (2004), who argued that participation in financial markets is strongly positively correlated with wealth, education, and social participation. Therefore, those who do not feel qualified do not participate directly. For those agents who participate, it is important with whom they are adjacent because the relationship directly determines the quality of information flow. The spectrum of adjacent agents is a necessary but not a sufficient condition for the quality of information one receives. Following the intuition of trust, I assume that agents are adjacent to a fix number of other agents. I also assume that they can only select and contact one of them in each time period. They are not able to receive opinions from more than one agent at a given time period of one iteration, while they are also not allowed to forward the news they receive to other adjacent agents before the iteration ends. Finally, when the adjacent agent is selected, the related agent faces another dilemma: whether to continue the existing alternative of the previous time period, or to switch to that which the adjacent agent had in the previous time period. There is another group of investors referred to as liquidity agents. The introduction of liquidity agents follows the idea that there is a small fraction of passive investors among the participants on the markets. These participants might also be characterized as loyal investors, as in Cohen (2009). They are introduced in order to keep information of every alternative alive. In a world of communicating agents who make decisions upon imitation, there is a possibility that every alternative that is dominated for some period of time dies off. In a setting such as mine, non-existing alternatives cannot be used in the future because they do not have values to which agents would challenge the alternatives they possess.

Decision making

When micromotives and actions of individual agents induce aggregate results, it is necessary to know as much as possible about the decision making of individuals. Well, this is not an easy question. It is reasonable to assume that agents certainly have some prior knowledge about investing that they have attained at universities and at other educational institutions. It is also reasonable to assume that different agents have different experiences, read different professional books, journals and newspapers, including occasional newspapers and magazines, use different data, follow different news providers, radio and TV stations, use different financial equations, have different preferences, communicate with different individuals, accidentally hear suggestions from unknown people, etc. Agents are highly heterogeneous as regards these issues. Inclusion of some of these above-mentioned factors into the model would certainly bring the model closer to reality, but the model would lose on the measurability and, consequently, its value. Contributions of these factors are very accidental and indeterminate, and their inclusion would also raise the question of how to receive adequate and accurate data for so many of them. The additional question is how one could measure and distinguish the effects of these different specifics, which definitely exist

and are also important. Besides, when using many different subjective variables, we are also faced with a causality dilemma. Making a too precise model with too many variables would mean making very nice and exact model but very inappropriate on the other hand. Such models would thus come at a cost.

To consider for these questions, I put all these important variables into a residual variable denoted the level of suspiciousness. It includes the stochastic nature of all the above-mentioned factors, along with some other factors. It gives the agents a “non-automata” and human characteristic. This makes the model a sort of a “dual-process” model, where agents contrast their cognition to emotion, or reason to intuition. The level of suspiciousness may also relate to “trembling hand perfection”, too small a gain when switching to another alternative (even more relevant if transaction costs are present), some intrinsic motivation, (dis)trust, temporary mood, or some of the previously mentioned general factors, etc. Thaler et al. (1997), for instance, argued that short evaluation periods force investors to make poorer decisions. Therefore, the variable, stochastic as it is, includes all the issues for which an investor might behave differently than expected, without attempting the difficult if not impossible task of singling out or modeling a specific reason for such behavior. How could one measure accurately (or daily) such random specifics as mistakes, eureka, daily mood, coincidence, even luck, and other random events or coincidental aspects of one’s behavior? Many decisions are done spontaneously and people do not even know why they did such.

Therefore, the definition of trust adopted in the dissertation relates not only to agents’ reliability in their information sharing but also to the entire psychology of their decision making. The use of suspicious agents does not imply that they always make random guesses; the larger the level of suspiciousness the more heuristically such agents act, even though agents are more inclined towards portfolios that significantly outperform others. In reality, there is not always a sharp distinction between unsuspicious and suspicious agents, nor is there a fundamental principle according to which agents would always be equally suspicious or would make the same decisions, because everyone behaves at least partly suspiciously to news, data, and their social network of friends and colleagues. I do not overlook that “do-nothing” is also a decision that was done.

When agents communicate with each other, communication always takes place before any decision is made and before returns are known. Agents can only discuss about the past. In addition, agents can only choose between something they have compared and have knowledge about, or make a random choice from all alternatives. Agents in the model are bereft of the last alternative so they either continue with the alternative they had in the previous period or switch to the alternative an adjacent agent had in the previous period. An important assumption of this selection stage is that agents do not select individual securities but entire portfolios, as proposed by Markowitz. Therefore, when an agent switches to a portfolio of an adjacent agent, I implicitly assume that an agent sells all stocks of the current portfolio and buys a mix of stocks in the portfolio of an adjacent agent. I further assume that agents are subject to no transaction costs when trading and that all stocks are liquid. Regarding the question of how (il)liquidity affects stock markets, it has been found that these effects are substantial (Amihud 2002, Pastor and Stambaugh 2003, Acharya and Pedersen 2005). To avoid this question, I use highly liquid stocks. The assumption of no transaction costs is used for simplicity, because they lower portfolio returns if applied. The next important assumption of the model is that the stocks from which agents make portfolios are infinitesimally separable. Without this assumption, agents with the worst-performing portfolio after the first iteration would need to bring new money into the game if they wanted to buy any other portfolio, by which we could confine the sample set of agents.

Chapter V

Two-asset portfolio selection

5.1 Introduction

Using the basic framework presented in Chapter 4, I start with a series of simple two-asset portfolio selection games. I retain the same model parameters and perturb only individual parameters per individual chapter, which allows me to extract and sever the effects of different variables in agents' decision making. I then analyze them and compare them with each other. These simple two-asset games represent the first step in understanding the relation between the returns, risk and the portfolio selection.

The network consists of $n = 1.000$ agents, each being adjacent to the six closest, with three on each side, and rewired with probability $p = 0.1$. Agents are initially split into four groups. A_S represents the proportion of agents who prefer risky portfolios and choose only risky securities. A_{Sp} represents the proportion of agents who prefer risky stocks but choose mixed portfolio. A_{Bp} represents the proportion of agents who prefer riskless securities and choose mixed portfolio, while A_B represents the proportion of agents who prefer riskless securities and choose a portfolio with only riskless securities. The proportion of agents that prefer riskless portfolios are denoted with u , with $u = A_B + A_{Bp}$. For a given level of u , games always start with equally shared agents among the two subgroups, thus $A_B = A_{Bp}$ and $A_S + A_{Sp}$. According to the general equation (4.1), agents accumulate wealth over time as to the (5.1):

$$\begin{aligned} W_{t+1}(A_S) &= W_t(A_S) \cdot [1 + Sr] \\ W_{t+1}(A_{Sp}) &= W_t(A_{Sp}) \cdot [1 + Sr \cdot q_t^i + Br \cdot (1 - q_t^i)] \\ W_{t+1}(A_{Bp}) &= W_t(A_{Bp}) \cdot [1 + Br \cdot q_t^i + Sr \cdot (1 - q_t^i)] \\ W_{t+1}(A_B) &= W_t(A_B) \cdot [1 + Br] \end{aligned} \tag{5.1}$$

W_t and W_{t+1} represent the wealth of an agent i in time intervals t and $t+1$. Values of portfolios in $t=0$ equal one. Br and Sr represent the returns of riskless and risky assets respectively over time. q_t^i represents the fraction of assets that agents prefer if choosing a mixed portfolio, while the rest, $(1 - q_t^i)$, represents the fraction of assets that agents do not prefer; that is, an agent who prefers risky stocks, but decides for a mixed portfolio, includes q_t^i stocks in his portfolio and $(1 - q_t^i)$ of riskless assets.

Each game of simulated data is run for 10.000 periods ($T = 10.000$) to allow for asymptotic behavior and is repeated 20 times. The games of real data have a sample size of 2.457 units ($T = 2.457$). Endgame decisions are then averaged over these repetitions and displayed on heat-map visualizations in which color-palettes present the proportion of agents per

individual portfolio. Throughout the chapter, I use $\kappa = 0.001$ for unsuspecting agents and $\kappa = 0.5$ for suspicious agents. All simulations were executed on the Hewlett Packard laptop with Intel Celeron 1.4 GHz processor and 500 MB of RAM.

5.1.1 Data

5.1.1.1 Riskless securities

To make the selection process more realistic, I assume that in every time period, the interval is set to one day, riskless securities B bring a constant nominal return of $Br = 0.000002$, corresponding to a yearly return of about 5%. There is an infinite supply of riskless securities, while agents cannot affect the prices and subsequently the return. At this point, it should be acknowledged that no financial asset can be completely risk free.

5.1.1.2 Risky securities (Levy-stable distribution)

In every time period, which resembles a day in the model, risky assets S bring the return Sr . Returns are generated from the Levy-stable distribution (Levy 1925). It allows for large fluctuation in returns, which makes it appropriate for modeling high variability. Financial time series is characterized by high variability in returns (Mandelbrot 1963, 1967, Fama 1965, Mantegna and Stanley 1995, Sornette 2009). In the Levy-stable distribution extreme events are not so exceptional events as in the Gaussian.

The Levy-stable distribution is characterized by four parameters: the coefficient of kurtosis $\alpha \in (0, 2]$, the coefficient of skewness $\beta \in [-1, 1]$, variance $\sigma > 0$, and the coefficient of the mean return $\mu \in \mathbb{R}$. α is also known as the stability index, which describes the concentration of the distribution function or the thickness of distribution tails. The smaller its value, the thicker the distribution tails. This means that the probability of extreme values occurring is higher. By definition, every random variable is uniquely determined only through its characteristic function (see Lukacs (1970) for an extensive survey on characteristic functions).

DEFINITION 5.1: Characteristic function of the Levy-stable distribution is of the following

$$\text{form: } \log \varphi_X(t) = \begin{cases} i\mu t - \sigma^\alpha |t|^\alpha \left\{ 1 - i\beta \text{sign}(t) \tan \frac{\pi\alpha}{2} \right\} & ; \alpha \neq 1 \\ i\mu t - \sigma |t| \left\{ 1 + i\beta \text{sign}(t) \frac{2}{\pi} \log |t| \right\} & ; \alpha = 1 \end{cases}, \text{ where } \sigma > 0, \alpha \in (0, 2], |\beta| \leq 1$$

$$\text{and } \alpha \in (0, 2] \text{ and } \text{sign}(t) = \begin{cases} -1 & ; t < 0 \\ 0 & ; t = 0 \\ 1 & ; t > 0 \end{cases}$$

Chambers et al. (1976) construct a direct method for simulating random variables, while Janicki and Weron (1994), and Weron (2001) provide the following formulas for simulation.

$$X = S_{\alpha,\beta} \left[\frac{\sin(\alpha(V + B_{\alpha,\beta}))}{(\cos(V))^{1/\alpha}} \right] \cdot \left[\frac{\cos(V - \alpha(V + B_{\alpha,\beta}))}{W} \right]^{(1-\alpha)/\alpha}, \quad \text{where} \quad B_{\alpha,\beta} = \frac{\arctan\left(\beta \tan \frac{\pi\alpha}{2}\right)}{\alpha}$$

and $S_{\alpha,\beta} = \left[1 + \beta^2 \tan^2 \frac{\pi\alpha}{2} \right]^{1/(2\alpha)}$. It follows

$$Sr = \sigma X + \mu \quad (5.2).$$

V is a random IID variable within the interval $\left(-\frac{\pi}{2}, \frac{\pi}{2}\right)$, and W is a random variable with the expected value 1. There is a special case when $\alpha = 1$. In this case, the solution is the following.

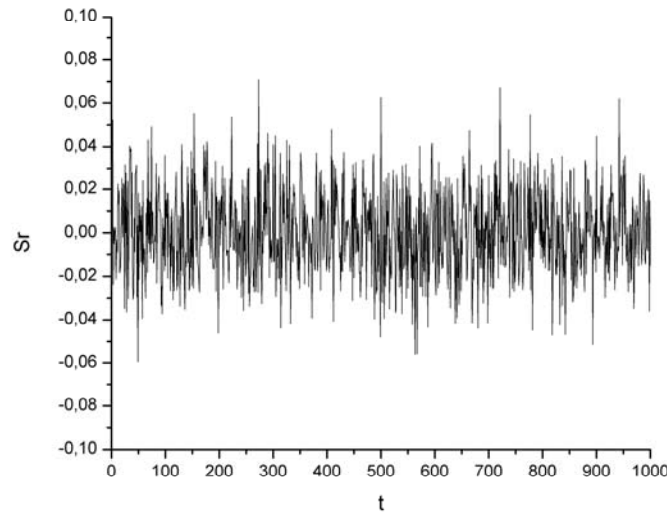
$$X = \frac{2}{\pi} \left[\left(\frac{\pi}{2} + \beta V \right) \tan V - \beta \log \left(\frac{W \cos V}{\frac{\pi}{2} + \beta V} \right) \right]. \text{ It follows}$$

$$Sr = \sigma X + \frac{2}{\pi} \beta \sigma \log \sigma + \mu \quad (5.3).$$

When generating Levy returns, I do not use a constant but a random seed, resulting in returns being different as the games repeat. Using a random seed is very meaningful for the analysis, because this makes results independent of a single random selection that could have been more favorable towards one alternative.

One demonstration of Levy returns at the base specification used in the model ($\alpha = 1.996$, $\sigma = 0.0141$, $\mu = 0.0009$ and $\beta = 0.2834$) is displayed in Figure 5.1.

Figure 5.1: Simulated Levy returns



5.2 Portfolio selection with riskless and risky securities

I start with the simple case, in which there are two types of securities: a risk free and a risky, while agents can also select a combination of the two. This is similar to that in Tobin (1958), Arrow (1965) and Pratt (1964). In the games of this section, I am interested how the mean return and risk influence portfolio selection patterns. In particular, I investigate how agents' decisions are influenced by small perturbations of μ and σ (denoted *mu* and *sigma* in figures).

It is standard in financial literature to assume that agents depart from alternatives as their risk increases and returns fall. This suggests that agents require a risk premium, or a reward, for bearing risk. The conclusion is consistent with the mean-variance solution. I introduce the following theorem.

THEOREM 5.1: If an agent is strictly risk averse then the quantity of risky securities that an agent will include in the portfolio is positive or zero, iff the risk premium is positive or zero.

Proof:

The proof is taken from LeRoy and Werner (2001). If V_t^S presents the value of risky securities of a portfolio, then the value of riskless securities of a portfolio equals to $V_t^P - V_t^S$. Return of such a portfolio then equals to $V_t^P \cdot R^B + (R^S - R^B)V_t^S$ and the optimal return for an agent is given as the solution of $\max_{V_t^S} E \left[u \left(V_t^P \cdot R^B + (R^S - R^B)V_t^S \right) \right]$.

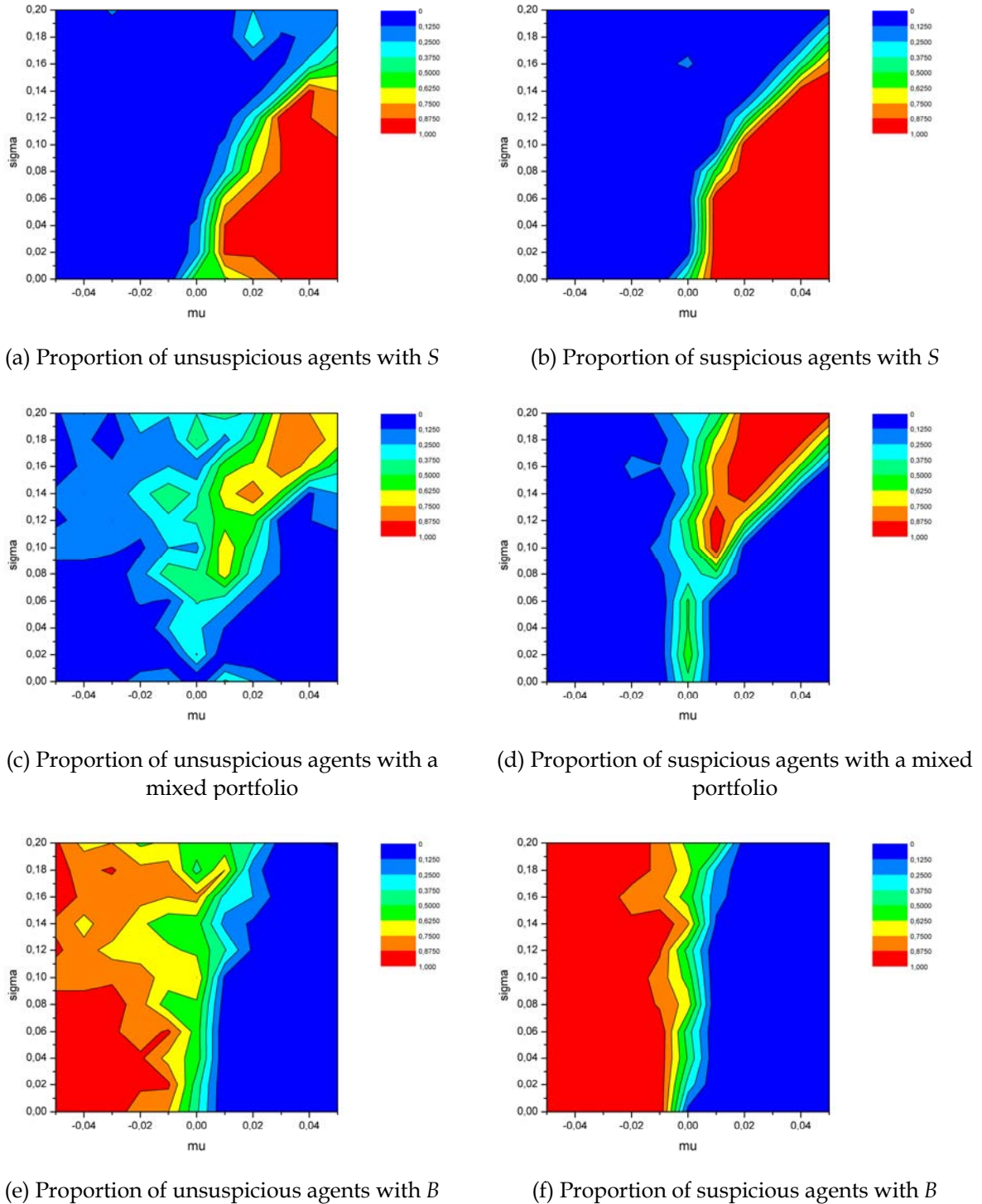
Because V_t^P is strictly positive, any zero holdings of risky securities means strictly positive holdings of riskless securities. This means that $V_t^S = 0$ is an interior point of the interval of the investment choices. In point $V_t^S = 0$, the derivative of the maximization problem of the expected utility equals $u' \left(V_t^P \cdot R^B \right) (\mu - R^B)$, with $\mu \equiv E(R^S)$. Because $u' \left(V_t^P \cdot R^B \right)$ is strictly positive, the derivative is positive (zero) iff $(\mu - R^B)$ is strictly positive (zero). Short sales and borrowings are not allowed, for which $(\mu - R^B)$ cannot be negative. **Q.E.D.**

If the risk premium is zero, then any non-zero investment in a risky security has a strictly riskier return than the riskless return. It follows from Theorem 5.1 that agents should possess only riskless securities. With the specification I use, it follows from equation (5.2) that expected returns of risky and riskless securities coincide when $\mu = 0.0000253$.

In Figures 5.2a-f, I use heat-map visualizations to present the proportion of agents with individual portfolios according to the pairs of μ (X-axis) and σ (Y-axis) over entire intervals $-0.05 \leq \mu \leq 0.05$ and $0 \leq \sigma \leq 0.2$. A step of 0.01 units is used on the X-axis and of 0.02 units on the Y-axis. Heat-map visualization provides a unique opportunity to study portfolio selection with regard to perturbations in pairs of variables. Thus, I can easily observe how agents move among different alternatives as the variables are perturbed. All three figures in the map sum to the red color. Because simulations were done on a slower computer, I was not able to make smaller steps and thus lost some "fine-tuning" on truncation error.

The 8-color spectrum (Z-axis) presents the proportion of agents per portfolio, extending from blue (low value) to red (the highest value). The color spectrum relates to the average proportion of agents per portfolio over 20 independent realizations of the games. Other variables are constant: $\alpha = 1.996$, $\beta = 0.2834$, $q_t^i = 0.5$. In addition, $u = 0.5$. Note: I combined fractions of agents with Bp and Sp into one fraction of agents with mixed portfolios. I could do that because $q_t^i = 0.5$, which makes Bp and Sp identical.

Figure 5.2: Proportion of unsuspicious and suspicious agents per portfolio



The figures exhibit some important features of portfolio selection. As suggested, risk and returns of a risky security largely affect portfolio selection, with the effect of returns being especially highly pronounced. This conclusion can also be supported by Table 5.1, which presents the correlation coefficients between the selection of different portfolios and the mean return and risk of a risky asset. S/MIX/B in the table signify risky/mixed/riskfree portfolios, while UN/SUS signify games with unsuspicious and suspicious agents, respectively. The correlation values for the selection of a riskless portfolio show that the decision for this portfolio is motivated only by returns.

Table 5.1: The correlation coefficients between the variables

	MU	SIGMA
S_UN	0.749	-0.346
S_SUS	0.717	-0.360
MIX_UN	0.326	0.521
MIX_SUS	0.330	0.433
B_UN	-0.915	0.026
B_SUS	-0.912	0.040

Figures 5.2a,b demonstrate that a risky portfolio is chosen for positive mean returns of a risky security; note that a riskless return is close to zero. However, as demonstrated by Figures 5.2e,f, agents choose a riskless portfolio when the mean return of a risky security is negative. Agents opt for a mixed portfolio under two circumstances: either both mean return and risk are high or the mean return of a risky security is slightly perturbed around zero (Figures 5.2c,d). The first case, that of both high returns and risk, suggests that agents are trying to avoid high risk no matter how large the positive expected returns are, thereby contradicting Theorem 5.1. Namely, when $\mu = 0.05$ and $\sigma = 0.2$, the expected return of a risky security is $Sr = 4.96\%$ (using Eq. 5.2). Following the mathematical solution, agents were expected to opt for a risky portfolio and not a mixed one. However, curvatures in the upper-right sections of Figures 5.2a,b and 5.2c,d indicate that the probability that agents will choose a mixed portfolio increases as risk and return increase. Thus, when risk is high, even high expected returns cannot prevent the renouncement of risky portfolios. This means that for highly risky though profitable portfolios not all stochastically dominant portfolios are chosen. Risk thus carries a negative connotation such that even higher returns do not cushion the cost of it. The intuitive explanation for the apparent paradox is simple. As *sigma* increases, more extreme returns are likely to happen, with negative extreme returns causing larger losses. Agents respond by avoiding such portfolios. In this situation, a mixed portfolio is more profitable choice than a riskless one.

Nontrivial characteristics in agents' portfolio selection take the flavor of Theorem 5.1 and could be partly explained by prospect theory, which proposes that agents' attitude toward gains may be quite different from their attitude toward losses, and by the Nash equilibrium concept, according to which not every desirable alternative is ex ante attainable. In the second case, agents opt for mixed portfolios in the transition from the two extremes. It is surprising that the transition area is wider in the case of unsuspicious agents. This might be the consequence of the random evolution of the returns of a risky security; that is, some consecutive negative outcomes in the beginning of a game might eliminate a risky portfolio from the spectrum of alternatives. Note that unsuspicious agents are very strict regarding returns and react strongly to deviations.

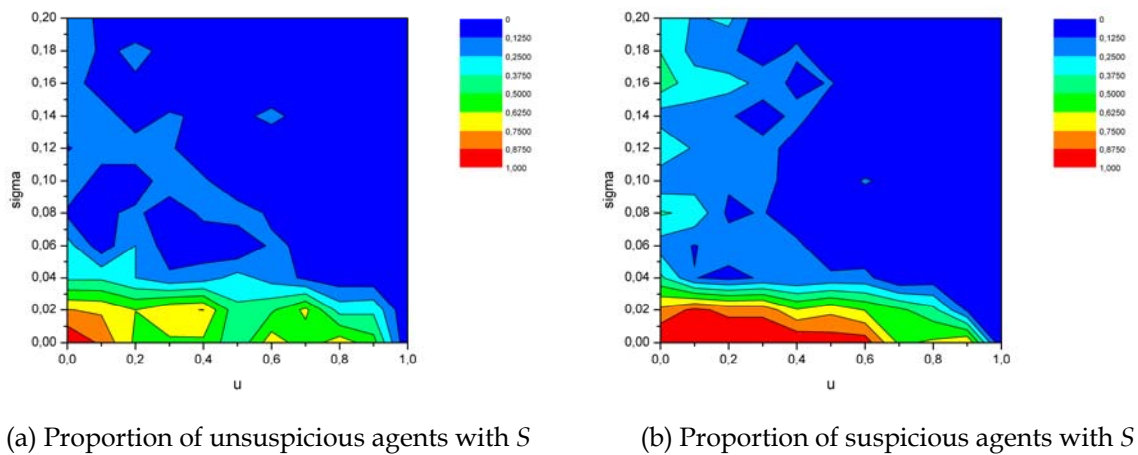
5.3 Influence of agents' initial preferences

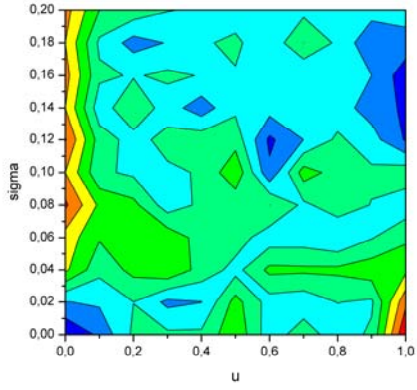
In the preceding chapter, I started the games with an equal proportion of agents per portfolio ($u = 0.5$). Here I examine the influence of a different initial proportion of agents per portfolio. In a connected network, information should propagate around the network, meaning that initial preferences should not affect agents' behavior except in the extreme cases where $u \rightarrow 0$ or $u \rightarrow 1$. However, in a stochastic game setting, in which agents' decisions are subject to stochastic returns over time and of agents' subjective choices, the initial proportion of agents might be relevant. For example, if only one agent possesses a portfolio, and this portfolio initially yields a negative return, the contact such an agent makes, and the decision he adopts are important for the development of the game. If he contacts someone whose past return was very high, it is very likely that he would switch to the alternative of that adjacent agent. This would mean that the agent's initial portfolio would be lost and eliminated from the scope of alternatives. On the other hand, if many agents possess a momentarily less efficient portfolio, it is likely that this portfolio would not be eliminated, as it is not likely that all would contact someone with the momentarily better portfolio, and even if this occurred, it is likely that not everyone would choose to switch. To examine these issues, I first conduct the simulations as to perturbations of σ and u and later also of μ and u .

5.3.1 Initial preferences vs. variance

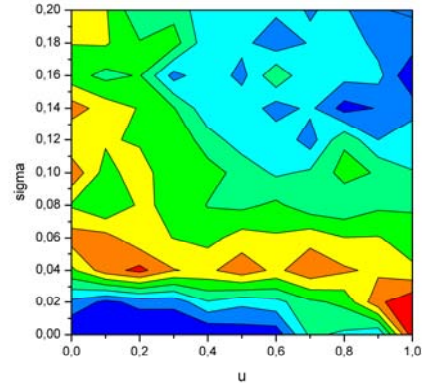
I first examine how initial preferences in connection to risk affect the portfolio selection. Hence, I perturb the games as to the initial proportion of agents with risky portfolios u and the variance σ . Figures 5.3a-f display the results. σ is plotted on the Y-axis with a step of 0.02 units on $0 \leq \sigma \leq 0.2$ and u is put on X-axis with the step of 0.1 units on $0 \leq u \leq 1$. The values of other parameters remain unchanged at $\alpha = 1.996$, $\beta = 0.2834$, $q_t^i = 0.5$ and $t = 10.000$. The decision for $\mu = 0.0009$ is straightforward, as it coincides with riskless return. Yet, riskless return has zero variance.

Figure 5.3: Proportion of unsuspicious and suspicious agents per portfolio

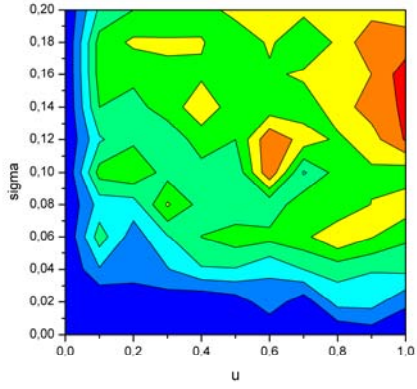




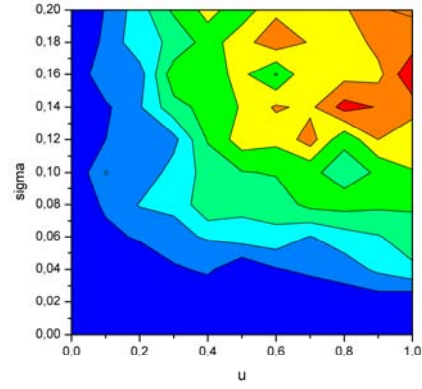
(c) Proportion of unsuspicious agents with a mixed portfolio



(d) Proportion of suspicious agents with a mixed portfolio



(e) Proportion of unsuspicious agents with B



(f) Proportion of suspicious agents with B

The plots indicate the averages over 20 independent repetitions of the games and the endgame decisions. The 8-color spectrum (Z-axis) presents proportions of agents per portfolio, and it extends from blue (low value) to red (the highest value). The figures are displayed at the initial values of u , which is not constant throughout the games, varying on the interval $(0,1)$.

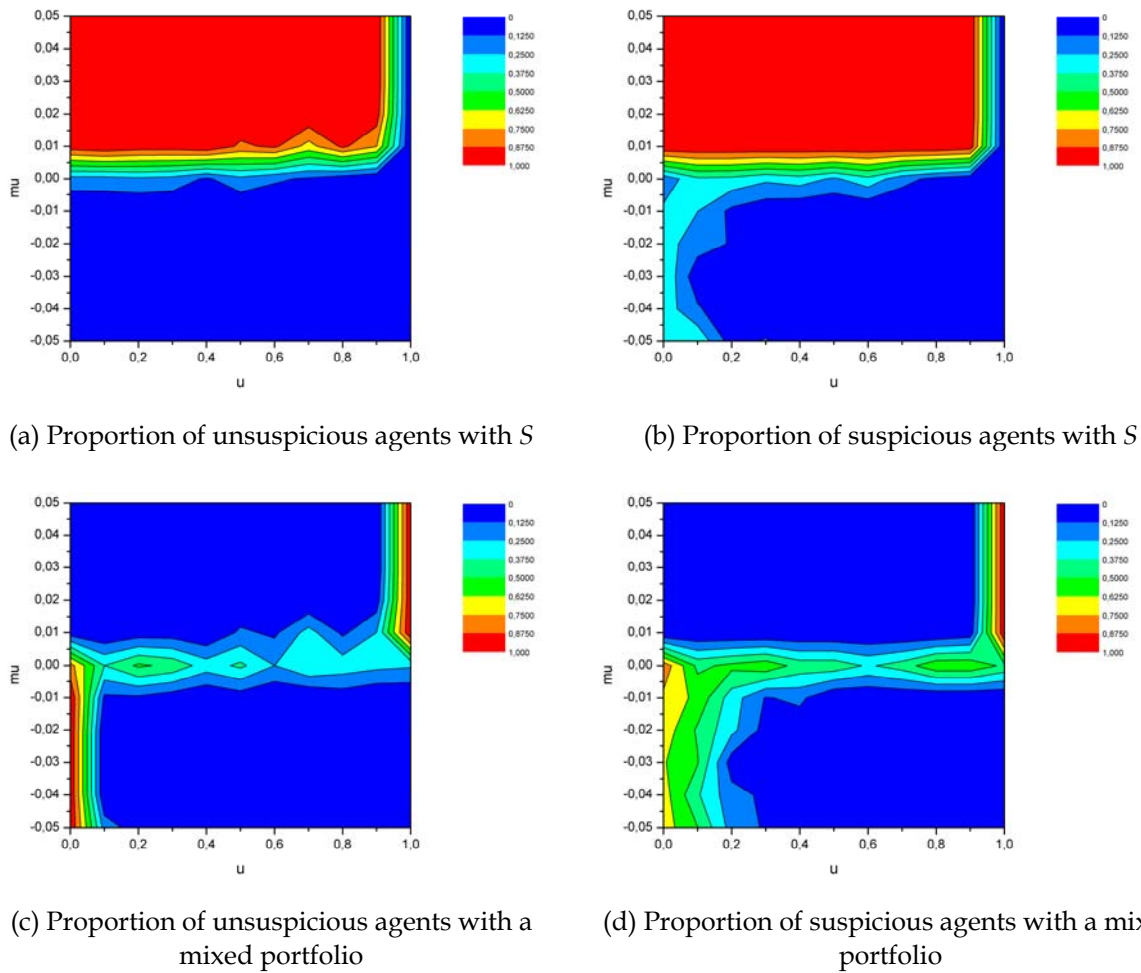
The figures indicate that agents respond to variance and much less to initial preferences, except for the extreme cases where $u \rightarrow 0$ or $u \rightarrow 1$. This means that information can efficiently propagate over a connected network as predicted. Therefore, even though a very small proportion of agents possess a more profitable alternative than others possess, information sharing leads to the spread of such an alternative and its dominance over a long time period. However, when the proportion of agents with a given portfolio is very small, its existence depends on the early returns of a risky security. The figures reveal that the “limiting” area is wider for suspicious agents. In between the two one-asset portfolios that agents choose, i.e. those involving zero or high risk, agents opt for mixed portfolios, as displayed in Figures 5.3c,d. Here, the initial proportion of agents affects which of the two alternatives is selected. However, as risk and the proportion of agents not preferring risky portfolios increase, the move toward the riskless portfolio also increases (Figure 5.3e,f).

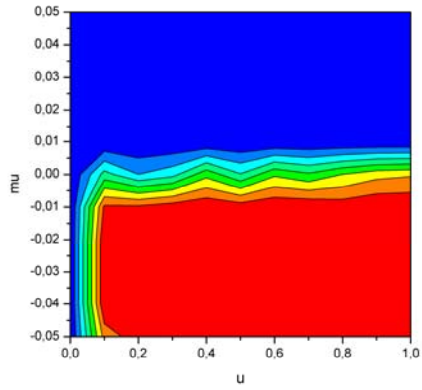
5.3.2 Initial preferences vs. mean

I now examine how initial preferences in connection to mean returns affect the portfolio selection. Following the same intuition as before, I perturb the games with regard to mean returns and the initial proportion of agents per portfolio. μ is perturbed on the step of 0.01 units on $-0.05 \leq \mu \leq 0.05$, while u is perturbed on the step of 0.1 units on $0 \leq u \leq 1$. The values of other variables remain unchanged with $\alpha = 1.996$, $\sigma = 0.0141$, $\beta = 0.2834$ and $q_t^i = 0.5$.

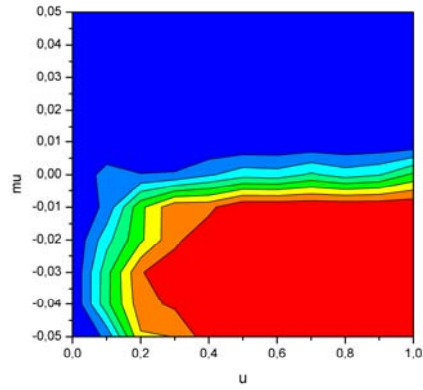
The results displayed in Figures 5.4a-f relate to the averages of the endgame decisions over 20 independent repetitions of the games. They present the proportion of unsuspicious and suspicious agents with a given portfolio. The 8-color spectrum (Z-axis) presents the proportion of agents per portfolio. Figures are displayed at initial values of u .

Figure 5.4: Proportion of unsuspicious and suspicious agents per portfolio





(e) Proportion of unsuspicious agents with B



(f) Proportion of suspicious agents with B

The figures paint consistent and expected pictures of a positive correlation between mean returns and the selection of risky portfolios. Despite the fact that two one-asset portfolios coincide at $\mu = 0.0000253$, both strict portfolios start to dominate far beyond that value: S from $\mu > 0.02$ and B from $\mu < -0.02$. Agents also opt for mixed portfolios between these two levels. In the neighborhood of $\mu = 0.0000253$, tiny differences in initial conditions make vast differences in the subsequent behavior of the system.

When $u = 0$, which means that the network is populated only with agents that prefer risky portfolios, agents opt for a mixed portfolio when $\mu < 0.00$, by which they minimize loss. At the other extreme, when $u = 1$, and there are only agents who prefer riskless portfolios, they choose mixed portfolios when $\mu > 0.00$, by which they maximize profit. I can thus conclude that initial preferences only matter at or near the two extremes, even though such does not restrain the abilities of agents to choose the better of given portfolios. Again, suspicious agents proved to be much less susceptible to small changes than unsuspicious agents, with the bordering color-palettes of suspicious agents being much wider than those of unsuspicious agents.

5.4 Portfolio selection with two risky securities

In the previous games, I examined how risk, variance and agents' initial preferences affect endgame portfolio decisions. Despite the fact that the results led to some very cogent conclusions, nothing has yet been said about the evolution of the selection process. This is going to be the focus of this section, in which I explore the evolution of single games over time. In the following games of this sequel I will take two risky securities and use real data from two financial corporations, Credit Suisse (CS) and Citigroup (C). Following the same intuition as before u now indicates the proportion of agents who prefer Credit Suisse.

Agents still face the same problem as before: to choose one of four portfolios in every time period. I simulate the games with unsuspicious agents in which $\kappa = 0.001$ and suspicious agents in which $\kappa = 0.5$. In all cases, reported and analyzed results relate to the average over 20 independent realizations of the games.

5.4.1 Data

In the games of this section, I use daily returns of the two stocks as listed on the New York Stock Exchange (NYSE: CS) and (NYSE: C), beginning January 21, 1999 and ending November 19, 2008. In both cases returns R_t are computed as relative differences in the

opening (P_t^O) and closing (P_t^C) daily prices $R_t = \frac{P_t^C - P_t^O}{P_t^O}$. The opening price is the first

price of the first transaction, while the closing price is the last price of the last transaction within the business day. NYSE opens at 9.30 and closes at 16.00. In reality, trading is characterized by, at least, two features. Firstly, stocks are traded nonsynchronously within this time at a high-frequency level. The nonsynchronous effect arises when asset prices are taken to be recorded at time intervals of one length when in fact they are recorded at time intervals of another length (Campbell et al. 1997). Secondly, stocks are also traded before the market opens and after it closes. I take this into consideration by tracking daily data, leveling the duration of trading days for the stocks and portfolios I use. The time period is chosen arbitrarily, resulting in a sample size of 2457 units ($T = 2457$). Table 5.2 and Figures 5.5 summarize some statistical properties of the two stocks. In both cases standard deviations are computed from the GARCH(1,1) model (Bollerslev et al. 1992).

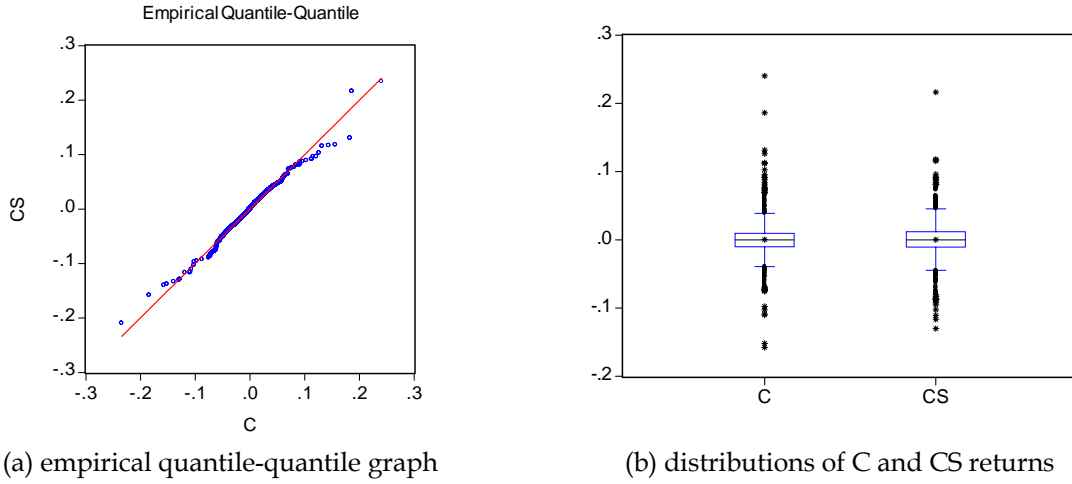
Table 5.2: Selected statistics of CS and C

	C	CS	C - 90%	CS - 90%
Mean	-0.000098	0.000163	-0.000153	0.000406
Median	0.000000	0.000000	0.000000	0.000000
Maximum	0.240268	0.234375	0.036160	0.036084
Minimum	-0.234450	-0.209112	-0.037049	-0.035809
Std. Dev.	0.023574	0.022851	0.014448	0.015247
Skewness	0.136186	-0.067226	-0.014188	0.014096
Kurtosis	16.71533	13.97700	2.941989	2.667758
1. Quartile	-0.010134	-0.010879	-0.008948	-0.009309
3. Quartile	0.009757	0.012034	0.008557	0.010679
Observations	2457	2457	2212	2212

The empirical quantile-quantile graph of the returns of the two stocks (Figure 5.5a) and the two boxplots (Figure 5.5b) indicate that both stocks are very risky and exhibit some extreme returns in both directions. The two rectangles around the mean in Figure 5.5b depict returns within the first and the third quartile. This interquartile range represents the middle 50 percent of returns. This area is slightly wider for CS at 239 bps as compared to C at 199 bps. The staples present the borders of inner fences that are defined as the first quartile minus 1.5 times the interquartile range and the third quartile plus 1.5 times the interquartile range. Outliers are displayed beyond the line and present extreme returns. CS has a slightly higher mean value and a slightly lower standard deviation than C. On the other hand, C has a slightly larger span (274 bps) as compared to CS (243 bps). Ninety percent of all returns are placed within -3.59% and 3.61% for CS and -3.70% and 3.62% for C. Despite CS having a lower overall standard deviation than C, its standard deviation is higher when considering 90% of the middle returns (152.47bps / 144.48bps). The leptokurtosis (excessive fourth moments) and heavy-tailed features of the data are evident in both cases. Over the entire span, C has a return distribution that is skewed to the right, which means it has relatively more low values, and CS is skewed to the left, which means it has relatively more high

values. However, within 90% of all returns, the opposite is demonstrated with C being slightly negatively skewed and CS slightly positively.

Figure 5.5: Returns of CS and C



The two series are just slightly positively correlated with the correlation coefficient of 0.543, which is slightly surprising finding, as both stocks belong to the same sector.

5.4.2 Unsuspicious agents

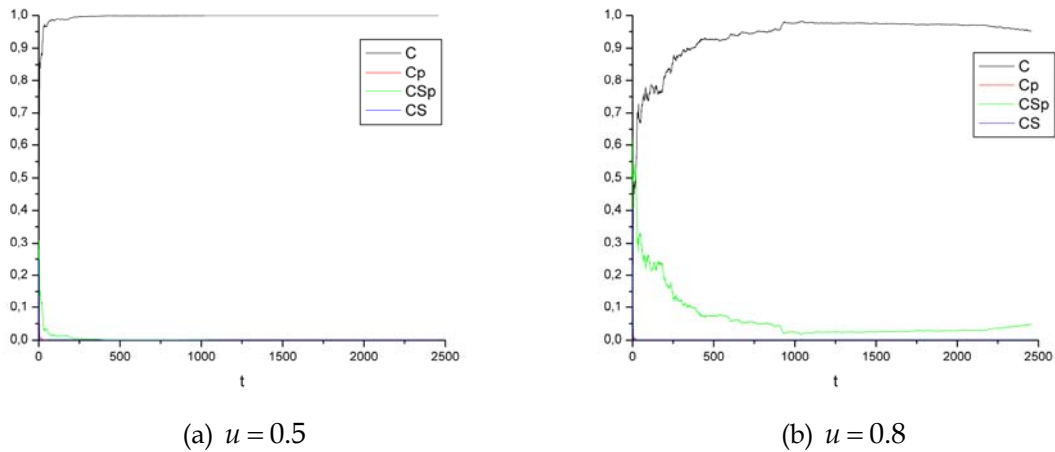
Table 5.3: Proportion of unsuspecting agents per portfolio

t	C (1)	C _p (2)	CS _p (3)	CS (4)	C (5)	C _p (6)	CS _p (7)	C (8)	C _r (9)	CS _r (10)
1	0.254	0.248	0.250	0.248	0.096	0.103	0.403	0.400	0.03165	0.00322
2	0.445	0.183	0.309	0.062	0.184	0.095	0.563	0.158	0.04198	-0.00321
3	0.624	0.078	0.289	0.009	0.284	0.051	0.623	0.042	-0.02686	0.01321
4	0.763	0.025	0.211	0.001	0.399	0.018	0.575	0.009	0.03132	0.00986
5	0.786	0.020	0.193	0.001	0.417	0.015	0.562	0.006	0.00978	0.02267
6	0.838	0.009	0.153	0.000	0.469	0.009	0.519	0.003	-0.02752	0.0157
7	0.857	0.007	0.137	0.000	0.488	0.007	0.504	0.002	-0.02673	-0.01879
8	0.842	0.009	0.150	0.000	0.460	0.008	0.530	0.002	0.02531	-0.00618
9	0.839	0.008	0.152	0.000	0.450	0.008	0.541	0.002	-0.02311	-0.00653
10	0.861	0.006	0.133	0	0.478	0.006	0.514	0.002	-0.00484	-0.00626
11	0.863	0.006	0.131	0	0.474	0.006	0.518	0.002	-0.00702	-0.00661
12	0.867	0.006	0.127	0	0.480	0.005	0.514	0.001	-0.03591	-0.01933
13	0.875	0.005	0.120	0	0.485	0.005	0.509	0.001	0.03499	0.00646
14	0.870	0.006	0.125	0	0.475	0.005	0.519	0.001	0.02345	0.02633
15	0.880	0.004	0.116	0	0.497	0.005	0.497	0.001	-0.0325	-0.01596
16	0.886	0.004	0.110	0	0.505	0.004	0.490	0.001	0.03029	0.02925
17	0.882	0.004	0.114	0	0.497	0.004	0.498	0.001	-0.00748	0.02039
18	0.885	0.004	0.111	0	0.499	0.004	0.500	0.001	-0.00215	-0.01362
19	0.877	0.005	0.118	0	0.469	0.004	0.526	0.001	0.02375	0.00614
20	0.879	0.005	0.116	0	0.467	0.005	0.527	0.001	0.02319	-0.01251

Figures 5.6 and Table 5.3 display the average evolution of individual games over time. In the first group of the games $u = 0.5$, while in the second $u = 0.8$. Figure 5.6a and columns 2-4 in the table present the proportion of agents with a given portfolio when $u = 0.5$, while Figure 5.6b and columns 5-8 in the table present the average proportion of agents with a given portfolio when $u = 0.8$. Cr in the table presents the returns of C and CSr the returns of CS. In both cases $q_t^i = 0.3$ and is constant throughout the games.

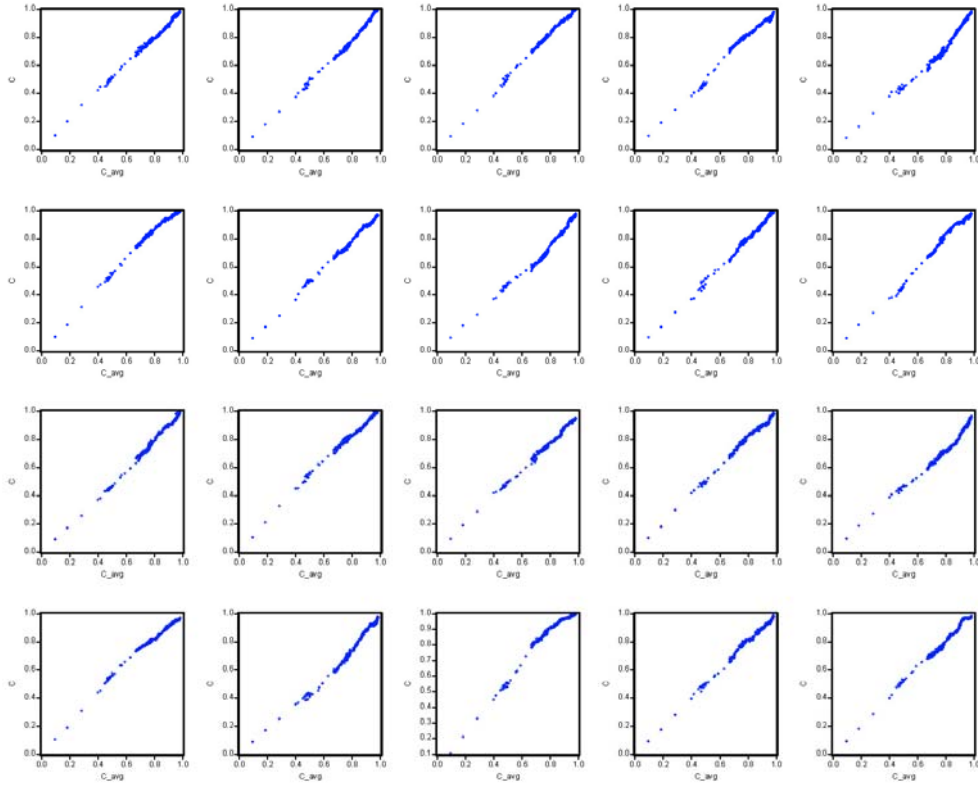
Following the simulation results as presented in the table, unsuspecting agents heavily and promptly respond to the returns. It is interesting to see that CS turns out to be a strictly dominated portfolio from the very beginning of the games, being eliminated after the ninth iteration at the latest and after the third iteration at the earliest, which is also the most frequent. An upward shift is very extensive even after the first iteration, in which the proportion of agents with C increases from 0.25 to 0.43. Consequently, this corresponds to a drop of about the same magnitude in the proportion of agents with CS. Yet, 60% of agents chose C in the third iteration and 80% in the sixth. At this stage, CS was already eliminated, while only about a percent of agents took Cp . This appears to reflect the effect of what might be called “unfavorable comparative initial returns.” In this period, the returns of CS were either negative when those of C were positive or they were positive but lower than those of C. In both repetitions, agents end the games with a unanimous decision for C.

Figure 5.6: Proportion of unsuspecting agents per portfolio



When comparing Figure 5.6a to 5.6b, we see that when the games were started with a larger proportion of agents with the unfavorable portfolios of CS and CSp, the agents did not end the games with a unanimous decision of C, as they did before. This may be explained thus: when the initial proportion of agents who prefer C and Cp was extremely low, information regarding the efficiency of the two portfolios spreads over the network much more slowly than in the case when more agents possessed the two dominant portfolios. In my case, this slower spread of information was sufficient to interfere with the prevalence of C over others, despite its initial “favorable” returns, driving them out as in the case of $u = 0.5$.

Figure 5.7: Single-game selections of C against the average game selection of C , $u = 0.8$



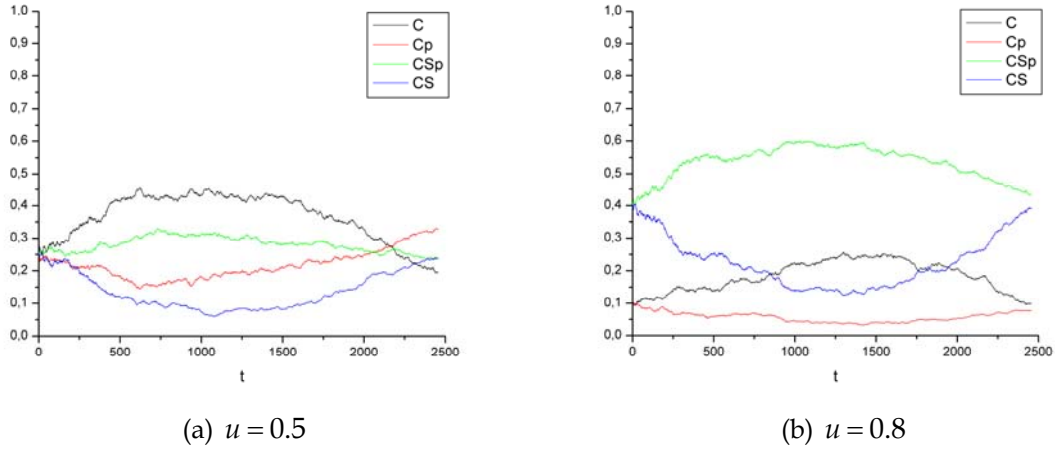
The correlation coefficients of individual games to the average game, which in all cases and for all portfolios exceed 0.95, reflect that unsuspicious agents were very consistent in their behavior; values close to 1 indicate almost perfect positive linear association between the two variables. To additionally illustrate the argument, I use scatterplots of the individual game selections of C against the average game selection of C (C_{avg}) for $u = 0.8$ (Figure 5.7). The X-axes in the figures show the fractions of agents with C averaged over all 20 independent realizations of the games, while the Y-axes show fractions of agents with C in single realizations of the games. If single-game decisions are highly correlated with the average-game decision and thus with each other, plots should exhibit diagonal lines from the origin.

The plots exhibit “near” diagonal lines. This is not surprising for $u = 0.5$, where C eliminated all other portfolios in the very early stages of the games. Thus, the games are slightly sensitive to initial conditions.

5.4.2 Suspicious agents

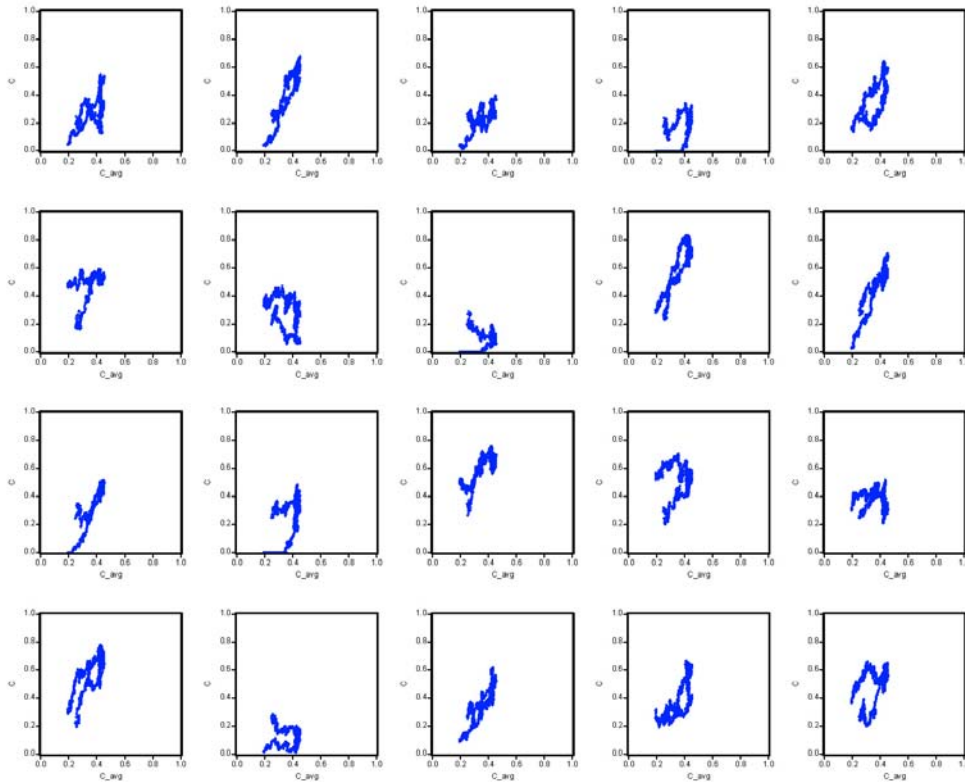
I now apply the games with suspicious agents, who are less likely to select the putatively better portfolio. All the developments of the games averaged over 20 independent repetitions are displayed in Figure 5.8, with $q_t^i = 0.3$ in both cases.

Figure 5.8: Proportion of suspicious agents per portfolio



Figures 5.9 demonstrate that suspicious agents behave much less consistently and also less predictably over time than do unsuspecting agents. In the figures single game selections of C are plotted against the average game selection. X-axes in the figure show fractions of agents with C averaged over all 20 independent realizations of the games, while Y-axes show fractions of agents with C per single realization of the game. Under the independence assumption, it is expected that plots of single games in Figure 5.9 would be “close” to diagonal lines, as in Figure 5.7.

Figure 5.9: Single-game selections of C against the average-game selection of C , $u = 0.5$



Contrary to those of unsuspecting agents, the plots related to suspicious agents clearly exhibit different shapes, reflecting huge inconsistencies in their selection patterns. Their final decisions do not converge to a unanimous selection as was the case of unsuspecting agents.

Thus, the flavor of chaotic behavior on the level of individual games of suspicious agents can be observed, as repetitions of the games never exhibit the same path-developments. At the same time, one can see an apparent consistency in selections when these individual games are averaged over many repetitions, as in Figures 5.8.

5.4.3 The need for liquidity agents

A very distinctive feature of social network games is herding. By definition, herding promotes synchronization which means that some (occasionally) unfavorable portfolios are driven out of the sample set until there is a single portfolio left. Bala and Goyal (1998) showed that as long as agents prefer higher payoffs and learn from their neighbors, all in the component settle down to play the same action from some time onwards with probability one, regardless of their initial actions.

THEOREM 5.2: There exists a time such that all agents in a component settle down to play the same action from that time onward (Bala and Goyal 1998).

Proof:

The proof is very intuitive and straightforward. Agents prefer an action that brings them the highest payoff. Recall that agents are able to switch to the action of their neighbors that brings the highest payoff, while they also deliver this information to their neighbors, and so on. As long as there exists an action that brings the highest outcome, there is a time after which everyone will play this action exclusively with probability one. **Q. E. D.**

Bala and Goyal also establish the payoff equalization result that, asymptotically, every agent from the network must receive a payoff equal to that of an arbitrary agent from the component, since otherwise an agent should copy the action of this other agent. I should acknowledge that in some cases the convergence time might be quite long.

The simulation games so far were subject to herding and in the cases with unsuspicious agents often converged to a unanimous decision. The process of herding is very strong when agents perfectly rebalance their portfolios, always choosing the alternative that performed best in the past. Such is the case with unsuspicious agents, contrary to the sluggishness of suspicious agents. Therefore, if a security experiences poor returns in some consecutive time period, even though the period is very short, this might eliminate portfolios that include such securities irrespective of their future performances, with the larger the proportion of such securities in a portfolio, the higher the probability that such a portfolio will be eliminated. In the framework of suspicious agents, synchronization is confined by the suspiciousness factor. Suspicious agents do not apply differences in portfolio values to their choice criteria as strictly as do unsuspicious agents. Hence, they choose portfolios much more arbitrarily than unsuspicious, with the result that they might hold unfavorable alternatives as well. In order to prevent synchronization, I introduce liquidity agents into the games. They hold their initial portfolio throughout the games, no matter the payoff.

DEFINITION 5.2: A liquidity agent is an agent who never changes his initial portfolio as the games proceed.

Some additional arguments for their presence would be the following. They might be characterized as conservative or highly persuaded individuals who are either satisfied with their portfolios or suffer from inertia or have some intrinsic reasons for their conservative

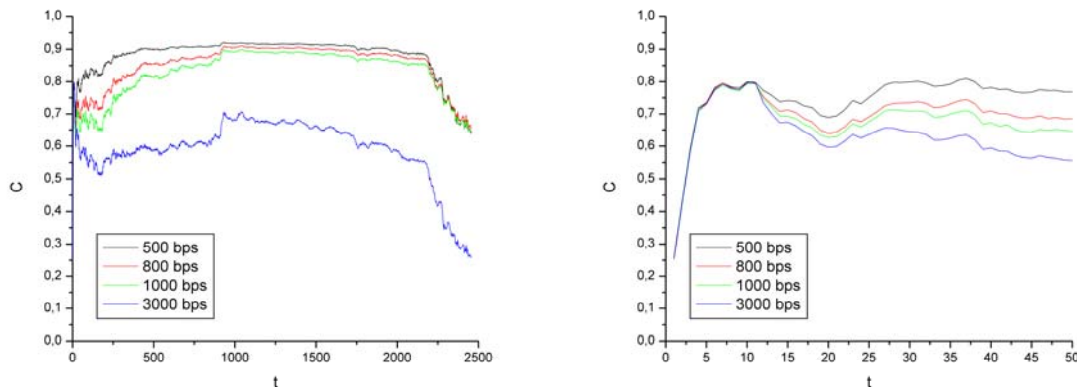
behavior, as argued by Osborne and Rubinstein (1990), and Lord, Ross and Lepper (1979), or as loyal investors (Cohen 2009). Such conservative agents are reluctant to search for evidence that contradicts their beliefs, and even if they find such evidence, they treat it with excessive skepticism. Hirshleifer (2001) argues that processing new information and updating beliefs is costly, which might explain an agent's conservatism. He adds that habits also economize on thinking and can play a role in self-regulation strategies. Constantinides (1990) argues that habit formation, which reconciles very large (too large) equity premium, might promote an agent's conservatism. I do not endogenize the reasons of agents' conservatism but take it as given. In real markets, not only do conservative individuals appear as liquidity agents but also market makers. By quoting sell and buy prices they provide and preserve liquidity. In the sequel, the games include liquidity agents.

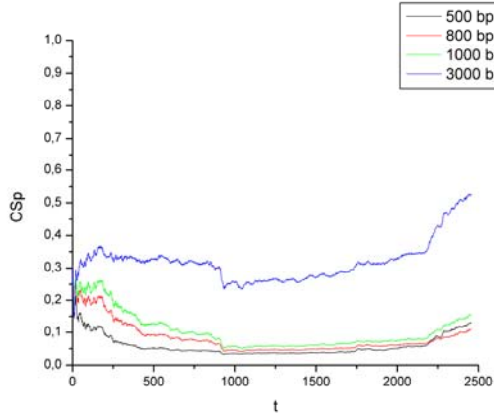
5.5 Portfolio selection with an exogenous shock

In this chapter, I examine the effects of a one-time shock to portfolio selection. It had been demonstrated long ago that agents who choose among risky alternatives take into consideration shocks to individual alternatives (Merton 1969). Shocks induce consequences by which they change the environment in which agents make decisions. Binmore and Samuelson (1994) and Binmore, Samuelson and Vaughan (1995) distinguished between shock effects in the short run, middle run, long run, and ultra-long run. The system does not have many chances to avoid the short-run consequences of a shock. Over the middle run, a shock is still perceived but the system starts to restore its usual framework. Over the long run, the system is completely back on track, despite the possibility of the continued perception of some consequences of the shock. No effect of a shock is perceived in the ultra-long run. A shock that changes the behavior of agents does leave its tracks over the ultra-long run, which means that historical factors and chance events push social phenomena to new patterns of behavior (Kandori, Mailath and Rob 1993, Sornette 2009).

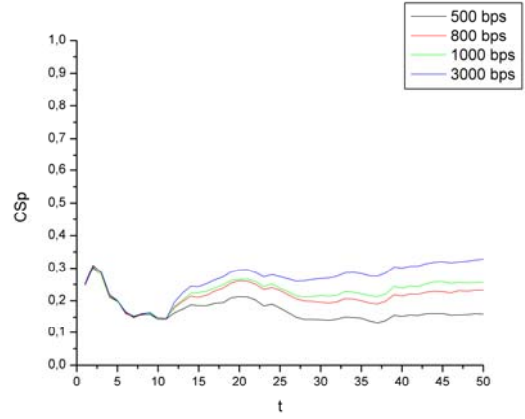
These games build on the previous game setting of Credit Suisse (CS) and Citigroup (C) but include liquidity agents. The liquidity agents are placed into five homogenous groups: $i = \{(100, 109), (200, 219), (400, 419), (600, 619), (970, 1000)\}$ and are assigned a random portfolio at the start of each game. As the games repeat, the liquidity agents might possess different portfolios and might be adjacent to different agents. A one-time shock is included as a one-time reduction in the return of C in $t = 10$. I simulate the games against different magnitudes of a shock: 500 bps, 800 bps, 1000 bps and 3000 bps.

Figure 5.10a: Proportion of unsuspecting agents per portfolio, $u = 0.5$



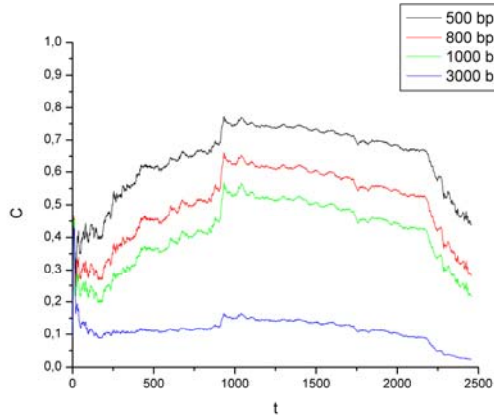


(a) entire game developments

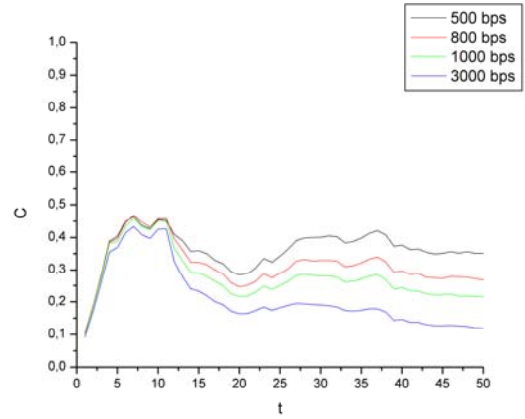


(b) first 50 iterations

Figure 5.10b: Proportion of unsuspicious agents per portfolio, $u = 0.8$



(a) entire game developments



(b) first 50 iterations

Only unsuspicious agents with $\kappa = 0.001$ are used in this chapter, because suspicious agents exhibited atypical behavior. As before $q_t^i = 0.3$. Results are displayed in Figures 5.10a ($u = 0.5$) and 5.10b ($u = 0.8$). The results relate to the average developments of the games of 20 independent repetitions. The upper (bottom) two figures display the fractions of agents with C (CSp), with the left figure displaying full developments of the games and the right figure the first 50 iterations. The first 50 iterations are displayed to present the short run effect of a shock and the course of its short-to-medium-run stabilization.

Table 5.4: Proportion of unsuspecting agents per portfolio under different shocks

t	C (1)	C _p (2)	CSp (3)	CS (4)	C (5)	C _p (6)	CSp (7)	CS (8)	Cr (9)	CSr (10)
1	0.258	0.248	0.247	0.247	0.103	0.097	0.397	0.402	0.03165	0.00322
2	0.428	0.193	0.302	0.077	0.186	0.089	0.541	0.184	0.04198	-0.00321
3	0.591	0.098	0.280	0.030	0.282	0.051	0.587	0.080	-0.02686	0.01321
4	0.719	0.046	0.212	0.024	0.388	0.023	0.540	0.049	0.03132	0.00986
5	0.734	0.043	0.199	0.024	0.404	0.022	0.527	0.048	0.00978	0.02267
6	0.781	0.034	0.162	0.023	0.449	0.017	0.490	0.043	-0.02752	0.0157
7	0.796	0.031	0.150	0.023	0.464	0.015	0.478	0.042	-0.02673	-0.01879
8	0.784	0.034	0.158	0.024	0.437	0.017	0.502	0.044	0.02531	-0.00618
9	0.780	0.035	0.159	0.026	0.427	0.017	0.510	0.046	-0.02311	-0.00653
10*	0.799	0.032	0.144	0.025	0.455	0.016	0.486	0.044	-0.00484*	-0.00626
11	0.798	0.033	0.145	0.024	0.453	0.016	0.487	0.044	-0.00702	-0.00661
12	0.773	0.036	0.163	0.028	0.409	0.018	0.523	0.050	-0.03591	-0.01933
13	0.758	0.038	0.174	0.029	0.391	0.019	0.536	0.054	0.03499	0.00646
14	0.737	0.042	0.188	0.032	0.357	0.021	0.563	0.060	0.02345	0.02633
15	0.742	0.041	0.185	0.032	0.359	0.022	0.561	0.059	-0.0325	-0.01596
16	0.739	0.043	0.185	0.033	0.350	0.022	0.568	0.060	0.03029	0.02925
17	0.725	0.048	0.193	0.035	0.329	0.023	0.584	0.064	-0.00748	0.02039
18	0.720	0.049	0.194	0.037	0.319	0.024	0.590	0.067	-0.00215	-0.01362
19	0.696	0.054	0.209	0.042	0.294	0.026	0.605	0.075	0.02375	0.00614
20	0.689	0.057	0.213	0.042	0.283	0.027	0.613	0.077	0.02319	-0.01251
21	0.693	0.054	0.212	0.041	0.288	0.026	0.611	0.075	0.04946	0.0034
22	0.712	0.049	0.203	0.037	0.306	0.023	0.603	0.068	-0.0216	0.02186
23	0.742	0.043	0.184	0.032	0.335	0.022	0.584	0.059	-0.00552	-0.04941
24	0.731	0.045	0.190	0.034	0.324	0.023	0.592	0.061	0.03784	0.00666
25	0.751	0.041	0.178	0.030	0.343	0.021	0.580	0.057	0.04229	0.00976

Table 5.4 presents the proportion of agents per portfolio in the first 25 iterations. Columns 1-4 exhibit the fractions of agents with a given portfolio when $u = 0.5$ and columns 5-6 the fractions of agents per given portfolio when $u = 0.8$. The last two columns display the returns of C and CS over time. An asterisk in the ninth column indicates a shock.

The unsuspecting agents very quickly responded to the shock. The shock started to spread over the network to adjacent agents, to adjacent agents of adjacent agents and so on. In most cases the proportion of agents with the alternative C shrank by 13-20 percentage points (4th row of Table 5.5), which occurred in just 10 intervals after the shock (5th row). Consequently, the fractions of agents with other alternatives increased. This period indicates a short run.

The recovery was slow. The pre-shock level of C is reported in the second row. On average, for a shock of 500 bps the system restored to the pre-shock level in about 20 intervals after the shock (6th row). Following the results, larger shocks needed a longer time to recover. A shock of 3000 bps never fully recovered, which means that it would also leave huge consequences over the ultra-long run. In addition, the effects of a shock are much larger when a smaller fraction of agents possessed an affected portfolio. After a shock of 3000 bps portfolio C, which was dominant within a no-shock environment, ended solely with liquidity agents.

Table 5.5: The effects of different shocks on C

	500 bps	800 bps	1000 bps	3000 bps
$u = 0.5$				
Shock	0.78	0.848	0.789	0.746
Bottom	0.654	0.708	0.583	0.549
Difference	0.126	0.14	0.206	0.197
Bottom – time	21	20	20	21
Before shock level – time	31	249	334	Never
After shock min	0.654	0.508	0.583	0.291
After shock max	0.91	0.926	0.937	0.697
End fraction of C	0.715	0.508	0.826	0.296
$u = 0.8$				
Shock	0.455	0.458	0.453	0.426
Bottom	0.283	0.246	0.217	0.164
Difference	0.172	0.212	0.236	0.262
Bottom – time	20	20	20	21
Before shock level – time	203	421	891	Never
After shock min	0.283	0.246	0.196	0.024
After shock max	0.773	0.662	0.568	0.326
End fraction of C	0.438	0.280	0.217	0.024

5.6 Some conclusions

I close this section with some brief conclusions, which can be summarized in the following lines:

- Mean return of the risky asset and the risk are two decisive factors of portfolio selection.
- The selection of a risky portfolio is motivated by positive returns and small variance.
- Agents choose mixed portfolios under the following two circumstances. In the transition from positive to negative mean returns, and when the mean returns of a risky asset and the risk are high.
- The selection of a riskless portfolio is motivated only by the negative returns of a risky asset and not the variance.
- The level of suspiciousness is significant over the course of portfolio selection, with unsuspicious agents behaving much more consistently than suspicious agents.
- Liquidity agents prevent full herding, for which they proved to be indispensable for the portfolio selection process to work smoothly.
- Shocks proved to be significant, with the short run of a strong enough shock being especially critical. If the system overcomes the first blow, and if the future returns of portfolios hit by the shock are favorable, conditions restore in time.

Chapter VI

Multiple-asset portfolio selection: the efficient frontier hypothesis

6.1 Introduction

Two-asset games that have been studied in the previous chapter represent a huge simplification of what agents face in reality. There are many kinds of assets in different markets, resulting in plenty of opportunities to build very different portfolios. Because of this number of stocks, from which investors choose, they are faced with searching problems when buying stocks (Barber and Odean 2008). For example, DJIA is an index of 30 stocks, Standard&Poors500 is an index of 500 stocks, while more than 3800 stocks are listed on the NASDAQ. Most countries worldwide have stock exchanges, with the most important being located in the US, Frankfurt, London, Tokyo, Zürich, Paris, Hong Kong, Shanghai, and Sao Paulo. There are markets for currencies, commodities, bonds and other kinds of debt, ETFs, funds, futures, etc. It is not surprising that ACE models are often criticized for having only a small number of assets, often one that is risk-free and the other risky (LeBaron 2006). In this chapter, I move to multiple-asset portfolio selection games.

The assumption of the model is that mixed portfolios can only be built out of an equal proportion of i assets from the total number of n available assets. An agent who makes a portfolio out of two stocks can only make a portfolio with equal share of the two stocks, and not a portfolio of two thirds of one stock and a third of the other. Therefore, the maximum

number of $K(n) = \sum_{i=1}^n \binom{n}{i} = 2^n - 1$ portfolios can be constituted. With two assets available, an

agent can make three portfolios; with three assets seven different portfolios; with four 15 portfolios; and with five assets 31, etc. The number of portfolios increases by a factor $2 + 1$. There are 32,767 different portfolios when $n = 15$, etc. In reality, agents can put a different proportion of assets into their portfolios, with the number of different portfolios approaching infinity. In the present case, I study the behavior of unsuspicious and suspicious agents when $n = 5$, which makes a sample set of 31 portfolios.

In the games from now on, I will be focused on the selection patterns according to the efficient frontier hypothesis (Markowitz 1952a, 1959). In its original form, this is a bi-criteria problem where a reasonable tradeoff between return and risk is considered, and where “mean-variance agents” choose their portfolios on the efficient frontier in (μ, σ) -space with minimum risk given the return and maximum return given the risk.

The idea behind the efficient frontier is very intuitive, but it avoids a very simple question as to whether agents are able to reach the presumed and desired equilibrium in a complex financial world that is characterized by the uncertain stock prices, investors’ preferences, limited cognitive abilities and non-standard behavior patterns, and interaction. The question is even more relevant in the light of many “profitable” opportunities this stochastic financial world offers to investors on a daily and intraday basis. Therefore, my remark does not go to the theory as such, because rational agents would certainly prefer minimum risk and

maximum return portfolios. But there is a set of unexplained questions beyond this puzzle related to what agents select.

6.2 Data

As in the games of previous chapters, agents consider only returns of portfolios they have, while means and variances of returns are used as the endpoints in the analysis and not as starting-point input variables.

Due to the large number of portfolios, I increase the number of agents to $n = 5000$ and the number of adjacent agents to the ten closest, with five on each side. The probability of rewiring remains intact at $p = 0.1$. Liquidity agents are placed in the following groups: $i = \{(700, 719), (1000, 1019), (1200, 1219), (1500, 1519), (2500, 2519), (3500, 3519), (4800, 4819)\}$. Again, I do simulations with unsuspicious ($\kappa = 0.01$) and suspicious ($\kappa = 0.1$) agents. With these parameter values, suspicious agents are suspicious enough, while they also retain a sufficient level of capabilities to select a better of the two alternatives they compare. Such suspicious agents do not make blind guesses.

The results are averaged over 30 independent realizations of the games. In the games, I consider average-game and endgame decisions. The examination of average-game decisions provides information on the desirability of individual portfolios throughout game developments, while endgame decisions provide information regarding the portfolios that were the most desirable in the end.

Table 6.1: Description of portfolios

S1	AA	S12	MSFT-KFT	S23	MSFT-XOM-KFT
S2	MSFT	S13	XOM-C	S24	MSFT-C-KFT
S3	XOM	S14	XOM-KFT	S25	XOM-C-MSFT
S4	C	S15	C-KFT	S26	AA-MSFT-XOM-C
S5	KFT	S16	AA-MSFT-XOM	S27	AA-MSFT-XOM-KFT
S6	AA-MSFT	S17	AA-MSFT-C	S28	AA-MSFT-C-KFT
S7	AA-XOM	S18	AA-MSFT-KFT	S29	AA-XOM-C-KFT
S8	AA-C	S19	AA-XOM-C	S30	MSFT-XOM-C-KFT
S9	AA-KFT	S20	AA-XOM-MSFT	S31	AA-MSFT-XOM-C-KFT
S10	MSFT-XOM	S21	AA-XOM-KFT		
S11	MSFT-C	S22	MSFT-XOM-C		

I take stocks of five companies from different sectors listed on the Dow Jones Industrial, NYSE: C, NYSE: KFT, NYSE: MSFT, NYSE: AA and NYSE: XOM. It must be noticed that effective as of June 8, 2009, Citigroup (NYSE: C) was delisted from the index due to significant government ownership. It was replaced by its sister insurance company Travelers (NYSE: TRV). The data refer to daily returns, which are calculated as the relative difference between the opening and closing prices of the work days with opening at 9:30 and closing at 16:00. As before, I use daily data by which I capture the effects of otherwise nonsynchronous trading features of the stocks and portfolios. The entire data set covers the period of January 2, 2009 to January 21, 2010, making a total number of 264 realizations per stock. The returns of the portfolios are calculated as the average returns of its stocks. I assume that mixed portfolios are constituted of equal proportions of different stocks. This makes a total number of 31 portfolios (Table 6.1). The data set was obtained from Yahoo!Finance financial portal.

In the analysis part I use a portfolio beta (Sharpe 1964). Beta is a well-established measure of a stock's risk or a portfolio's risk against market risk, although there is no agreement on how to measure risk adequately. According to beta, the risk of an asset (or portfolio) is measured by covariance in the assets' (or portfolio's) return with the return of the market. Beta measures the part of the asset's (or portfolio's) statistical variance that cannot be removed by the diversification. Given that the unsystematic risk can be diversified by taking many such positions, beta is a measure of a portfolio's systematic or non-diversifiable risk.²² In general, the lower the correlation among security returns, the larger the impact of diversification. The degree of portfolio diversification is measured through the coefficient of determination (R-square coefficient); the closer it is to 1, the better is the diversification. A poorly diversified portfolio will have a small value of R-square (0.30 - 0.40), while the corresponding R-square value of a well-diversified portfolio would be between 0.85 and 0.95. Statman (1987) argued that a well-diversified portfolio should consist of at least 30-40 stocks. Goetzmann and Kumar (2008) examined the portfolios of more than 40,000 equity investment accounts from a large discount brokerage during a six year period (1991-1996), and showed that a vast majority of U.S. investors held under-diversified portfolios. Tobin (1958) proposed a diversification involving the purchase of different mutual funds, where the number of funds is smaller than the number of individual assets in the portfolio.

Table 6.2: Beta coefficients of portfolios

	Beta	R ²	S11	1.513	0.848	S22	1.147	0.897
S1	1.246	0.574	S12	0.433	0.551	S23	0.426	0.633
S2	0.551	0.431	S13	1.444	0.835	S24	1.113	0.891
S3	0.413	0.490	S14	0.364	0.499	S25	1.068	0.871
S4	2.475	0.753	S15	1.395	0.813	S26	1.171	0.988
S5	0.314	0.264	S16	0.737	0.732	S27	0.631	0.760
S6	0.899	0.681	S17	1.424	0.972	S28	1.147	0.992
S7	0.830	0.670	S18	0.704	0.729	S29	1.112	0.980
S8	1.861	0.936	S19	1.378	0.965	S30	0.938	0.924
S9	0.780	0.642	S20	0.658	0.703	S31	1.000	1.000
S10	0.482	0.587	S21	1.345	0.961			

Table 6.2 reports betas for the portfolios and the corresponding R^2 . In my case, portfolio S31 represents a market portfolio because it consists of all available stocks and thus represents the highest possible degree to which an agent can diversify risk. This is a poor proxy of the real-world market portfolio, which would be a portfolio made of all endowments in the world. The choice for a market portfolio S31 would designate a naïve 1/n allocation (Benartzi and Thaler 2001). Because S31 represents the market, its variance represents the market risk σ_M . With the market risk at hand, I can calculate β coefficients of portfolios

simply as $\beta_i = \frac{\sigma_i}{\sigma_M} \rho_{i,M}$, where $\rho_{i,M}$ is the correlation of portfolio i to the market portfolio. In

order to get the required β coefficients of individual portfolios, I estimate a linear equation that expresses returns of individual portfolios as a linear function of the market return. Specifically, $R_{i,t} = \alpha_i + \beta_i R_{M,t} + \varepsilon_{i,t}$, where $\varepsilon_{i,t}$ is the regression error, with $E(\varepsilon_{i,t}) = 0$ and

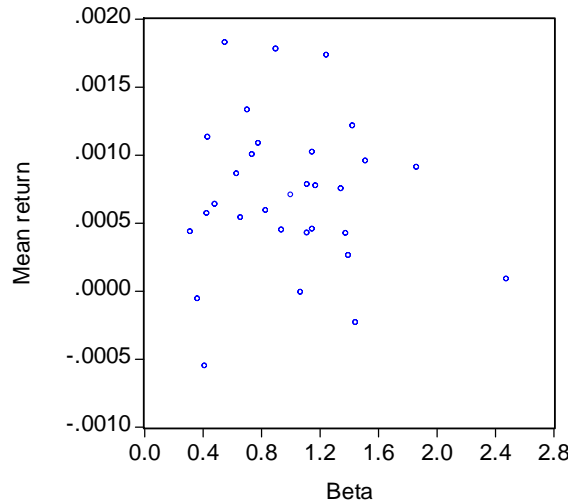
²² Using betas does not suggest that riskier (high beta) portfolios should always yield higher returns. Campbell and Vuolteenaho (2004) decomposed the beta of a stock into two components; one reflecting news about the market's future cash flows and one reflecting news about the market's discount rates. By doing that, they defined a "good" beta and a "bad" beta, with the good beta defining risky stocks with high returns.

$Var(\varepsilon_{i,t}) = \sigma_i^2$. Since the market beta of a portfolio is also the slope of the regression of its return on the market return, the correct interpretation of beta is that it measures the sensitivity of the portfolio's return to variation in market return. Stocks about as volatile as the market will have a coefficient around 1.0, whereas those less (more) volatile will show lower (higher) coefficients. Stocks that move opposite to the market will have negative betas.

Following the betas and the fraction of agents per portfolio, an average beta coefficient of the sample is calculated as $\bar{\beta} = \frac{1}{N} \sum_{i=1}^N \beta_i$, while a weighted beta is calculated as $\bar{\beta}_w = \frac{1}{N} \sum_{i=1}^N \beta_i h_i$, where h_i represents a fraction of agents with portfolio i , while $\sum_{i=1}^N h_i = 1$. For subsamples, in which $\sum_{i=1}^N h_i \neq \sum_{i=1}^N q_i$, a fraction of selected portfolios have to be re-calculated so as to reach the required condition $\sum_{i=1}^N h_i = 1$. Both betas are applicable in assessing the agents' attitude towards risk.

S5 is the lowest beta portfolio (0.314). It is followed by S14 (0.364), S3 (0.413), S23 (0.426), S12 (0.433) and S10 (0.482). S14 is a combination of S2 and S5, while S23 also includes S3. These portfolios have less than half the risk of the market. Portfolios that include Citigroup stocks, S4, are placed on the side of the riskiest portfolios, which are S4 (2.475), S8 (1.861), S11 (1.513), S13 (1.444), S17 (1.424). Figure 6.1 displays mean returns of portfolios (Y-axis) against their betas (X-axis).

Figure 6.1: Mean return vs. Beta for portfolios



In Chapter 6.2, I analyze the average-game results, while the endgame results of the same game realizations are examined in Chapter 6.3. Endgame and average-game results relate to the same games, notably the endgame results present the average proportion of agents per portfolio of 30 independent repetitions in $t = 264$, while average-game results present the average proportion of agents per portfolio over all 264 time periods and over all 30 repetitions. The intuition of making two separate analyses comes from the time-dependent nature of the portfolio selection process, for which the endgame decisions might not adequately reflect game developments. Yet, endgame decisions present the tendency (or a

direction) of agents' behavior. Therefore, to grasp both trends, both aspects should be considered.

6.3 Average-game decisions

The proportion of unsuspicious agents with selected portfolio averaged over the repetitions and time periods as to the mean return and risk, represented by the standard deviation of returns, are reported in Table 6.3 and displayed in Figure 6.2.²³ Black triangles in the figure designate portfolios chosen by less than 1.5% of agents; black circles designate portfolios chosen by more than 1.5% but less than 5% of agents; while gray squares designate portfolios chosen by more than 5% of agents. The horizontal axis shows portfolio risk, measured by the standard deviation of portfolio return; the vertical axis shows expected return. The curve depicts the efficient frontier and is apparent.

Table 6.3: Fractions of unsuspicious agents per portfolio in the average-game setting

	<i>Mean</i>	<i>Stdev</i>	S11	0.23	0.71	S22	0.24	0.53
S1	0.18	0.25	S12	27.18	7.82	S23	11.07	2.37
S2	8.78	4.39	S13	0.18	0.47	S24	0.59	1.16
S3	1.07	0.85	S14	8.24	3.91	S25	0.39	0.82
S4	0.17	0.59	S15	0.33	1.16	S26	0.20	0.37
S5	29.48	6.78	S16	0.49	0.56	S27	1.42	0.76
S6	0.46	0.46	S17	0.20	0.38	S28	0.28	0.54
S7	0.19	0.26	S18	1.61	1.00	S29	0.24	0.45
S8	0.15	0.28	S19	0.15	0.29	S30	1.08	0.97
S9	0.53	0.51	S20	0.75	0.57	S31	0.33	0.50
S10	3.60	1.32	S21	0.19	0.47			

The results provide strong support for the efficient frontier hypothesis of conservative and risk-averse agents who are not willing to take high risk. Namely, the chosen portfolios tend to be clustered around the efficient frontier and also in the neighborhood of the bifurcation point. S5 tops the list with 29.48% of unsuspicious agents. It is followed by S12 (27.18%), S23 (11.07%), S2 (8.78%) and S14 with an average share of 8.24% of unsuspicious agents. The most-preferred portfolio, S5, is a single-asset portfolio of KFT. S12 (MSFT-KFT) is a two-asset portfolio made of the most-desired asset S5 and the fourth most-desired portfolio, S2. S23 (MSFT-XOM-KFT) is a three-asset portfolio of S2, S5 and S3; S3 is the lowest-return asset and among the least-desired portfolios. Obviously, KFT was a leading stock in this setting.

From all the portfolios, S14 is the minimum variance (risk) portfolio, while S2 is the highest mean portfolio. S3 is the lowest mean portfolio and S4 is the riskiest portfolio, while both were strictly avoided in the average-game setting. The two most desired portfolios were chosen by 56.66% of unsuspicious agents and the first five by 84.75% of all unsuspicious agents. Only liquidity agents selected portfolio S4.

²³ *Stdev* in Tables 6.3 and 6.4 designate standard deviations of fraction of agents holding certain portfolio, averaged over the repetitions of the game. Appendix 1 displays entire development of the game.

Figure 6.2: Selected portfolios of unsuspicious agents

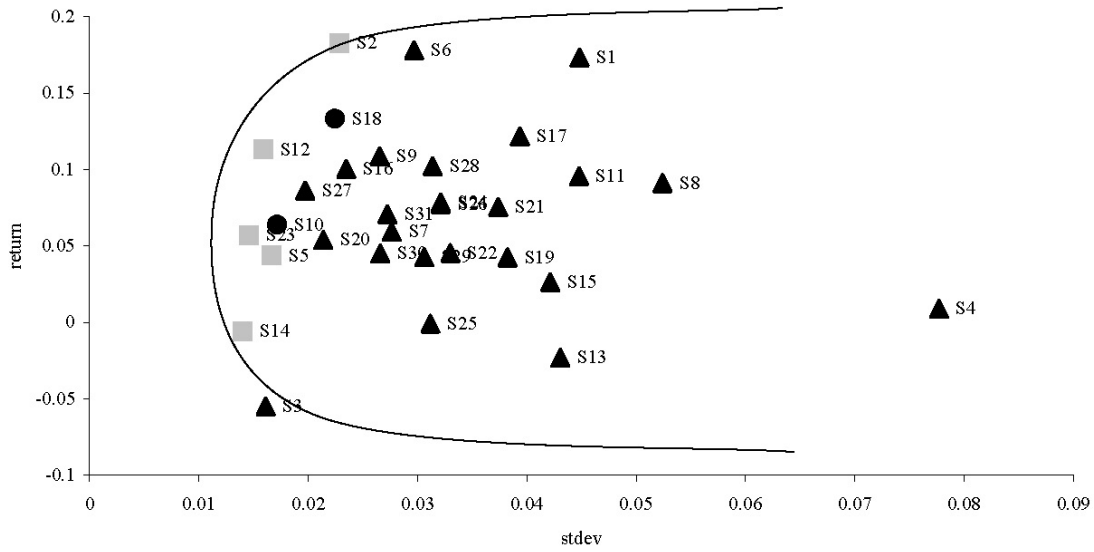
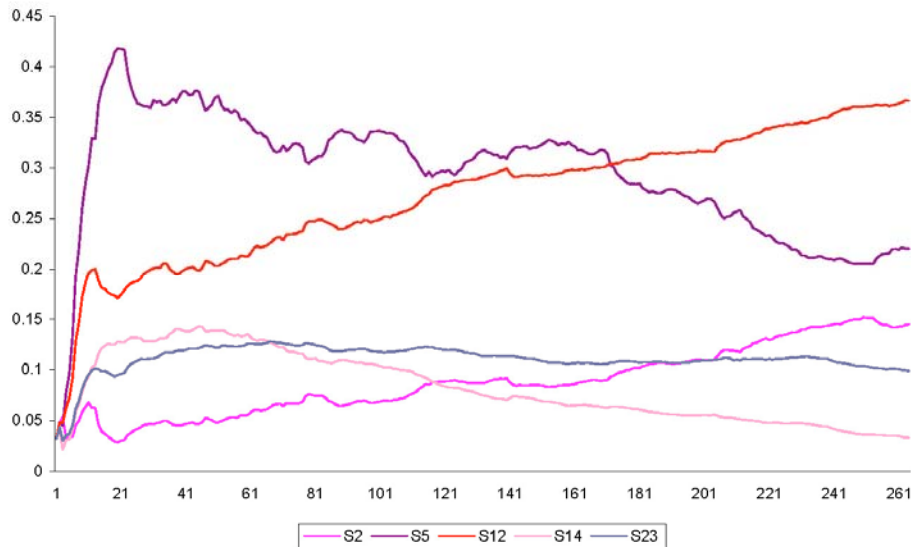


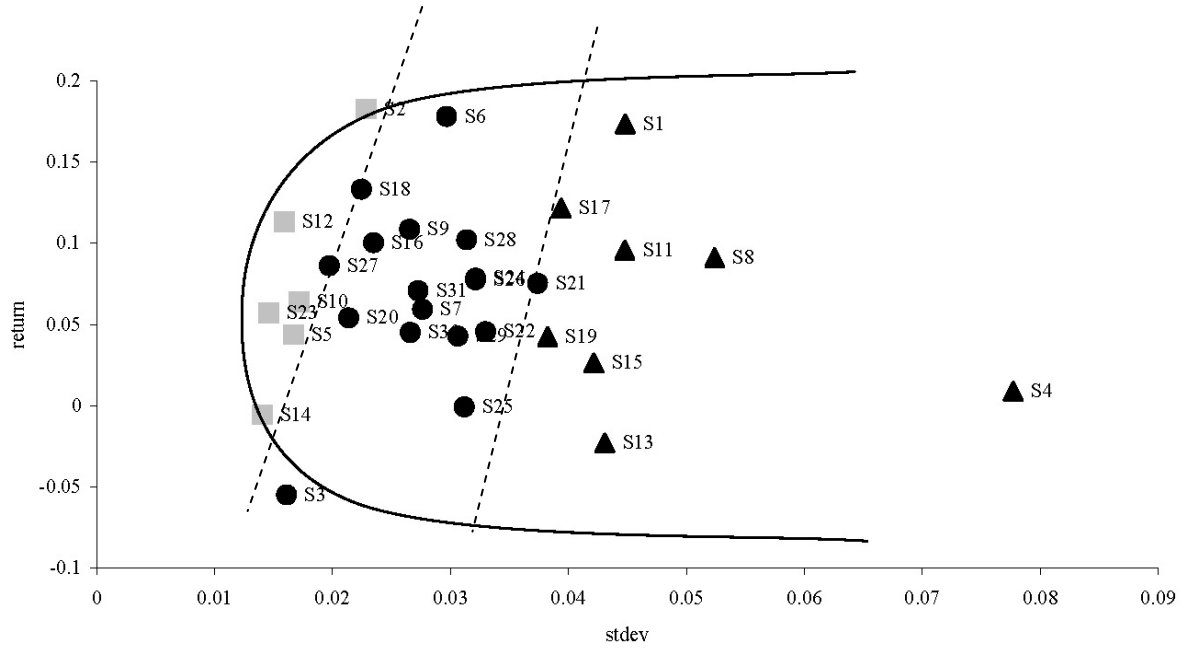
Figure 6.3 shows overshooting in the early phases of the selection process, presumably caused by the initial conditions in which all portfolios were equally held. After the peak, the desirability of each portfolio started to follow its “equilibrium” path. Overshooting is especially evident in the efficient frontier portfolios. Such overreaction to past information is consistent with predictions of the behavioral decision theory of Kahneman and Tversky (1982).

Figure 6.3: Simulation time-paths



The average-game decisions of suspicious agents averaged over 30 independent realizations are displayed in Figure 6.4. Dashes in the figure present the borders of three clustered sections as to the portfolio desirability.

Figure 6.4: Selected portfolios of suspicious agents



Following the figure, selected portfolios can be grouped into three clusters, as represented by the dashes. This is not surprising, given that suspicious agents are to a lesser extent able to pursue the “winner takes all” scheme. It is then reasonable to expect that proportion of other portfolios is accordingly higher, and that the portfolios selected by suspicious agents are much more evenly distributed than those of the unsuspicious. On average, suspicious agents mostly opted for portfolios S2 (9.87%), S12 (7.94%), S23 (6.47%), S5 (6.40%) and S10 (5.73%), all of which are efficient frontier portfolios. Although it appears that suspicious agents are willing to bear greater risk than unsuspicious agents, they avoid the riskiest portfolios. Desirability of portfolios seems to be decreasing with the level of risk. The riskiest portfolio, S4, performed the worst. Table 6.4 brings additional results. Appendix 2 displays the entire development of the game.

Table 6.4: Fractions of suspicious agents per portfolio in the average-game setting

	Mean	Stdev	S11	1.37	0.70	S22	2.19	0.66
S1	1.39	0.79	S12	7.94	1.29	S23	6.47	1.67
S2	9.87	3.08	S13	0.82	0.50	S24	2.85	0.86
S3	3.58	2.22	S14	5.14	2.60	S25	1.73	0.64
S4	0.25	0.53	S15	0.97	0.61	S26	1.93	0.68
S5	6.40	2.67	S16	4.15	0.99	S27	4.73	0.92
S6	4.15	1.82	S17	1.14	0.70	S28	2.23	0.77
S7	2.09	0.53	S18	4.80	1.17	S29	1.66	0.57
S8	0.49	0.49	S19	1.38	0.63	S30	2.84	0.76
S9	3.78	1.14	S20	3.41	0.77	S31	3.00	0.88
S10	5.73	1.53	S21	1.51	0.70			

Synchronization patterns of suspicious agents were not so intense as they were with unsuspicious agents. The two most-desired portfolios of suspicious agents, S2 and S12, were on average chosen by “only” 17.81% of agents, while the first five portfolios accounted for “only” 36.41% of the suspicious agents. On the other hand, the five least-desired portfolios

were on average chosen by 0.83% of unsuspicious agents and 3.67% of suspicious agents. MSFT and KFT were two leading stocks in the setting of suspicious agents.

Discussion

One message of the Markowitz model is that portfolio selection is not just picking different securities but selection of the right ones according to one's risk aversion. Risk-averse agents differ from risk-seeking agents in that they are motivated by the desire for security, while the latter by the desire for potential gain. Given the behavior of both unsuspicious and suspicious agents, the results suggest that the riskier the portfolio, the more likely it is that agents will avoid it. Namely, the transition from squares to triangles is almost linear in risk. The main difference in the behavior of each cohort is that the transition from most desired to least desired is very discrete in the case of unsuspicious agents, while much slower in the case of suspicious agents. There are barely any black circles in the figure of unsuspicious agents, while three sub-sections are evident for suspicious agents. In both cases, portfolios S2 and S3 demonstrate that agents are capable of selecting high mean portfolios and avoiding low risk portfolio, if such a low risk portfolio is also a low mean portfolio. While such is not evident for unsuspicious agents who avoid risk, diagonal dashes in the case of suspicious agents clearly demonstrate that those agents were more eager to bear risk, yet they required higher returns for bearing additional risk. However, the agents did not select high returns when the risk was too high, as in the case of S1. Such high-risk-high-returns portfolios were also avoided in Chapter 5.2. In addition, the steeper dashes signify that average-game decisions were more motivated by variance and less by returns.

Following the figures and the tables, the decisions of unsuspicious agents can be grouped in two clusters: five portfolios from the efficient frontier, which were chosen by more than 5% of the agents each (S10 can also be added to this group, as it lies on the efficient frontier and was chosen by 3.6%), and the rest. From the rest, four portfolios slightly step out: S3 (1.07%), S18 (1.61%), S27 (1.42%), S30 (1.08%). S3 is among the least risky portfolios but has the lowest return, while S18 and S27 lie very close to the efficient frontier yet are slightly riskier. S1 and S6 are both high-return and high-risk portfolios and were avoided by unsuspicious agents.

Selected portfolios of suspicious agents can be grouped into three clusters, as represented by the dashes: the six portfolios from the efficient frontier, being chosen by more than 5% of the agents; the four least-desired portfolios as chosen by less than a percent (S4, S8, S13 and S15); and the portfolios that lie between the two groups. The least-desired portfolios from the second group are the riskiest portfolios and also exhibit the lowest returns. Most portfolios of the third group are riskier than those of the first group and less risky from those of the second. There are three outliers to this apparent linearity-in-risk rule. S1 and S11 are as risky as those in the second group, but exhibit higher returns. S3 is among the safest but exhibited the lowest return. All three belong to the third group of portfolios.

Because suspicious agents are much more inclined towards riskier portfolios, their weighted beta of 0.731 is much higher than that of unsuspicious agents (0.459). Both values are much below market risk, which indicates that agents in general behave in a risk-averse manner and are extremely cautious in taking extra risk, even though suspicious agents take slightly higher risks than do unsuspicious agents.

The most-desired portfolio of unsuspicious agents, S5, has the smallest beta of only 0.314, while the second most desired, S12 has beta of only 0.433. The five most-desired portfolios of

unsuspicious agents have an average beta of 0.418 and weighted beta of 0.396. The five most-desired portfolios of suspicious agents also have small betas on average (0.441), with a weighted beta of 0.451. This finding is not surprising as the unsuspicious agents were much more capable of selecting “winners”. As “winners” refer to the lowest-beta portfolios, this is a logical consequence of the fact that every additional portfolio has a larger beta. On the other hand, the ten least-desired portfolios of unsuspicious agents have an average beta of 1.469 and weighted beta of 1.450, while those of suspicious agents have an average beta of 1.519 and weighted beta of 1.391. Under both settings, only liquidity agents played portfolio S4, which is the portfolio with the largest beta of 2.475. These results show that agents avoid having high beta portfolios; obviously, the losses from those portfolios were sufficient to deter agents from selecting them. This is an implication of Fama and French (1992), whose research did not support the prediction that average stock returns are positively related to market betas. The figures also exhibit that a market portfolio, S31 in my case, is not mean-variance efficient. Either its risk is too large for the given return, or the return is too small for the given risk. Clearly, S3 is a bad-beta portfolio.

To see how agents weigh between the risk and returns, I examine three cases. One is S2 (MSFT) in relation to S6 (AA-MSFT) and S18 (AA-MSFT-KFT). The other is S3 (XOM) in relation to S14 (XOM-KFT). The last is S20 (AA-XOM-MSFT) to S23 (MSFT-XOM-KFT). The first three portfolios are very similar to each other, and the same is true for the other two pairs.

S2 was the portfolio with the highest mean return and a moderate variance. S2 had quite the same risk as S18 but a much higher mean return, while it had a mean return very similar to S6 but a substantially smaller risk. On average, S2 was chosen by 8.78% of unsuspicious agents and 9.87% of suspicious agents, which made it the fourth most-desired portfolio. On the other hand, S18 was chosen by no more than 1.61% of unsuspicious agents and 4.80% of suspicious agents on average, while S6 was chosen by just 0.46% of unsuspicious and 4.15% of suspicious agents. Unsuspicious agents were not willing to give up the additional “riskless” return of S2, yet the willingness of suspicious agents towards bearing more risk and taking less profit could be noticed in both cases.

S3 was slightly more volatile than S14 but exhibited a significantly lower mean return (in fact, the lowest among all portfolios). However, S3 was on the average chosen by 1.07% of unsuspicious agents and 3.58% of suspicious agents. On the other hand, S14 was chosen by 8.24% and 5.14% of unsuspicious and suspicious agents, respectively.

An examination of S23 and S20 revealed the two portfolios to have mean returns very close to each other but significantly different variance. Unsuspicious agents largely chose S23 (11.07%) and left S20 mostly to liquidity agents. Unsuspicious agents required a higher premium to hold a riskier portfolio and were not ready to trade larger risk for nothing. Contrary to them, suspicious agents were more willing to trade higher risk to the return, as 3.41% took S20 compared to 6.47% who took S23.

Following these observations, it could be said that when agents select portfolios, they first make a sort of the “green-line area” that contains satisfying portfolios in relation to their returns and risk. The width of this area depends on the level of agents’ suspiciousness. In contrast to unsuspicious agents, who very accurately select portfolios that are more lucrative, suspicious agents’ decisions are distributed among many portfolios that are close together. The intuition for the behavior of suspicious agents is straightforward. Namely, when two suspicious agents compare their outcomes, the probability that they would take a less

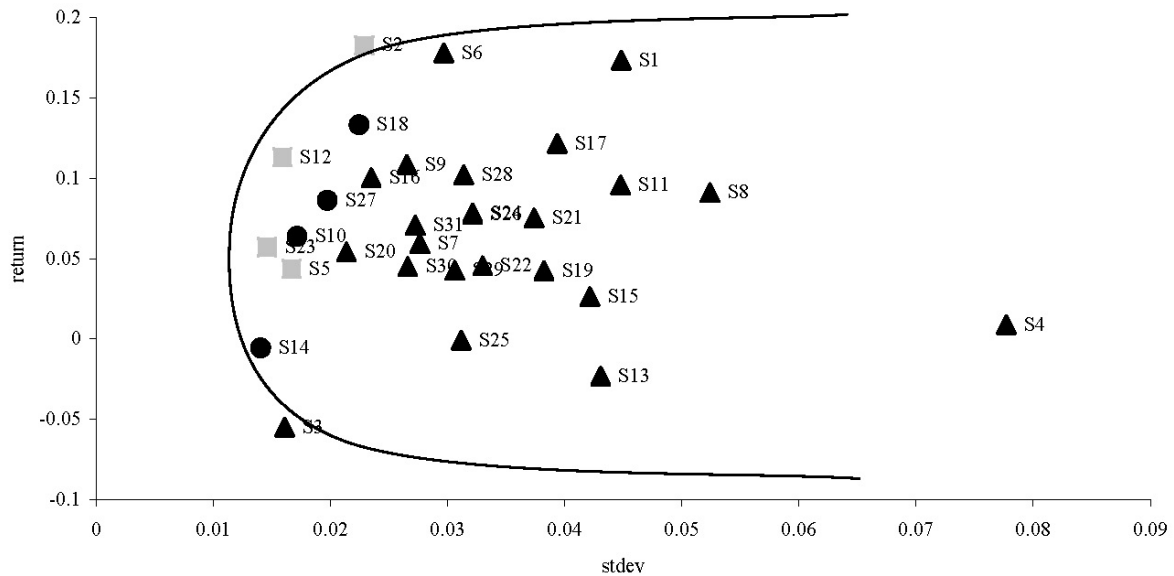
lucrative portfolio is different from zero. Therefore, when the two returns are close together, it is very likely that suspicious agents may select a less lucrative portfolio. As portfolio S3 indicates, agents may not want to opt for the least risky portfolios that also fail to yield satisfactory return, which is also in line with the mean-variance model of Markowitz.

Finally, the coefficient of correlation of $r_{US,S} = 0.681$ indicates that in the average-game setting the behavior of unsuspicious and suspicious agents exhibits a very similar pattern.

6.4 Endgame decisions

Using the same game realizations, I now analyze only the agents' end-period decisions in $t = 264$. The results presented in Figure 6.5 and reported in Table 6.5 relate to the average of 30 endgame decisions of independent game repetitions.

Figure 6.5: Selected portfolios of unsuspicious agents



Following the results, we see that unsuspicious agents mostly ended the games with S12 (36.64%), and S5 (22.02%). These two portfolios were followed by S2 (14.49%) and S23 (9.91%). S12 is a two-asset portfolio of S5 and S2, and S23 is a three-asset portfolio of S2, S5 and S3. All of these are low-risk portfolios from the efficient frontier. There are plenty of high risk and unprofitable portfolios that were strictly avoided: S4 (0.08%), S13 and S15 (0.10%), and S8, S11 and S19 (0.11%). Except for S4 (C) and S19 (a three-asset portfolio of AA-XOM-C), the rest are two-asset portfolios that include the riskiest stock S4. Because of the riskiness of S4, the inclusion of an additional stock cannot reduce the risk sufficiently to make mixed alternatives more desirable. The two leading stocks are KFT (S5) and MSFT (S2). The top five portfolios were chosen by 86.4% of all unsuspicious agents on average, while on the other side, 25 out of 31 possible portfolios were chosen on average by the last decile of agents. This indicates a discrepancy between the most- and the least-desired portfolios. The endgame decisions of unsuspicious agents may be grouped into three clusters represented by the three different symbols in the above figure. Clearly, the transition from the most- to the least-desired portfolios is very straight with a tiny transition line created by portfolios S10 (3.33%), S14 (3.33%), S18 (2.24%) and S27 (1.58%).

Table 6.5: Fractions of unsuspecting agents per portfolio in the endgame setting

	Mean	Stdev	S11	0.11	0.05	S22	0.12	0.08
S1	0.28	0.21	S12	36.64	5.70	S23	9.91	1.89
S2	14.49	4.60	S13	0.10	0.03	S24	0.30	0.24
S3	0.32	0.28	S14	3.33	1.11	S25	0.13	0.1
S4	0.08	0.04	S15	0.10	0.05	S26	0.18	0.12
S5	22.02	2.97	S16	0.64	0.66	S27	1.58	0.85
S6	0.81	0.53	S17	0.21	0.21	S28	0.22	0.17
S7	0.18	0.16	S18	2.24	0.13	S29	0.14	0.09
S8	0.11	0.05	S19	0.11	0.06	S30	0.69	0.51
S9	0.59	0.47	S20	0.66	0.46	S31	0.23	0.24
S10	3.33	1.23	S21	0.13	0.12			

The results for suspicious agents are represented in Figure 6.6 and Table 6.6. Obviously, the transition from the most- to the least-desired portfolios of suspicious agents is not discrete, but again resembles a fuzzy principle. Selected portfolios can be grouped into three clusters, as indicated by the dashes. The first group consists of the most-desired portfolios: S2 (15.07%), S12 (7.68%), S6 (7.36%) and S18 (6.53%). These are high-return and low-risk portfolios. The vast majority of the portfolios belong to the second group of moderate-to-high return and moderate-to-high-risk portfolios. The third group consists of the least-desired portfolios: S4 (0.17%), S13 (0.59%) and S15 (0.68%), along with the portfolio S8 (0.46%), which are low-return and moderate-to-high-risk portfolios. This group also includes S3, which is the lowest-return and (almost) the lowest-risk portfolio. The five most frequently chosen portfolios were selected on average by 41.6% of all suspicious agents, while the last decile of agents was comprised of 11 out of 31 portfolios. Interestingly, the decisions of suspicious agents put S5, which was the second-most-desired portfolio of unsuspecting agents, in the second group of moderate-to-high return and moderate-to-high-risk portfolios.

Figure 6.6: Selected portfolios of suspicious agents

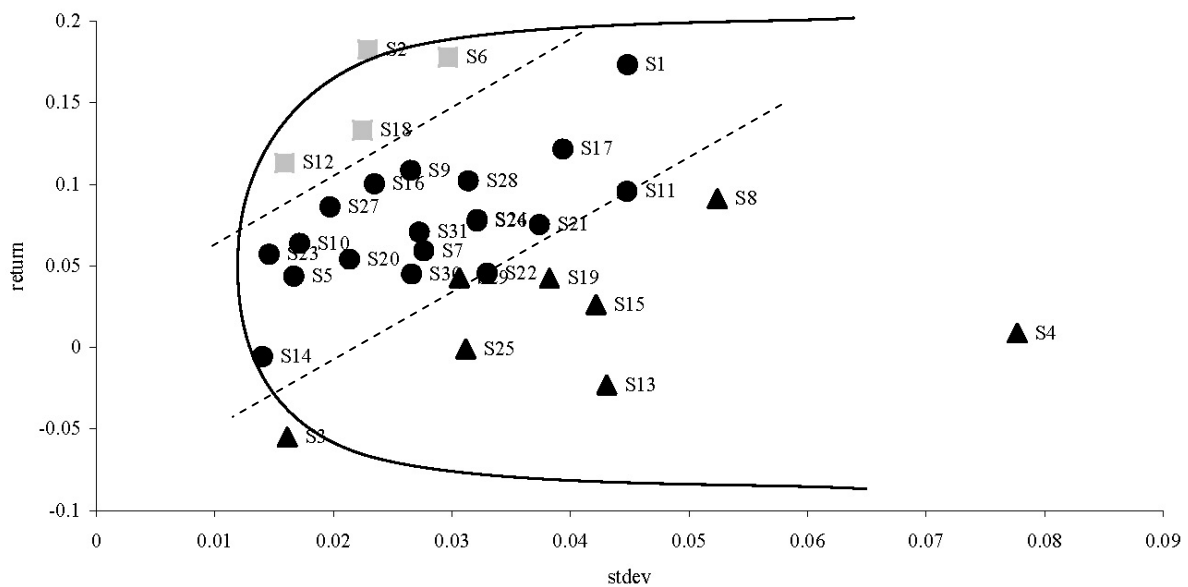


Table 6.6: Fractions of suspicious agents per portfolio in the endgame setting

	Mean	Stdev	S11	1.51	1.41	S22	1.97	1.40
S1	2.28	2.32	S12	7.68	2.43	S23	4.64	2.19
S2	15.07	5.38	S13	0.59	0.65	S24	2.98	1.74
S3	0.92	0.66	S14	2.06	0.93	S25	1.09	0.81
S4	0.17	0.25	S15	0.68	0.67	S26	2.29	1.54
S5	3.19	1.58	S16	4.96	2.70	S27	4.60	2.42
S6	7.36	4.41	S17	1.68	1.88	S28	2.83	1.93
S7	2.07	1.52	S18	6.53	3.43	S29	1.38	0.95
S8	0.46	0.52	S19	1.48	1.32	S30	2.35	1.84
S9	4.91	3.24	S20	2.94	1.87	S31	3.53	1.81
S10	4.11	2.32	S21	1.68	1.55			

In their endgame decisions, suspicious agents still prefer the lowest risk portfolios and are willing to take on more risk than unsuspecting agents. The same conclusion was reached in the average-game setting. In the endgame setting of suspicious agents, the leading stock was MSFT (S2).

Discussion

The picture of endgame decisions shares many similarities with that of the average-game in the main conclusion that the riskier the portfolio, the smaller its desirability. In both cases, the transition from the most to the least desired portfolios followed a fuzzy principle. However, more gently sloping dashes signify that endgame decisions are more stimulated by returns and not so much by risk. The corresponding coefficient of correlation between the average-game and the endgame decisions of $r_{AVG,END} = 0.943$ for unsuspecting agents and $r_{AVG,END} = 0.838$ for suspicious agents supports this observation. However, there are some major differences in the two. Clearly, the transition from the most-desired portfolios to the least-desired is diagonal, with high-mean and low-risk portfolios being the most desired, and the low-mean and the high-risk portfolios the least desired.

Unsuspecting agents ended the games on average with a weighted beta of 0.467, which is much lower than that of suspicious agents 0.778. The five most-desired endgame portfolios of unsuspecting agents have a weighted beta of 0.419. This is again much lower than beta of the five most-desired portfolios of suspicious agents, which is 0.637. Regarding the least-desired portfolios, a weighted beta of unsuspecting agents was 1.424 and that of suspicious was 1.280. This is a logical consequence of the fact that unsuspecting agents highly disregard risky portfolios and do so much more than suspicious agents. Therefore, not only are unsuspecting agents more risk averse as the games proceed but also are risk averse in their endgame decisions.

The coefficient of correlation between the endgame selections of unsuspecting and suspicious agents is $r_{US,S} = 0.515$, reflecting a moderate (dis)similarity in the behavior of the two groups. The greatest part of this difference does not lie in the selection of winners, but rather in the proportion of these winners and by corollary also in that of the “losers”.

6.5 Consistency in selection

In this section, I test for consistency in the agents' portfolio selection.²⁴ In stochastic games in which agents make decisions based on interactions with others, it is reasonable to expect that in independent game repetitions agents would fail to make identical decisions, despite unchanged external conditions.

Particularly, I am interested in the persistence in choices. A consistently chosen portfolio should exhibit small variability in its holdings in each time period over independent repetitions. I utilize the share of the portfolio holdings as an indicator. I take aggregated data of shares of agents per portfolio since I do not collect data on particular portfolios that were possessed by individual agents throughout the games.²⁵ I take two different measures: coefficient of variation and Monte Carlo simulations.

6.5.1 Coefficient of variation

The coefficient of variation (CV) is defined as a ratio between the standard deviation and the mean, $c_v = \sigma/\mu$. CV values are calculated for each portfolio holding in each time period over all 30 independent repetitions of the game.

I am interested in the variability of single time periods, i. e. $t=1,2,\dots,264$, as the games repeat. I then average the values of CV over all 264 time periods for each portfolio. A portfolio whose holdings in each time period over all repetitions are stable should exhibit a small CV value. I truncate the bottom line of portfolio holdings to assess the proportion of liquidity agents per portfolio. Therefore, if less than 0.5% of agents possess a given portfolio in a given time unit, then the value is set to 0.5%. I thus avoid the possibility of high variability in the proportion of liquidity agents, which might not have been meaningful. For example, if 0.1% of liquidity agents were initially found to possess a given portfolio in the first realization of the game and 0.2% in the second, this would signify 100% variability in the holdings of liquidity agents. However, in both cases only liquidity agents would possess a given portfolio, which would mean that the variability is in fact zero and not a hundred percent. Results for unsuspicious (US) and suspicious agents (S) are reported in Table 6.7.

Table 6.7: CVs of unsuspicious and suspicious agents

	US	S	S11	9.32	75.83	S22	15.88	58.93
S1	17.47	80.02	S12	24.51	31.05	S23	25.09	38.00
S2	35.11	34.92	S13	7.77	67.57	S24	42.10	46.93
S3	52.94	49.12	S14	30.46	39.03	S25	27.52	62.16
S4	7.06	37.13	S15	10.38	64.04	S26	18.33	57.69
S5	20.71	34.35	S16	66.47	45.48	S27	52.94	44.01
S6	37.44	61.10	S17	22.53	80.11	S28	26.59	56.87
S7	23.16	56.01	S18	57.17	46.22	S29	18.35	57.64
S8	9.11	59.13	S19	10.86	74.43	S30	58.02	58.44
S9	53.13	58.68	S20	58.92	50.82	S31	39.93	47.93
S10	38.82	42.94	S21	13.91	75.67			

²⁴ I interchangeably use terms consistence and persistence.

²⁵ When working with proportions of chosen portfolios, it might be the case that even though the series repeated itself, different agents might hold the same portfolios. I do not control for that.

As far as unsuspecting agents are concerned, the least-desired portfolios (S4, S13, S8, S11, S15 and S19) those laying the furthest from the portfolios of the efficient frontier, exhibit the smallest average row variability in holdings, that is below or slightly above 10%. This means that the average per-period holdings of these portfolios were the most stable within all independent repetitions of the game. Such a result is compelling as it indicates that agents might be capable of allocating their least-preferred portfolios and that they persistently avoid them, at least in such a small market.

It is also compelling to see that agents are slightly more capable of avoiding the least-desired portfolios than of allocating those that are the most desired. Namely, the variability of most-desired portfolios, those from the efficient frontier, S5, S12, S23, S2 and S14, was very similar for both groups of agents. Yet it ranged from 20.71% (S5) to 35.11% (S2) for unsuspecting agents and from 31.05% (S12) to 39.03% (S14) for suspicious agents. Regarding the most-desired portfolios of unsuspecting agents, the smallest row variability was exhibited by the most desired portfolio S5, followed by the second most S12 (24.51% variability), and then S23 (25.09%), S14 (30.46%) and S2 (35.11%). However, as reported in Table 7.3, the average holdings of S14 (8.24%) and S2 (8.78%) were very close together.

Because the suspicious agents were not as capable as the unsuspecting in selecting winning and avoiding losing portfolios, their row variabilities are larger than those of unsuspecting agents. However, the smallest row variability was exhibited in portfolios from the efficient frontier that were the most-desired, i. e. S12, S5, S2, S23, and S14, as well as the least-desired portfolio S4. All of these portfolios are followed by some neighboring portfolios, i. e. S10, S27, S16 and S18. This means that suspicious agents are far more capable of being persistent regarding the most-desired portfolios and are also able to persistently avoid the least desired ones. However, they are not so consistent regarding portfolios that lie in-between. In contrast to unsuspecting agents, this result indicates that suspicious agents fail to identify properly the least-desired portfolios, and for this reason they may either hold them too long or trade them too much. The implication is similar to that identified in Odean (1998). Altogether, the unsuspecting agents are more capable of being persistent than suspicious agents, which is not surprising.

6.5.2 Monte Carlo

Although the analysis of CVs is compelling, it is by no means complete. CV measures the “row” dispersion of portfolio holdings in each time period over repetitions. If variability is low then the portfolio is said to be persistently chosen. However, the measure has its limitations. The use of CV might fail to acknowledge the potential linear dependence of game repetitions. To control for this, I now study the persistence of choices by way of an analysis of one-period transitions of portfolio selections by using Monte Carlo method.

I employ the six-step procedure of the Monte Carlo method:

1. Data transformation.
2. Random choice of one from the 30 repetitions per selected portfolio.
3. Random choice of one repetition from the next, $t+1$, period.
4. Square the difference between (2) and (3).
5. Sum (4) over 10.000 Monte Carlo runs for every time period.
6. Report the median of all time-periods.

Before running the Monte Carlo, the data had to be transformed because the different initial holdings of portfolios over repetitions (initial setting-up was done randomly with a variable “seed”) prevented proper inter-period comparability. I used the last time period as the base so as to minimize the influence of the initial set-up. The data for each portfolio in every repetition of the game is, hence, expressed as a ratio to the value of portfolio holdings in the last period of that repetition as $\tilde{X}_t = X_t / X_{264}$.

Starting with the initial time period t , I first set the computer algorithm to choose randomly one repetition from all 30 repetitions per selected portfolio (A), and then, irrespective of the first selection, one repetition from the next $t + 1$ time period (B). After the selection of both repetitions, I store the value of the portfolio holding under (B), compare its value to the value of (A) in time period $t + 1$ and square the difference. If these portfolio holdings were chosen consistently, there should then be no difference between both compared values irrespective of the repetition number. I then sum the square differences over all 10.000 runs for every time period and finally report the median of all time periods as the “persistence factor” of the portfolio.²⁶ The implication is simple, the lower (the larger) the value, the larger (the lower) the level of persistence. Table 6.8 reports results of the Monte Carlo.

The idea underlying Monte Carlo is that if a portfolio is chosen consistently over all repetitions of the games, then for its transition from one period t to the next consecutive period $t + 1$ state it should be irrelevant from which of the 30 repetitions of the game observations were taken. In perfectly consistent decision making, an agent would always opt for the same choice regardless of the transition from one time period to the next being made within the same repetition of the game or even within two different repetitions. If in a particular case repetitions themselves influenced and affected a different choice, then this would indicate that agents failed to have clear preferences regarding such a portfolio.

Table 6.8: Medians of sum of squares of the difference

	US	S	S11	1310	896429	S22	10378	76915
S1	2608	3735	S12	39	1468	S23	213	5324
S2	87	334	S13	325	44102	S24	7712	51176
S3	804228	489909	S14	4829	79743	S25	12509	36583
S4	0	816	S15	784	179501	S26	4872	5621
S5	312	142580	S16	5066	3532	S27	2709	398750
S6	1645	490	S17	2611	5934	S28	5638	2618
S7	4269	10603	S18	385	796	S29	3735	56333
S8	560	11231	S19	623	21631	S30	5657	38936
S9	3498	1987	S20	2199	86009	S31	5327	31181
S10	1499	10142	S21	2281	22005			

Unsuspecting agents most consistently chose portfolio S4 with a median of 0, which indicates a perfect fit. Not only did agents consistently avoid S4, but they did it in the very early stages of the games. The S4 portfolio is followed by portfolios S12 and S2, which still exhibited very large levels of persistence, and then by portfolios S23 and S5 with a bit lower (still very high) persistence levels. The grouping is very similar to that of the CV analysis above with one exception. Namely, in the CV analysis portfolio S4 followed the group of the efficient frontier portfolios but did not lead the group as in the present case.

²⁶ Median is used instead of the mean to reduce the influence of extreme values. For instance, first few transitions exhibit large changes.

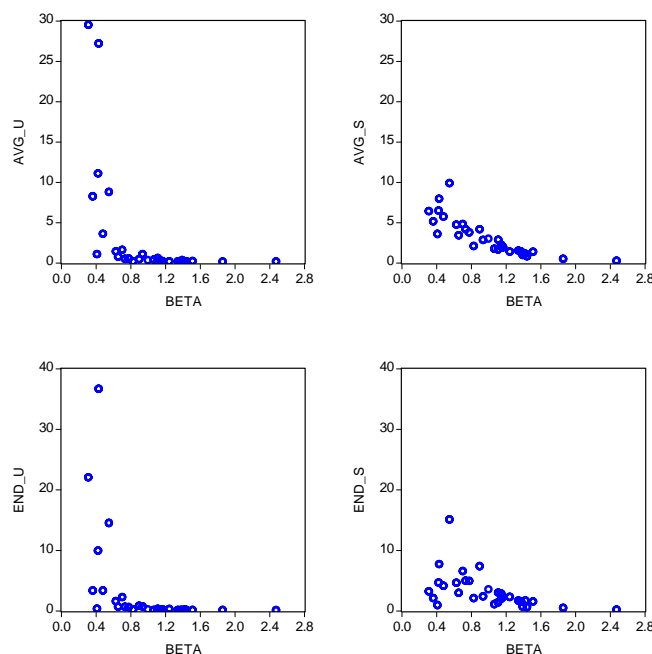
The level of persistence of other portfolios decreases with their distance from the most consistent portfolios. Portfolios in the above figures found to be in or near the center exhibit the lowest levels of consistency. The least consistent portfolio is S3, which is a portfolio from the inefficient frontier.

The differences in the suspiciousness factor once again entailed agents altering their behavior. Under the new circumstances suspicious agents were ready to bear additional risk, being hence more consistent in opting for those portfolios yielding larger returns even though being more risky (volatile). These are portfolios S6, S18 or S9. However, it has been demonstrated that the behavior of suspicious agents is much less consistent than that of unsuspicious agents, implying that suspicious agents in general exhibit much lower preference over portfolio choice.

6.6 Discussion

Much of what has been said above is displayed in Figure 6.7. The figure plots the unsuspicious and suspicious agents' average-game and endgame selections against the beta coefficients of portfolios. Dots in the plots represent different portfolios according to their betas (X-axes) and the fraction of agents having selected them (Y-axes). "S" and "U" in the plots designate suspicious and unsuspicious agents, respectively; and "AVG" and "END" designate average-game and the endgame selection, respectively.

Figure 6.7: Scatter graphs of unsuspicious and suspicious agents' average-game and endgame selections against the beta coefficients of portfolios



As regards the unsuspicious agents, the figure clearly presents that they highly prefer less risky portfolios. In addition, they are capable of selecting winners, while the suspicious agents are not. Some additional results are reported in Table 6.9. The first row of the table reports the percentages of agents with the five the most desired portfolios. The second one reports the numbers of portfolios (out of 31) that is possessed by the last decile of agents.

Weighted beta row reports the weighted betas of desired portfolios, while the nether two report the weighted betas for five the most desired and ten the least desired portfolios. The last row reports the lambda values from the power law distribution.

Table 6.9: Overview of results

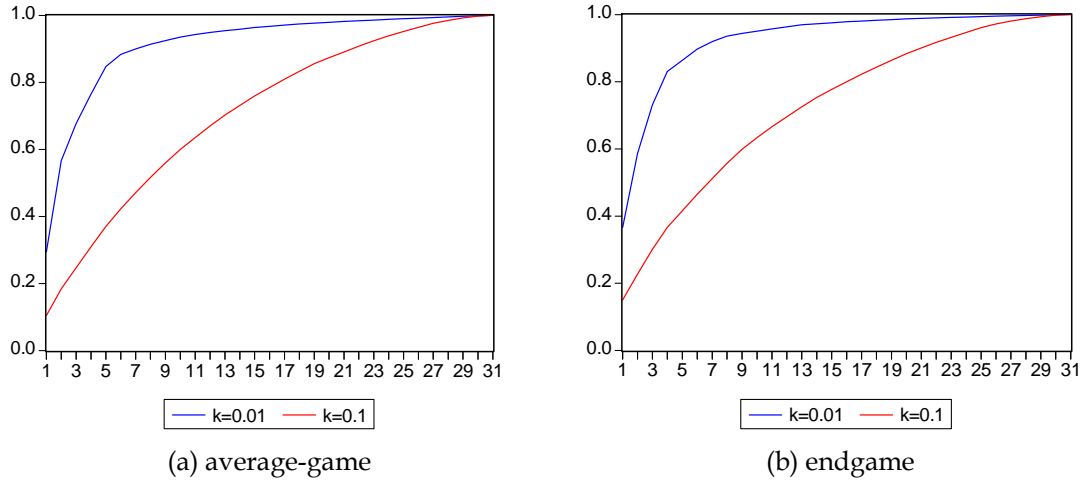
	Unsuspicious agents		Suspicious agents	
	AVG	END	AVG	END
Proportion of agents				
Top 5 (%)	84.75	86.40	36.41	41.60
Least 10% (No./31)	24/31	25/31	10/31	11/31
Weighted beta	0.459	0.467	0.731	0.778
Top 5	0.396	0.419	0.451	0.637
Least 10	1.450	1.424	1.391	1.280
Lambda	1.826	2.030	0.838	0.945

In order to illustrate the argument of the table, Figure 6.8 plots the cumulative distributions of selected portfolios in the average-game and the endgame settings. The portfolios depicted in the figure are numbered in accord with their desirability (descending order) and not as defined in Table 6.1. The portfolio selection of the average-game decisions depicts a power-law distribution of the type $y = Ax^\lambda$, with parameter $\lambda = -1.826$ ($R^2 = 0.97$) for unsuspicious agents and $\lambda = -0.838$ ($R^2 = 0.75$) for suspicious agents. In the endgame setting, the corresponding lambda values equal $\lambda = -2.030$ ($R^2 = 0.98$) for unsuspicious agents and $\lambda = -0.945$ ($R^2 = 0.77$) for suspicious agents. The power-law exponents were obtained by using the least squares method.²⁷ The characteristic of a power law distribution is that most agents opt for a small number of portfolios, while a small number of agents choose the vast majority of remaining portfolios. High lambda values for unsuspicious agents indicate a striking “winner takes all” behavior. On the other hand, lambda values of suspicious agents are significantly lower than 1, indicating a substantial deviation from the “rich get richer” pattern. The power-law parameters are larger in the endgame setting than in the average-game setting, which means that a synchronization process was revealed over the course of the game, with unanimous decisions being avoided.

The figure reflects a “winner takes all” scheme in the selection process, which is highly significant within unsuspicious agents. The top five portfolios of unsuspicious agents were chosen by 84.75% of unsuspicious agents, and 24 of all 31 possible portfolios were chosen by the last decile of unsuspicious agents on average. Such an outcome is an implication of herding, which was highly pronounced in the setting of unsuspicious agents. As was also argued by Banerjee (1992), Bikhchandani et al. (1992, 1998) and Lux (1995), herding was induced by local communication on the network. In the present case, I would argue that absolute herding was prevented by liquidity agents. On the other hand, the top five portfolios of suspicious agents accounted for 36.41% of all suspicious agents with the last decile of suspicious agents having 10 out of the 31 possible portfolios on average. Suspicious agents tended to select portfolios more evenly across the given alternatives.

²⁷ The correlation coefficient has typically been used as an informal measure of the goodness of fit of a distribution to a power law (Chakrabarti and Faloutsos 2006).

Figure 6.8: Cumulative distributions of decisions



As regards the persistence in selection, the first impression is that the decisions of suspicious agents are much less persistent on average than that of unsuspecting agents, as their Monte Carlo values are much higher than those of unsuspecting agents, the Monte Carlo test revealing the persistence of choices between consecutive time periods. As such, suspicious agents appear to make less consistent inter-period transitions. Now, let us say that portfolios from the two most consistent groups are designated as consistent, then simulation results indicate that unsuspecting agents most consistently opted for the following two types of portfolios: those from the efficient frontier, and those the farthest apart from the first group. Keep in mind that consistency does not imply desirability as one could also consistently avoid adopting any particular alternative. In general, portfolios from the first group were mostly desired, while those from the second group were mostly avoided. One exception is portfolio S14, which is a part of the efficient frontier but at the same time exhibits a very low level of consistency. There is no appealing explanation for this.

Desirability does not concord with the return levels. That is something one would expect, since agents weigh returns to risks. For example, portfolios with the largest average returns are S2, S6, and S1. From these, S2 was also highly desirable by unsuspecting agents, while the other two were not. Their higher average returns evidently had not outweighed their higher risks (volatilities).

However, the correlation between the average holding rates of portfolios and the variability of their returns is a bit more pronounced and negative, of course, with the coefficient of correlation of $r_{AVG,VAR} = -0.44$. The sign of correlation is as expected – more variability attenuates the desirability of the portfolio. Combining both observations, I may conclude that when forming their trading strategies unsuspecting agents are more systematically focused on the variability (or the risk) of their holdings than their returns. The implication so far is instructive, yet surprising in that agents in the model follow returns and not the risk. Portfolios of the efficient frontier should be consistently maintained.

Let us look now at the consistency levels of portfolios S10 and S27, both of which can be found alongside the efficient frontier portfolios. The above tables show that both of them exhibit significantly lower levels of persistence than the efficient frontier portfolios. An intuitive explanation for this may be that on average when deciding which portfolio to acquire agents opt for the “first best” from the efficient frontier than rather than their closest

neighboring portfolios. The profile of portfolio S10 might serve as an indicator corroborating my assertion. This is a portfolio that was held on the average by the fifth largest group of all agents, 3.6%. I would say that S10 is an example of a portfolio that an agent would not be eager to change once owning it, but also one that other agents would not be eager to obtain.

Portfolios from the efficient frontier should be among the most consistently chosen portfolios and most of them are with the exception of S14, which overtly breaks this rule. It is indeed highly desirable with an average holding rate above 8% as well as among the least variable as measured by the CV coefficient. However, its Monte Carlo result implies that agents exerted a highly inconsistent trade policy towards it. The portfolio was namely put into the last third among all portfolios. Our argumentation for such a portfolio development is as follows: even though the portfolio as such yields highly stable returns and has the lowest volatility, the returns are very low, fluctuating around a zero mean. Unsuspicious agents, who have been shown to weigh returns against volatility, definitely appreciated the portfolio's low volatility and hence made it desirable. However, its lack of promise regarding gain prevented it from being persistently desired.

Some portfolios were fairly stable within particular repetitions but highly volatile between repetitions. For suspicious agents portfolio S4 is one such example. Higher row volatility on the one hand and lower column volatility on the other might indicate that the holding of such a portfolio would be stabilized at different levels over time in individual repetitions. Stabilization at different levels preserves the row volatility between repetitions but at the same time eliminates the column variability. Liquidity agents, who persist on their initial portfolios and do not trade them regardless of the returns, would very likely hold such portfolios.

The other peculiarity worth noting is portfolio S5 as held by suspicious agents (and to a bit lesser extent also portfolio S3 of unsuspicious agents) in that it exhibited the second lowest level of row variability but at the same time was among the portfolios with the largest between-period variability. The Monte Carlo test indicated that agents did not have any consistent preference for the portfolio, while the small row variability suggests that the holdings of the portfolio had not stabilized.

Simulation results also indicate that suspicious agents are more eager to possess more risky assets than unsuspicious agents. Two such evident examples are portfolios S6 and S18, both of which gained regarding average holdings, while the efficient frontier portfolios S5 and S12 lost a big chunk of their shares. Portfolio S1 remains as one of the least-desired portfolios even though exerting the third largest average return. This indicates that suspicious agents despite being more risk loving still weigh return against risk. S1 was also among the first third of the most consistently chosen portfolios by suspicious agents.

Suspicious agents mostly opted for portfolio S2 with the average share of nearly 10%, which is far below the average share of the top portfolio selected by unsuspicious agents (S5), being selected by nearly 30% of all unsuspicious agents. Nevertheless, S2 was also the most consistently chosen portfolio by suspicious agents, which is an indication of the shift towards the more profitable but also the more risky portfolios. The increase in the holding of portfolios S6 and S18 is just another implication of change in their behavior.

Chapter VII

Multiple-asset portfolio selection in a bull and a bear market

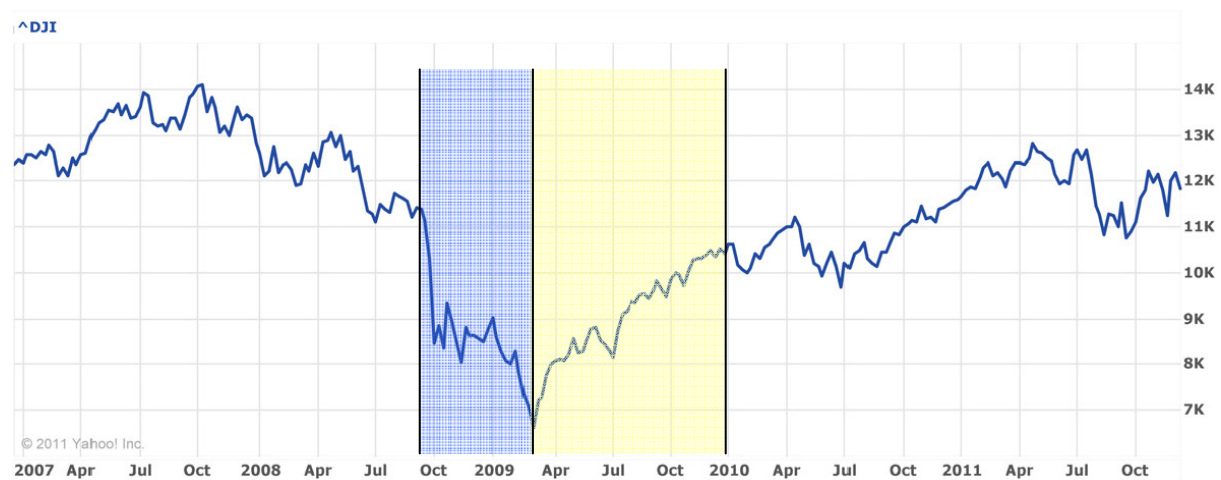
7.1 Introduction

In the previous chapter, it was demonstrated that agents are capable of choosing portfolios from the efficient frontier as predicted by Markowitz, although they were only able to follow returns. In addition, agents exhibited a risk-averse behavior, as they chose low-risk portfolios that were closer to the bifurcation point. This is an encouraging result. However, the time span was chosen arbitrarily and did not contain any significant trend, while history of financial markets has shown that stock markets can exhibit very large and persistent moves upwards and downwards. On the other side, empirical studies have demonstrated that trends are significant for agent's behavior. Among others, Kahneman and Tversky (1979) have argued that agents behave differently in "good" times than in "bad" times. They also have argued that agents have convex value functions for losses and concave for gains (Tversky and Kahneman 1991). Fama and Schwert (1977) argued that expected returns on risky securities are higher in bad times, since people are less willing to hold risky assets at such times. To address this issue, I now simulate the portfolio selection games in a bear and in a bull market.

7.2 Data

There are $n = 5000$ agents in the market with each of them adjacent to ten closest agents (five on each side) and rewired to a randomly selected agent with a probability $p = 0.1$. Again, liquidity agents are placed in the following homogeneous groups: 700-719, 1000-1019, 1200-1219, 1500-1519, 2500-2519, 3500-3519 and 4800-4819. At the start of each game, a random portfolio is assigned to each of them, which they hold throughout the games.

Figure 7.1: Dow Jones Industrial Average



The portfolios are the same 31 as defined in Table 6.1. Again, I utilize the daily closing prices of selected stocks on the NYSE as data and calculate the returns as the relative difference between the two consecutive days, which also captures after-hours and pre-market trades. The time interval starts on September 22, 2008 and ends on January 11, 2010. The data set is divided into two sub-periods, bear and bull part (see Figure 7.1). The figure represents the development of the DJIA index in the 5-year period from December 18, 2006 to December 12, 2011. Both trends are clearly present. A bear market (blue area) designates a widespread decline in stock prices, while a bull trend (yellow area) signifies an overall rise in prices. I was not interested in the reasons for both trends but just took them as they were. The figure also exhibits short-term regime reversals within each of the trends.

Table 7.1: Stock returns in a bear and a bull market

	AA	C	KFT	MSFT	XOM
Yield – bear (in %)	-78.62	-91.10	-31.91	-34.45	-14.81
Yield – bull (in %)	185.13	55.79	25.93	86.28	4.97

The bear market started on September 22, 2008 and ended on March 13, 2009, while the bull market succeeded it, starting on March 16, 2009 and ending on January 11, 2010. March 14 and March 15, 2009 were non-trading days. The bear market consisted of 120 intervals and the bull market of 209. Table 7.1 reports overall returns for each stock within both sub-periods, from which large differences in the stock returns in the two sub-periods can be seen. The worst investment would have been one dollar invested in C at the beginning of the bear market as it ended in only 8.90 cents. In the bull market, a dollar invested in AA produced a yield of a dollar and 85.13 cents. XOM was just slightly shaped by the bear market but did not exhibit any large positive move in the bull market either. It would lead to only a 14.81% loss in the bear market and would produce less than a 5% yield in the bull market. Thus, it could be characterized as safe investment.

Table 7.2a: Beta coefficients and R2 of portfolios in a bear trend

	Beta	R ²	S11	1.309	0.833	S22	1.114	0.931
S1	1.205	0.680	S12	0.582	0.733	S23	0.629	0.754
S2	0.711	0.650	S13	1.316	0.858	S24	1.024	0.892
S3	0.724	0.615	S14	0.588	0.706	S25	1.028	0.909
S4	1.907	0.651	S15	1.180	0.769	S26	1.137	0.992
S5	0.453	0.552	S16	0.880	0.807	S27	0.773	0.831
S6	0.958	0.794	S17	1.274	0.962	S28	1.069	0.982
S7	0.965	0.764	S18	0.790	0.830	S29	1.072	0.985
S8	1.556	0.893	S19	1.279	0.968	S30	0.949	0.955
S9	0.829	0.769	S20	0.794	0.805	S31	1.000	1.000
S10	0.718	0.706	S21	1.188	0.937			

Beta coefficients of the portfolios and their corresponding coefficients of determination (R-squares) in both sub-periods are reported in Tables 7.2a,b. They were obtained by the method of OLS. A beta coefficient reflects portfolio risk against market risk. It measures the correlation between individual and market portfolios. The coefficient of determination measures the degree to which an individual portfolio is diversified in relation to the market portfolio. Namely, it measures the proportion of individual portfolio variance that is explained by market variance. Therefore, the difference up to unity is the proportion of portfolio specific risk that could have been diversified. Again, S31 signifies a market

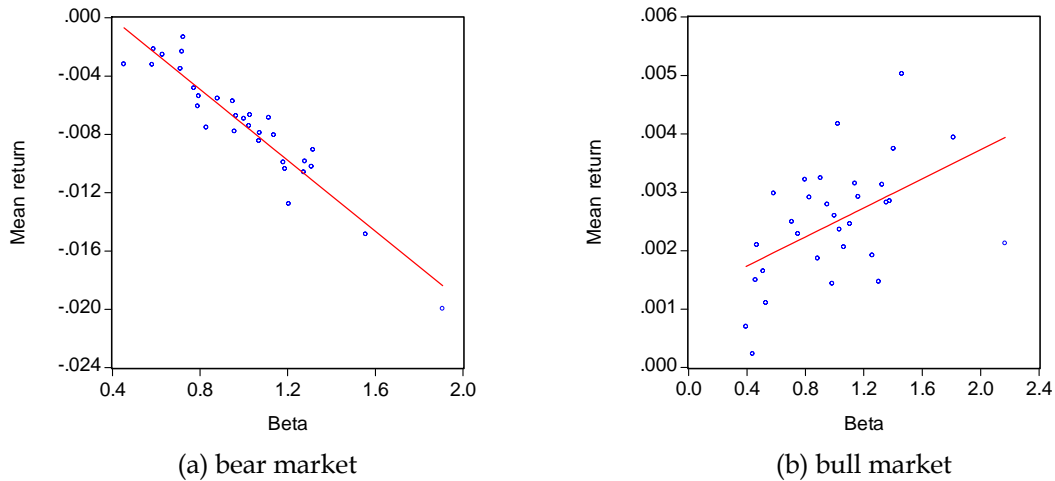
portfolio. The data indicate that high (low) beta portfolios remain so irrespective of bull or bear, despite there being a higher variability in returns in the bull market.

Table 7.2b: Beta coefficients and R² of portfolios in a bull trend

	<i>Beta</i>	<i>R</i> ²	S11	1.378	0.775	S22	1.063	0.837
S1	1.461	0.540	S12	0.467	0.484	S23	0.458	0.568
S2	0.584	0.352	S13	1.303	0.749	S24	1.034	0.830
S3	0.439	0.385	S14	0.394	0.448	S25	0.985	0.799
S4	2.167	0.641	S15	1.258	0.719	S26	1.163	0.982
S5	0.530	0.241	S16	0.828	0.713	S27	0.708	0.753
S6	1.022	0.655	S17	1.404	0.959	S28	1.140	0.985
S7	0.950	0.647	S18	0.798	0.715	S29	1.104	0.969
S8	1.814	0.902	S19	1.355	0.947	S30	0.885	0.873
S9	0.905	0.624	S20	0.750	0.700	S31	1.000	1.000
S10	0.511	0.497	S21	1.326	0.937			

Figure 7.2 displays mean returns of portfolios (Y-axis) against their betas (X-axis) in the bear and the bull markets. As the CAPM model predicts, the bear market exhibits negative beta premium and the bull market a positive. This means that low (high) beta portfolios should have been the most desired by the agents in the bear (bull) market. I would like to stress that both figures are built on daily data and include both pre-hour and after-hour trades. Compared to the stocks in the bear market, those in the bull market exhibited smaller standard deviations in returns.

Figure 7.2: Mean return vs. Beta for portfolios in a bear and a bull market



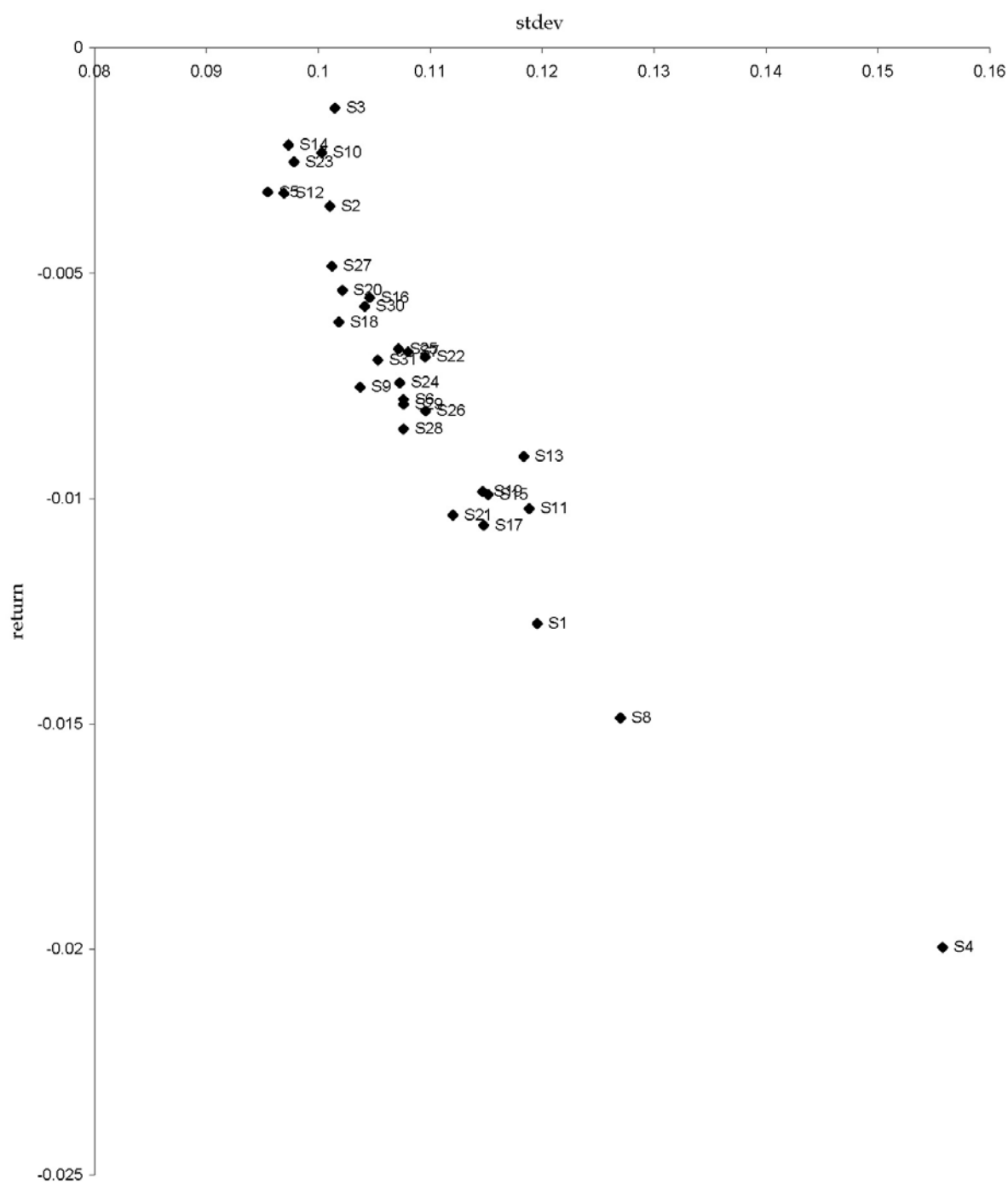
7.3 Results and discussion

Again, I ran 30 independent repetitions of the games for each sub-period and averaged the results. I considered the games of unsuspicious and suspicious agents and, as in the previous chapter, examined the average-game and endgame decisions.

7.3.1 Bear trend

I first examined the bear trend, which is characterized by large standard deviations and some highly negative mean returns. Portfolios that included C and AA, especially S1, S4 and S8, were highly risky portfolios with huge variation in returns. On the other hand, portfolios with XOM, i.e. S3, S10 and S14, exhibited slightly positive mean returns, while also being of small risk. Figure 7.3 plots mean returns of the portfolios (Y-axis) to their standard deviations (X-axis).

Figure 7.3: Efficient frontier portfolios – bear



As reported in Table 7.3a, unsuspicious (US) and also suspicious agents (S) were capable of selecting less risky portfolios that included XOM while avoiding highly risky portfolios of C and AA. As in the previous chapter, the average-game setting refers to the average selection of agents throughout the games.

Table 7.3a: Fractions of unsuspicious (US) and suspicious (S) agents per portfolio in a bear trend, the average-game decisions

	US	S	S11	2.37	1.82	S22	5.22	3.22
S1	0.22	0.30	S12	1.21	4.55	S23	5.06	8.37
S2	2.99	4.76	S13	6.10	2.80	S24	1.23	1.82
S3	41.97	23.20	S14	5.72	10.28	S25	2.81	2.83
S4	2.11	1.32	S15	0.92	1.33	S26	0.42	1.16
S5	0.42	3.81	S16	0.31	1.72	S27	0.31	1.68
S6	0.23	0.58	S17	0.34	0.62	S28	0.28	0.83
S7	0.26	0.89	S18	0.21	0.89	S29	0.32	1.01
S8	0.31	0.47	S19	0.38	0.92	S30	2.97	3.26
S9	0.18	0.57	S20	0.26	1.51	S31	0.40	1.35
S10	14.22	11.50	S21	0.27	0.64			

Almost 42% of all unsuspicious agents possessed S3 throughout the games. This is not surprising in that S3 (a single stock portfolio of XOM) brought the highest average return. This portfolio was followed by S10 (14.22%), S14 (5.72%), and S23 (5.06%) that also lie on the efficient frontier or in its closest neighborhood, and S13 (6.10%) and S22 (5.22%) which do not. These latter two could signify the occurrence of risk seeking in choices when prospects are negative, as noted by Markowitz (1952b) and Kahneman and Tversky (1979). This indicates that agents attempted to obtain profits on the variance. Risk seeking could also be perceived when comparing portfolio S13 to S28, which have similar mean returns, but with S13 having a larger variance. S13 was chosen by 6.10% of unsuspicious and 2.80% of suspicious agents, while in both cases only liquidity agents chose S28. S4 was clearly the worst portfolio and alternative, with the smallest mean and the highest variance, yet on average 2.11% of unsuspicious and 1.32% of suspicious agents selected it.

Considering suspicious agents only, the five most desired portfolios were selected by 73.01% of all suspicious agents. The selected portfolios of suspicious agents were more evenly distributed than those of unsuspicious agents, with S3 (23.20%), S10 (11.50%), S14 (10.28%) and S23 (8.37%) from the efficient frontier still being the most desired.

Table 7.3b: Fractions of unsuspicious (US) and suspicious (S) agents per portfolio in a bear trend, the endgame decisions

	US	S	S11	0.10	0.10	S22	0.21	0.59
S1	0.09	0.11	S12	1.11	4.83	S23	5.97	10.29
S2	2.47	4.16	S13	0.10	0.24	S24	0.09	0.19
S3	62.19	37.74	S14	7.14	14.75	S25	0.14	0.48
S4	0.08	0.09	S15	0.09	0.10	S26	0.09	0.23
S5	0.38	4.04	S16	0.14	1.12	S27	0.18	1.08
S6	0.10	0.16	S17	0.09	0.11	S28	0.07	0.13
S7	0.09	0.30	S18	0.10	0.48	S29	0.08	0.22
S8	0.09	0.09	S19	0.10	0.14	S30	0.37	0.94
S9	0.09	0.23	S20	0.14	0.89	S31	0.11	0.32
S10	17.90	15.74	S21	0.10	0.10			

As can be seen from Table 7.3b, unsuspicious agents were capable of following the “winner takes all” principle, as only four of 31 alternatives were chosen by more than 5% of agents. These are S3 (62.19%), S10 (17.90%), S14 (7.14%), and S23 (5.97%). These portfolios accounted for 93.20% of all selections by unsuspicious agents, and all the portfolios are from the efficient frontier. Of the remaining portfolios, all but S2 (2.47%) and S12 (1.11%) ended with liquidity agents. In all four settings, XOM (S3) was the leading stock. The weighted beta of unsuspicious agents was 0.842 in the average-game setting and 0.714 in the endgame setting. The five most-desired portfolios in the average-game setting have an average (weighted) beta of 0.892 (0.789), while the five most desired in the endgame setting have an average (weighted) beta of 0.674 (0.706). The high-beta portfolios S13 (1.316) and S22 (1.114), which were chosen by 6.1% (2.80%) and 5.2% (3.22%) of unsuspicious (suspicious) agents in the average-game setting but ended the games with liquidity agents, produced the great bulk of the difference between the betas of the average- and end-game settings. On the other hand, both beta values largely depended on S3, which was chosen by almost 42% of agents on average and by more than 62% in the end. The ten least-desired portfolios have an average (weighted) beta of 0.945 (1.487) in the average game setting and 1.166 (1.160) in the end game setting.

The picture is not much different when suspicious agents are examined. They too were capable of playing the “winner takes all” strategy and to an exceedingly high degree selected the same portfolios as did unsuspicious agents: S3 (37.74%), S10 (15.74%), S14 (14.75%) and S23 (10.29%). These four accounted for 78.52% of all selections. The weighted beta of suspicious agents was 0.808 in the average-game setting and 0.696 in the endgame setting. The five most-desired portfolios in the average-game setting have an average (weighted) beta of 0.674 (0.684), while the five most-desired in the endgame setting have an average (weighted) beta of 0.648 (0.679). The ten least-desired portfolios of suspicious agents have an average (weighted) beta of 1.111 (1.088) in the average game setting and 1.293 (1.257) in the end game setting.

Examining the results, it is evident that agents concentrate their endgame decisions in a bear trend much more than in a bull market and are able to select low-risk and high-return portfolios. This means that agents’ choices were very close to optimal. In addition, selected portfolios of suspicious agents were slightly more evenly distributed than that of the unsuspicious agents.

Table 7.4: CVs of unsuspicious and suspicious agents

	US	S	S11	9.43	25.41	S22	29.11	35.97
S1	0.51	1.68	S12	57.89	40.67	S23	33.74	29.38
S2	44.51	28.60	S13	21.25	36.61	S24	22.28	35.24
S3	14.03	16.52	S14	31.61	22.37	S25	27.58	40.86
S4	8.27	9.48	S15	9.83	20.95	S26	3.52	32.23
S5	25.37	39.15	S16	3.04	40.57	S27	13.36	41.95
S6	0.99	22.86	S17	1.76	11.55	S28	2.15	30.41
S7	0.90	40.90	S18	1.23	45.87	S29	2.46	29.92
S8	1.28	5.47	S19	1.63	30.55	S30	42.84	34.59
S9	0.67	29.52	S20	1.96	43.76	S31	4.86	35.52
S10	24.56	19.29	S21	1.55	17.18			

The CV and Monte Carlo tests were used for testing the consistency of selection. Table 7.4 reports the results for unsuspicious (US) and suspicious agents (S). If less than 0.5% of agents

possessed a given portfolio in a given time unit, then the value is set to 0.5%. This was done in order to avoid a possible large variability in the holdings of liquidity agents, which might not be meaningful. The table clearly reveals that decisions of unsuspicious agents exhibit quite a small degree of variability as the games are repeated. This is especially true for the least-desired portfolios. This is not surprising given that I truncated the holdings of liquidity agents. The most-desired portfolios (S3, S10, S14 and S23) exhibit quite a small variability that is not exceeding 34%, although the larger the proportion of agents per portfolio the smaller the variability in holdings. The least consistent portfolios were those that either did not end with liquidity agents or were not the most desired, such as S2 and S12. This is also the reason that the CVs of suspicious agents were higher than those of unsuspicious agents.

Table 7.5: Medians of sum of squares of the difference

	US	S	S11	117730	177042	S22	2466410	19956
S1	951	7667	S12	75968	48811	S23	3168	1196
S2	3575	1333	S13	5585360	54851	S24	478540	485670
S3	307	340	S14	1408	648	S25	181188	770585
S4	87687	3282	S15	25602	9103	S26	33154	25409
S5	58912	1463	S16	28150	7575	S27	69253	1996
S6	6316	9595	S17	5898	39218	S28	146572	4633220
S7	5133	1150530	S18	10889	227040	S29	9334	6240
S8	917	79428	S19	12430	56259	S30	3897070	3884
S9	1457	621128	S20	933	12366	S31	53111	730177
S10	846	809	S21	2487	510585			

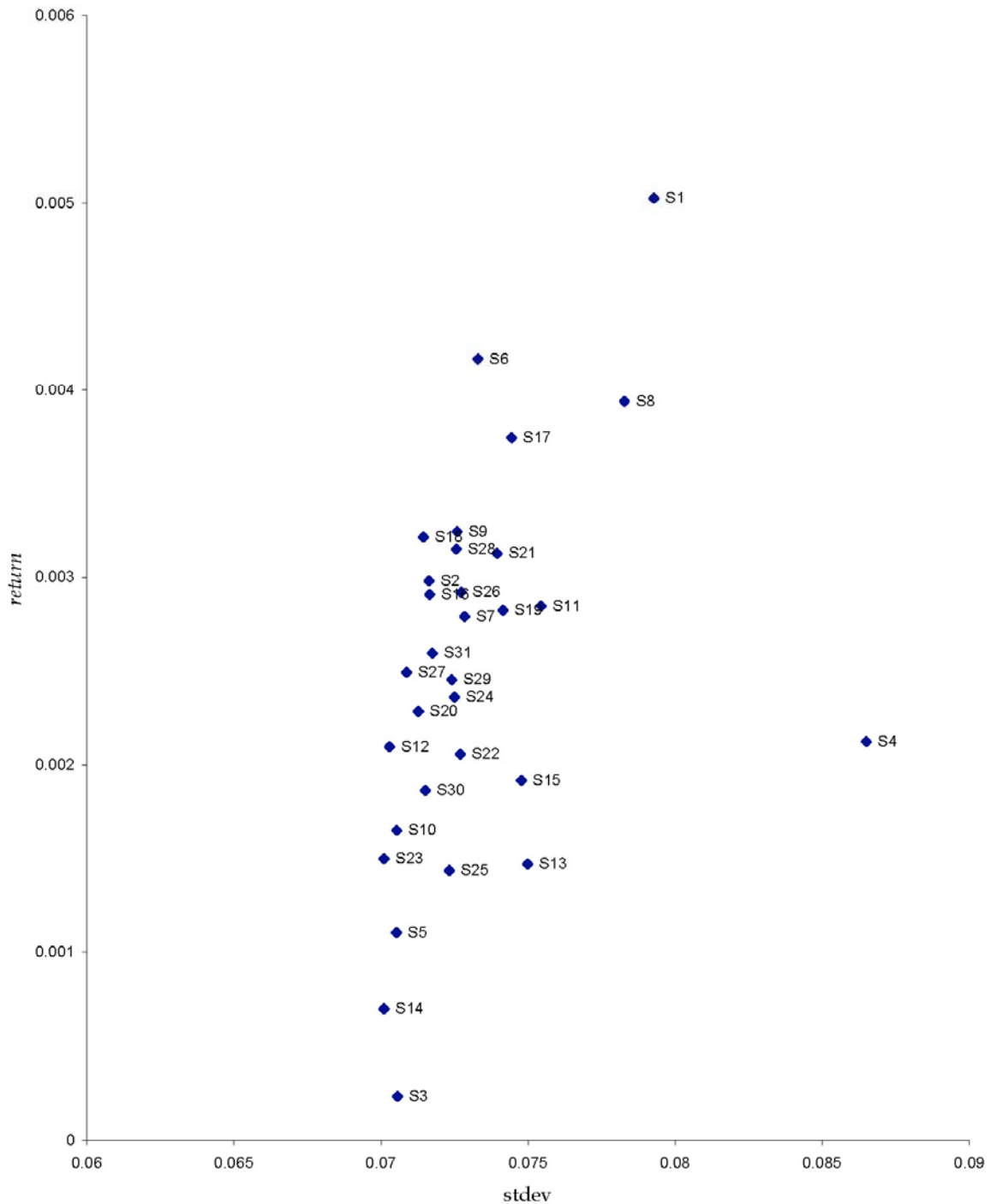
According to the Monte Carlo results from Table 7.5, the most consistently chosen portfolios of unsuspicious agents were S3, S10, S8, S20, S1, S14 and S9, while those of suspicious agents were S3, S14, S10, S23, S5 and S27. Of these, S3, S10 and S14 were the most-desired portfolios, with S23 under the suspicious agents also being so. The least consistent portfolios were those whose proportion had either risen or fallen over time (S13, S11, S22, S24, S28, S31, S7 for suspicious agents, and S30 for unsuspicious agents). Such portfolios exhibited huge differences between the average-game and the endgame analyses. These portfolios were the furthest apart from the most consistently chosen portfolios and were found to be in the center of Figure 7.2. However, suspicious agents were less consistent in their selection, which resulted from their inability to select the “winners” to the same extent as unsuspicious agents.

7.3.2 Bull trend

I now turn to the bull trend. Following the data, a bull trend was found to have succeeded the bear trend. It is characterized by positive shifts in returns. Figure 7.4 displays mean returns (Y-axis) to standard deviations (X-axis). The bull trend is characterized by slightly higher mean returns and large standard deviations.

Considering single stocks, AA (S1) and MSFT (S2) exhibited the highest mean return, being 0.50% and 0.30%, respectively. On the other hand, XOM (S3) was on the lower tail with the mean return of 0.023%. C (S4) was the riskiest with a standard deviation of 8.65%, and XOM (S3) and KFT (S5) were the safest with standard deviations of 7.05%. The shape of the figure exhibits a slightly positive correlation between mean and the standard deviation ($r_{\text{MEAN},\text{STDEV}} = 0.385$).

Figure 7.4: Efficient frontier portfolios – bull



Following Table 7.6a, the most-desired portfolios of unsuspecting agents were S8 (41.70%), S17 (13.70%), S4 (11.05%), S21 (7.37%), S19 (6.27%) and S1 (3.36%). Of these, only S1 is from the efficient frontier, while S17 is very close to it. S8 clearly lies outside the efficient frontier; it is riskier than S6. Generally, desired portfolios lie on the inner side of the imaginary hyperbola, which means that in this case the agents selected riskier portfolios. The winning portfolios are multiple-stock portfolios.

Table 7.6a: Fractions of unsuspicious (US) and suspicious (S) agents per portfolio in a bull trend, the average-game decisions

	US	S	S11	2.83	3.60	S22	0.46	1.36
S1	3.36	14.91	S12	0.14	0.70	S23	0.15	0.61
S2	0.13	1.59	S13	0.89	1.51	S24	0.46	1.80
S3	0.19	0.38	S14	0.17	0.38	S25	0.30	1.05
S4	11.05	6.11	S15	0.76	1.93	S26	2.09	3.19
S5	0.17	0.39	S16	0.37	2.18	S27	0.21	1.11
S6	1.58	6.30	S17	13.70	7.93	S28	2.02	3.61
S7	0.54	2.20	S18	0.31	2.67	S29	1.13	2.19
S8	41.70	14.75	S19	6.27	4.15	S30	0.24	0.99
S9	0.43	3.29	S20	0.22	1.30	S31	0.65	2.18
S10	0.13	0.75	S21	7.37	4.89			

The most-desired endgame decisions of the unsuspicious agents were S8 (50.11%), S17 (17.37%), S21 (6.37%), S1 (5.66%), and S6 (2.25%) together accounting for 84.83% of all their selections (see Table 7.6b). From these only S1 and S6 lie on the efficient frontier, with S17 being very close to it. In the endgame selections, AA (S1) was the leading stock, and again the winning portfolios were multiple-stock portfolios.

Table 7.6b: Fractions of unsuspicious (US) and suspicious (S) agents per portfolio in a bull trend, the endgame decisions

	US	S	S11	2.17	2.77	S22	0.16	0.61
S1	5.66	24.59	S12	0.09	0.32	S23	0.09	0.26
S2	0.13	1.79	S13	0.11	0.57	S24	0.20	1.24
S3	0.11	0.10	S14	0.09	0.12	S25	0.08	0.35
S4	0.10	3.35	S15	0.17	0.86	S26	1.29	2.43
S5	0.25	0.15	S16	0.28	1.78	S27	0.13	0.68
S6	2.25	9.52	S17	17.37	9.16	S28	1.72	3.14
S7	0.29	1.54	S18	0.26	2.91	S29	0.44	1.40
S8	50.11	16.77	S19	4.00	2.75	S30	0.09	0.40
S9	0.43	3.49	S20	0.12	0.69	S31	0.30	1.57
S10	0.09	0.34	S21	6.37	4.36			

The weighted beta of unsuspicious agents during the bull trend was 1.600 in the average-game setting and 1.610 in the endgame setting. The five most-desired portfolios in the average-game setting had an average (weighted) beta of 1.613 (1.712), while the five most-desired in the endgame setting had an average (weighted) beta of 1.634 (1.692). The ten least-desired portfolios of the bull trend had an average (weighted) beta of 0.573 (0.596) in the average game setting and 0.672 (0.674) in the end game setting.

Suspicious agents were still capable of playing the “winner takes all” strategy and to a very high degree selected the same portfolios as unsuspicious agents did. These are S1 (24.59%), S8 (16.77%), S6 (9.52%), S17 (9.16%) and S21 (4.36%). These five accounted for 64.38% of all their selections. The weighted beta of suspicious agents during the bull trend was 1.317 in the average-game setting and 1.346 in the endgame setting. The five most-desired portfolios in the average-game setting had an average (weighted) beta of 1.574 (1.587), while five most-desired in the endgame setting had an average (weighted) beta of 1.405 (1.471). The ten least-desired portfolios of suspicious agents had an average (weighted) beta of 0.613 (0.677) in the average game setting and 0.704 (0.841) in the endgame setting.

Table 7.7 shows the average values of CV over all 209 time periods for each portfolio of unsuspecting agents (US) and suspicious agents (S). Again, if less than 0.5% of agents possessed a given portfolio in a given time unit, the value is set at 0.5%.

Table 7.7: CVs of unsuspecting and suspicious agents

	US	S	S11	38.35	34.16	S22	12.82	47.88
S1	31.13	16.89	S12	0.51	40.95	S23	0.47	38.00
S2	0.24	58.40	S13	14.36	52.08	S24	19.68	55.33
S3	0.46	11.16	S14	0.45	16.41	S25	1.91	54.43
S4	20.78	29.79	S15	23.86	48.82	S26	38.56	39.42
S5	0.43	28.80	S16	12.89	49.96	S27	1.94	50.20
S6	40.88	27.20	S17	16.07	29.40	S28	46.97	39.52
S7	20.42	44.99	S18	14.20	45.36	S29	39.70	41.23
S8	6.61	19.53	S19	28.07	38.15	S30	3.70	42.50
S9	16.54	39.36	S20	2.13	56.16	S31	27.34	45.73
S10	0.53	44.87	S21	25.84	31.46			

Within unsuspecting agents, portfolios S2, S3, S5, S10, S12, S14, S20, S23, S25, S27 and S30 exhibited the lowest row variability in the bull trend that was not exceeding 5%. These portfolios have the lowest variance, were the least desired, and ended up with the liquidity agents (Table 7.6a, Figure 7.2). As can be seen from the table, suspicious agents behave less consistently over time.

Table 7.8: Medians of sum of squares of the difference

	US	S	S11	12463	2998	S22	134300	2182880
S1	309	265	S12	6615	73898	S23	1328	1703
S2	5518	1531	S13	78240	100291	S24	152316	4994
S3	7431	48318	S14	7061	261609	S25	2034	17258
S4	9291	9250	S15	81889	959069	S26	36027	6402
S5	4504	103892	S16	450027	8536	S27	33213	22804
S6	1004	676	S17	313	2668	S28	4606	9460
S7	12060	37204	S18	13822	1315	S29	17734	3068
S8	59	812	S19	7387	8894	S30	54837	11137
S9	48888	5412	S20	35987	25621	S31	3169	6355
S10	2424	1059915	S21	4927	3654			

According to Monte Carlo, unsuspecting and suspicious agents most consistently chose portfolio S8 with a median of 59 and 812, respectively, followed by portfolios S1, S6 and S17, which still exhibited very high levels of persistence (Table 7.8). These three were the most-desired portfolios in both the average and the endgame settings. Portfolios S22, S15, S10, S13, S14, S16, and S5 exhibit the lowest levels of persistence. These are portfolios with the lowest mean returns and the lowest variance, and were among the least desired. Again, the level of persistence of other portfolios decreased with their distance from the most consistent portfolios. Comparing between the two groups of agents we see that the behavior of the suspicious agents was much less consistent than that of the unsuspecting agents, implying that suspicious agents in general exhibit much lower preference over portfolios.

7.3.3 Discussion

Much of what has been said above is displayed in Figures 7.5-7.6 and Table 7.9. Figure 7.5 plots the unsuspicious and suspicious agents' average-game and endgame selections against the beta coefficients of portfolios in the bear and the bull trends. As in the previous chapter, dots in the plots represent fractions of agents with different portfolios (Y-axes) plotted against their betas (X-axes). "S" and "U" in the plots designate suspicious and unsuspicious agents, respectively; and "AVG" and "END" designate average-game and the endgame selection, respectively. In both trends, figures on the left (right) relate to the unsuspicious (suspicious) agents and the upper (bottom) figures to the average-game (endgame) decisions.

Figure 7.5: Scatter graphs of unsuspicious and suspicious agents' average-game and endgame selections against the beta coefficients of portfolios in the bear and the bull markets

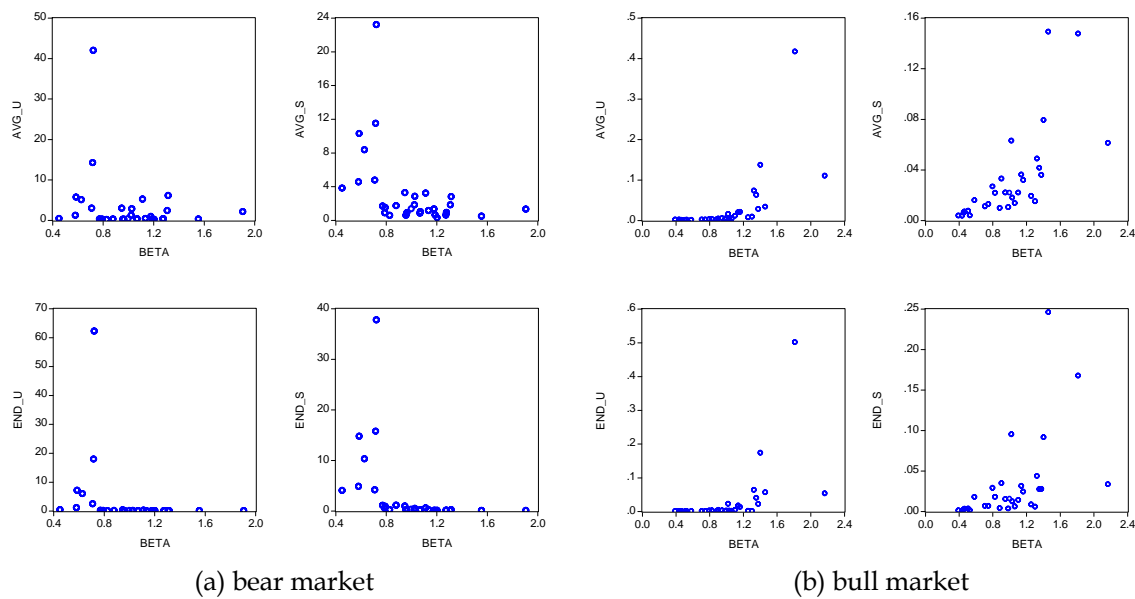
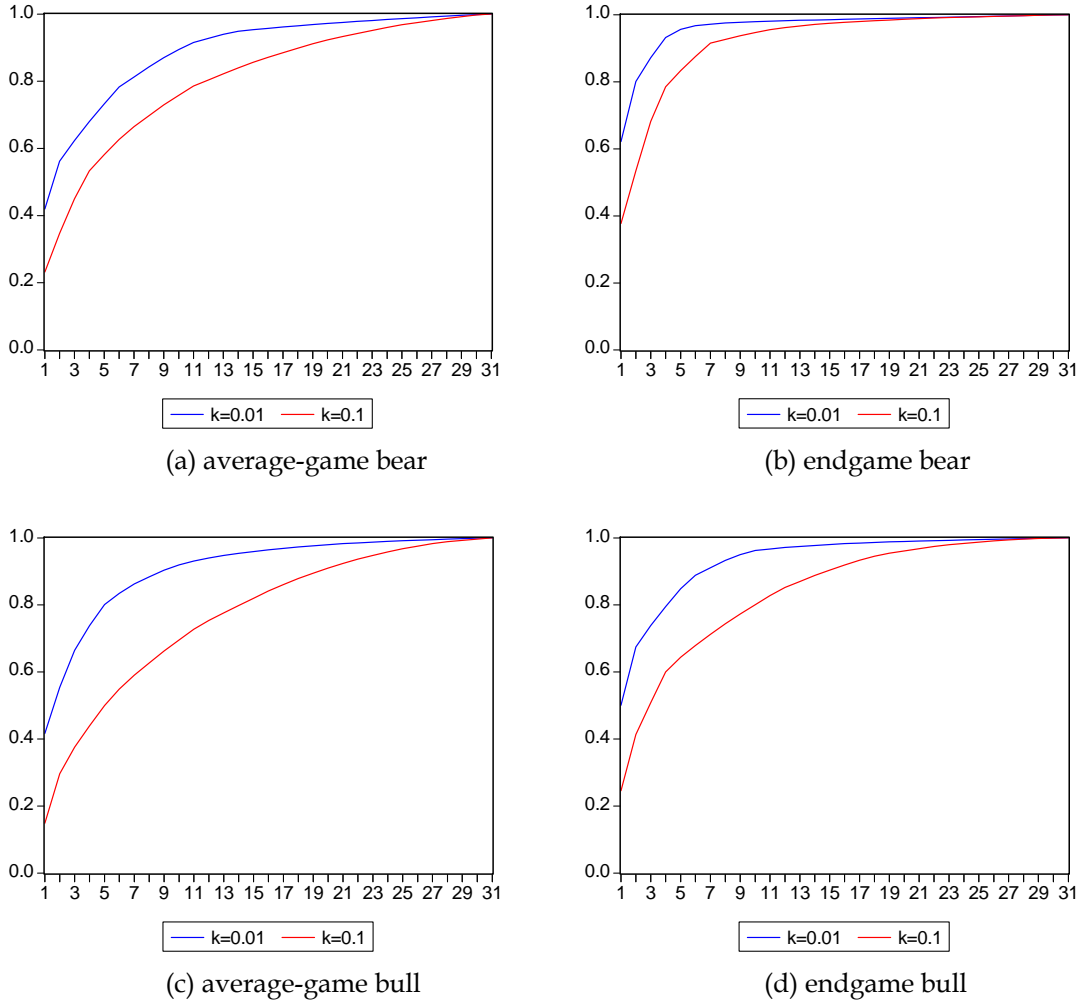


Figure 7.6 displays the cumulative distributions of unsuspicious and suspicious agents' average-game and endgame selections in the bear and the bull trends. The distribution plots set out some interesting features. In all settings of our simple game, agents were capable of selecting "winning" portfolios, which, following the figures of the bull and bear trends, lie on the efficient frontier or in its closest neighborhood. This is a very powerful conclusion, because it suggests that agents make the efficient frontier decisions accurately over time while not knowing the entire sample mean and variance statistics.

Agents were particularly selective during the bear trend, where 62.19% of all ended with the "winning" portfolio S3, 80% with the first two portfolios, and 95.7% with the first five portfolios. It is interesting that the winning portfolio was a one-asset portfolio (*XOM*), and the next two, two-asset portfolios that included *XOM* and either *MSFT* and *KFT*, which were the next two least-losing stocks. As for the market portfolio S31, it ended with liquidity agents in four of eight settings, with unsuspicious and suspicious agents in the endgame setting of the bear trend, with unsuspicious agents in the average-game setting during the bear trend, and with suspicious agents in the endgame setting of the bull trend. In the bull trend, 0.3% of unsuspicious agents ended with the market portfolio (0.65% in the average-game setting), while 1.57% of suspicious agents chose it in the average-game setting. In

addition, during the bear trend 2.18% of suspicious agents selected it in the average-game setting.

Figure 7.6: Cumulative distributions of decisions in a bear and bull market



When markets are risky or in a downtrend and agents are trying to avoid risk, it is to be expected that they would prefer low-beta portfolios, while preferring slightly higher beta portfolios in an up-trend. In an uptrend, beta refers to deviations from the mean on a scale of positive returns. Therefore, the weighted beta of endgame settings is much higher during a bull trend than during a bear trend (0.714/0.696 in the bear trend and 1.61/1.35 in the bull trend for unsuspicious/suspicious agents). The same is true of the average-game settings (0.84/0.81 in the bear trend and 1.60/1.32 in the bull trend for unsuspicious/suspicious agents). In addition, agents are also much more unanimous in their decisions in the bear trend than in the bull trend. Namely, more than 62% of unsuspicious agents selected the winning portfolio during the bear trend but far less during the bull trend (50.11%). This conclusion might be an implication of the “safety first” principle, which is much more relevant in a bear market. It also suggests some flavor of the prospect theory of Kahneman and Tversky. This is also consistent with the findings of Barberis et al. (2001) who argued that agents are less prone to take risk in a bear markets. In the games, agents’ decisions are very consistent in both bull and bear market.

Table 7.9: Overview of results in a bear and a bull markets

	Unsuspicious agents		Suspicious agents	
	AVG	END	AVG	END
Bear Market				
Proportion of agents				
Top 5 (%)	73.23	95.67	57.90	83.35
Least 10% (No./31)	21/31	28/31	13/31	25/31
Weighted beta	0.842	0.714	0.808	0.696
Top 5	0.789	0.706	0.684	0.679
Least 10	1.487	1.160	1.088	1.257
Lambda	1.672	2.017	1.885	2.037
Bull Market				
Proportion of agents				
Top 5 (%)	80.00	84.83	50.01	64.38
Least 10% (No./31)	23/31	25/31	12/31	17/31
Weighted beta	1.600	1.610	1.317	1.346
Top 5	1.712	1.692	1.587	1.471
Least 10	0.600	0.674	0.677	0.841
Lambda	1.820	2.088	1.077	1.883

The computed power law parameter of the average-game setting of the bear trend is $\lambda = -1.672$ ($R^2 = 0.95$) for unsuspicious agents and $\lambda = -1.885$ ($R^2 = 0.83$) for suspicious agents. In the endgame setting, the corresponding parameters are $\lambda = -2.017$ ($R^2 = 0.91$) for unsuspicious agents and $\lambda = -2.037$ ($R^2 = 0.97$) for suspicious agents. Both power-law parameters are much higher in the endgame decisions than in the average-game, which indicates that agents gradually approached their desired portfolios as the games proceeded. In the endgame settings, both cohorts display a striking “winners take all” scheme.

The power-law parameter of unsuspicious agents in the average-game decisions of the bull trend is $\lambda = -1.820$ ($R^2 = 0.98$), while it is $\lambda = -1.077$ ($R^2 = 0.89$) for suspicious agents; the corresponding coefficients of the endgame decisions are $\lambda = -2.088$ ($R^2 = 0.97$) for unsuspicious and $\lambda = -1.883$ ($R^2 = 0.81$) for suspicious agents. Slightly smaller lambda values of the bull trend compared to the bear trend indicate agents’ weaker ability to select the winning portfolios in the bull trend compared to that in the bear trend. This is especially true for the suspicious agents’ average-game decisions in the bull trend, where the “rich get richer” pattern is barely met. Again, the endgame decisions of both cohorts exhibit a striking “winners takes all” scheme.

Chapter VIII

Multiple-asset portfolio selection with news

8.1 Introduction

In this last part of the dissertation I extend the baseline model by introducing news directly into the agents' decision making functions. Before, news events were present indirectly through stock returns, while this extension presumes that news events directly affect agents' buying activities. For instance, if the news is bad, an agent may not be willing to buy. News refers to some significant events that should induce price and volume shifts. By definition, news in its content is that which was not previously known.

The debate as to whether and how news and public information affects trading activity and stock prices continues despite many years of research (see Fama (1998), Campbell (2000), and MacKinlay (1997) for a short overview of the topic). Its origins can be traced back at least to the dissertation of a French mathematician Louis Bachelier in 1900. The efficient market hypothesis, as the name implies, maintains that market prices fully reflect all available information. Therefore, when information arises, the news spreads very quickly and is incorporated into the prices of securities rapidly and effectively (Fama et al. 1969). Samuelson (1965) argued that properly anticipated prices fluctuate randomly. Chen et al. (1986) argues that stock returns are exposed to systematic economic news, while Kandel and Pearson (1995) argue that shifts in the trading volumes and stock returns occur around public announcements.

The post-earnings-announcement drift was first reported by Ball and Brown (1968). Maheu and McCurdy (2004) argue that unusual news events cause infrequent large moves in returns and occur even though the dates of many standard events, such as earnings reports and press releases, are usually anticipated in advance. Nevertheless, many events cannot be anticipated. Hong, Lim and Stein (2000) found that negative firm-specific information diffuses only gradually across the investing public. This might signify that prices are slow to reflect bad public news. More recent work has shown that the average effect of announcements is completed very quickly, usually within 20 minutes of the announcement. Bernanke et al. (2005) analyze the impact of unanticipated changes in the Federal funds target on equity prices. They found that on average over the May 1989 to December 2001 sample, a "typical" unanticipated 25 basis point rate cut has been associated with a 1.3 percent increase in the S&P 500 composite index. As they argue, the estimated response varies considerably across industries, with the greatest sensitivity observed in cyclical industries like construction, and the smallest in mining and utilities. They also argue that most of the response of the current excess return on equities can be traced to policy's impact on expected future excess returns. Boyd et al. (2005) focus on equity prices' response to unemployment news and find that on average, an announcement of rising unemployment is good news for stocks during economic expansions and bad news during economic contractions. Andersen et al. (2007) characterized the real-time interactions among U.S., German and British stock, bond and foreign exchange markets in the periods surrounding U.S. macroeconomic news announcements, and found that announcement surprises produce conditional mean jumps. In particular, bad macroeconomic news has the traditionally-

expected negative equity market impact during contractions, but a positive impact during expansions.

Hong and Stein (1999) argue that different agents receive different pieces of information at irregular time intervals and fail to extrapolate news to the future. Barber and Odean (2008) argue that agents are much more likely to be net buyers of attention-grabbing stocks, e. g. stocks in the news, stocks with extreme one day returns, and stocks experiencing high abnormal trading volume. Barber et al. (2001) show that returns of the highest-rated stocks are tightly concentrated around the day of the recommendation release, while those of the lowest-rated stocks are more widely dispersed over time. Using a representative-agent model with standard preferences and biased beliefs, Barberis et al. (1998) found that stock prices both underreact and also overreact to given data. As Womack (1996) argues, in the presence of underreaction to news, returns that follow are of the opposite sign from what they were before the news release as the time from the event passes. Easterwood and Nutt (1999) argue that agents underreact to negative news but overreact to positive news. De Bondt and Thaler (1985), and Lakonishok et al. (1994) argue that long-term past losers outperform long-term past winners over a subsequent of three to five years. To the contrary, Jegadeesh and Titman (1993, 2001) argue that over a horizon of three to twelve months past winners on average continue to outperform past losers. Moskowitz and Grinblatt (1999) indicate that buying stocks from past winning industries and selling that of past losing industries might be profitable. However, as Korajczyk and Sadka (2004) pointed out, such profits are not robust to trading costs. Cohen and Frazzini (2008) examine the co-movements in stock prices within linked firms and find the effect very significant.

The assumption of this chapter is that agents decide according to returns and news. Therefore, all the differences in the conclusions as to the base case scenario of Chapter 6 go to the news part. I use real data on both returns and news.

8.2 The model

The model here is an extension of the multiple-asset portfolio selection model of Chapter 6. So, in every time period there is a constant number of $n = 5.000$ agents, each of whom is linked to ten closest agents (five on each side) and rewired with the probability $p = 0.1$. Agents accumulate wealth over time and have to choose from 31 different portfolios as presented in Table 6.1.

As in the basic framework, the time period starts on January 2, 2009 and ends on January 21, 2010, which makes a total number of $t = 264$ intervals. Agents still face the same problem as before, and use a reinforcement learning mechanism. As before, I include the level of suspiciousness, which is given by an exogenous factor, reflecting a non-negative probability that an agent will depart from adopting the most promising alternative of the two being compared.

Apart from the basic framework, I now assume that agents follow not only the returns of their stocks and portfolios but also news that is relevant to those stocks and portfolios ($R_{i,t}^{News}$). News comes in irregular periods and not for all stocks at once, though in reality some news might be anticipated and even announced by firms. Because news is announced

only for single stocks at specific times and not for entire portfolios, portfolio news

$P_t^{News} = \frac{1}{n} \sum_{i=1}^n R_{i,t}^{News}$ is computed as the average news of stocks that are included in a portfolio.

However, when news is announced about stocks that are in agents' portfolios, I assume that agents calculate the portfolio news and then compare the two portfolios. If the reported news related to the agent's portfolio or to that of a selected adjacent agent, the agent always selects the portfolio that is subject to more promising news no matter the solution of (4.3). If news is announced for only one of the two portfolios and is "negative," the agent chooses a portfolio with no news. If no reported news is related to any of the two compared portfolios, agents make decisions in accord with (4.3). Loosely speaking, I consider news to be multiple and credible shocks. I implicitly assume that shocks to individual stocks may be correlated.

8.3 Data

The initial task in conducting an event study is to select and evaluate the news. In extracting the news as few significant events as possible should be lost in the data. A huge amount of firm-specific, sector-specific or macroeconomic news arriving within days makes this part of the task quite vulnerable to such losses. I followed a simple and intuitive rule, namely that significant news should be followed by shifts in trading volumes and also in prices. This is similar to Kandel and Pearson (1995) who report on the volume-return shifts around earnings announcements, and to Barber and Odean (2008), who infer the reach and impact of events by observing their effects on trading volume and returns.

Generally, stocks react strongly to earnings reports, hence I took such as relevant news. The main characteristic of the reports is that they provide retrospective information, which does not attempt to increase the firm's value but rather to measure the value and "take a picture" of the firm's position at a given moment in time (Tirole 2006). On the other hand, prospective monitoring is a forward-looking activity, in that it attempts to increase a firm's future value. Therefore, events that relate to a firm's future prospects and thereby could affect the firms' future earnings do seem relevant. Some examples of such are: Alcoa, an aluminium producer, being related to the construction sector and aluminium prices; Kraft Foods being involved in the Cadbury (UK chocolate maker) deal; oil prices being significant to Exxon Mobil's earnings; Citigroup being very susceptible to news on financial crisis; and Microsoft launching Windows 7 in the given period. Generally, such events are complex events, consisted of many sub-events, each having a well-formed event structure.

I assume that macroeconomic factors and events, except oil prices, affect companies to the same extent. Faccio (2006) demonstrates that the same news can sometimes be good and sometimes bad for financial assets. Namely, although political involvement in the economy is generally considered very bad for the economic growth and value of firms, it is highly positive for preferential or politically-connected firms. Similarly, TARP program and the US Treasury injections were considered highly significant and positive actions for the survival of Citigroup at one point, for which these actions contributed to a rise in the price of its stock. However, the actions were viewed as highly negative a couple of months later, signifying that the bank was not sound and strong.

Another aspect of connectedness among firms relates to a lead-lag pattern, where news regarding individual firms, e.g. earnings announcements or capital requirements in the

banking sector, is used to formulate expectations regarding the related firms. This aspect pertains to the correlation or cointegration in stocks, which raises the important question of how news about individual stocks affects the returns of other stocks (Cohen and Frazzini 2008). Namely, firms do not exist in a vacuum, but are linked to each other through many types of explicit and implicit relationships. Therefore, shocks to individual firm might be contagious.

In addition, options expire every third Friday in a month. As this date approaches, future and spot prices of underlying assets converge. In general, call (put) options should always be exercised at the expiration date if the stock price is above (below) the strike price. This might also affect trading volumes, especially in connection to reported news. Finally, daily stock returns also appear as news, and as such are a factor in the phenomenon of news influencing prices.

Identification of news events is followed by evaluation (Table 8.1). Here I employ a very intuitive and straightforward mechanism by which every piece of news is assigned to one of three categories. If the news was followed by a rise in the stock prices, the news is designated as positive news and assigned number 1. News is designated as negative news if it was followed by a fall in the prices and -1 is assigned. Neutral news (0) is that which did not significantly influence a change in prices. To evaluate the news I used the rule-of-thumb.

Table 8.1: The list of evaluated news of selected stocks

AA		KFT		MSFT		XOM		C	
Jan 6	-1	Jan 21	0	Jan 6	-1	Jan 5	-1	Jan 15	-1
Jan 12	-1	Jan 29	-1	Jan 16	-1	Jan 15	1	Jan 27	1
Feb 10	-1	Feb 3	-1	Jan 21	-1	Jan 29	1	Feb 19	-1
Mar 4	-1	Feb 11	1	Feb 2	1	Feb 20	1	Feb 20	1
Mar 16	0	Feb 25	-1	Feb 24	-1	Feb 26	-1	Feb 26	-1
Mar 18	1	Mar 17	-1	Mar 9	1	Mar 5	1	Mar 10	1
Mar 30	1	Mar 27	-1	Mar 20	1	Mar 20	1	Mar 16	1
Apr 7	1	May 4	1	Mar 30	1	Apr 29	-1	Mar 18	-1
May 7	-1	Jun 30	1	Apr 23	1	Jun 14	1	Mar 20	1
May 14	1	Jul 22	1	Jun 16	0	Jun 19	-1	Apr 1	0
Jun 1	1	Aug 4	0	Jun 18	1	Jul 14	1	Apr 12	1
Jun 10	1	Sep 4	-1	Jul 8	0	Jul 29	-1	Apr 16	-1
Jul 8	1	Oct 15	1	Jul 22	1	Aug 18	1	Apr 20	1
Jul 21	-1	Nov 3	-1	Jul 23	-1	Sep 30	-1	May 5	1
Aug 18	-1	Nov 13	1	Aug 20	1	Oct 28	-1	May 6	-1
Sep 14	1	Dec 17	1	Sep 30	-1	Dec 14	-1	May 7	1
Oct 7	1	Jan 5	1	Oct 14	1	Jan 20	-1	Jul 16	0
Oct 28	1	Jan 19	-1	Oct 23	1			Jul 27	1
Dec 1	1			Dec 18	1			Aug 4	-1
Dec 10	1							Aug 14	1
Dec 18	1							Aug 26	1
Jan 11	-1							Sep 14	-1
								Oct 14	0
								Dec 14	-1
								Jan 15	1

I set the time period to a day, by which I avoid to some difficulties in the event studies. This allows me to grasp the entire market reaction to the news, including over- or underreactions

and stabilization. Both phenomena can be perceived in the data. I also capture the phenomena of nonsynchronous trading, which is signified by pre-market and after-market trading, as well as tick-by-tick trading at the ultra-high-frequency level. Not all securities are traded in equal periods at the ultra-high-frequency level, due to the fact that news comes in irregular intervals, frequently before the market opens at 9.30 or after it closes at 16.00; hence many securities are also traded beyond those hours. This is especially the case when some news is expected to be announced, due to which the spreads between the closing price and the next day opening price might be very large. If news was reported before the market opened, I considered it news of the previous day, because agents are informed at that time and could use the news in their decision that day. This is similar to the suggestion provided in Campbell et al. (1997).

The news data was received from different financial newspapers and portals, particularly Dow Jones, Bloomberg, Reuters, Wall Street Journal and its MarketWatch subdivision, and the Internet portals Yahoo, Google, and others. I also used press releases of the companies. Below, I provide brief explanations of selected news events from the table. M in the data designates million traded stocks and B billion traded stocks.

Alcoa (NYSE: AA)

In an after-hour report of January 6, 2009 Alcoa announced it would slash 13,500 jobs (13% of its workforce) by the end of the year as a way to remain competitive during the global economic recession. Executives from Alcoa also released their plans to reduce its total annualized aluminium production by 18%. Following the news, Alcoa shares opened 9.2% below the January 6 close and lost an additional 1.1% during the day on a volume of 35.3M shares.

On January 12 after the market close, Alcoa reported that they had missed the fourth-quarter consensus earnings expectations by 0.18USD per share. Alcoa reported a loss of 0.28USD per share and a 19.1% fall in the year-over-year revenues, ahead of the consensus estimate. Executives from Alcoa said its results were impacted by a 35% decline in aluminium prices during the quarter and a sharp drop in demand. January 13 volume reached 44.9M and shares sank 5.1% from the January 12 close.

On February 10, Alcoa lost 10.7% on a volume of 44.5M shares. During the day, Standard&Poor's cut its rating to BBB-, the lowest investment grade, as falling metal prices made it more difficult to renew loans.

In the morning of March 5, Merrill Lynch/Bank of America was out neg. on Alcoa, lowering their target price to 3USD from 6USD after reduced earnings outlook. On a volume of 46.8M shares, Alcoa lost 15.7%, reaching day low of 5.12USD (17.9% below March 4 close).

In an after-hour report of March 16, Alcoa announced they would cut dividends by 82% to lower costs and improve liquidity and warned of a first quarter loss. Following the news, March 17 started 11.6% below the March 16 close and reached a volume of 84M. March 19 saw the rates of two big houses, JP Morgan Chase (raised from neutral to overweight) and Credit Suisse (resumed at outperform). Alcoa shares rose almost 17% on March 19 after JP Morgan analyst Michael Gambardella upgraded the stock to overweight from neutral and lifted its price target to 12USD from 8USD. Alcoa was heavily traded on March 19 and March

20, reaching volumes of 242.2M on March 19 and 106.6M on March 20. The price rallied to an intraday high of 8.20 on March 26. Options expired on March 20.

On March 30, Moody's Investor Service confirmed Alcoa's Baa3 rating and did not downgrade it to junk status, saying that earnings should improve on cost cutting and moderate improvements in the sector. Following the news, shares were up 8.4% on the March 31 open and gained an additional 1.2% during the day on a volume of 83.4M.

In the after-market earnings report of April 7, Alcoa posted a higher-than-expected first quarter loss (0.59USD per share to estimated 0.57USD) with the quarterly year-over-year revenues down by 44% as aluminium prices dropped and revenues plunged, still ahead of the consensus. Yet, the company also said procurement efficiencies and reduced overhead would eliminate more than 2.4 billion USD in annual costs. Shares were flat in premarket trading but the volume was high, reaching 75.3M.

On May 7, Australia's Alumina Ltd, a joint venture partner with Alcoa, forecasted a further 7% contraction in aluminium demand in the year, mostly in western countries. On the day, Alcoa shares were down 10% on a volume of 56.7M traded shares.

In May, options expired on May 15. Alcoa shares reached a volume of 46.1M and a rise in the prices. Stocks ended 3.3% above the May 14 close and 5.01% below the Monday, May 18, close.

Alcoa completed a divestiture of the wire harness and electrical portion of the EES business to Platinum Equity effective June 1, 2009. On June 2, Alcoa increased by 7% on a volume of 56.7M. A day before, Alcoa had underlined its long-term partnership with Renault on their truck segment. On June 11, Alcoa shares rose 6.1% on a volume of 61.9M. I have not noticed any special news that had raised the prices and the volume.

After the close of July 8, Alcoa announced in a report that its loss was lower than expected (actual loss of 0.26USD per share versus the expected 0.38USD; year-over-year revenues were reported to sink 41.4%). The news shifted the opening price of July 9 to 5.6% above the closing price of July 8. During the day, the price sank 7.6% on a volume of 93M traded shares. The following day, a negative trend turned bullish, with an intraday high of 14.62USD.

On July 21, Alcoa lost 5.5% on a volume of 46.7M traded shares. No special news was reported on the day, except some rumors about the efficiency of China and the US stimulus plan.

On August 19, Alcoa declined on a Goldman Sachs downgrade from buy to neutral. The brokerage cut its rating on the aluminum stock because it has surged sharply in recent weeks and industry conditions could deteriorate. Following the news, August 19 opened 5.2% below the August 18 close and ended 1.9% above the opening on a volume of 42.6M.

In partnership with BHP Billiton and Rio Tinto Alcan, Alcoa opened the Juruti Bauxite Mine in Brazil on September 15. Alcoa's share in the investment was estimated at 2.2 billion USD. The news was announced before the market opened. Shares of Alcoa rose 7.3% on September 15 on a volume of 49.8M and additional 3.4% on September 16 on a volume of 45.2M.

October 8 was another highly trading day with 120.8M traded shares. Following the after-close report of October 7, Alcoa posted better-than-expected third quarter earnings (profit of 0.04USD per share versus estimated loss of 0.09USD). As said, the results were achieved through cost cutting and higher aluminium prices. Alcoa had cut its workforce by 30% since the economic downturn had begun a year prior. The company's revenues had also beaten expectations. Following the news, October 8 started at 15.01USD, 5.7% above October 7 close, yet the price sank to 14.35USD by the day's close.

Alcoa shares rose after the report that GDP grew at a 3.5% clip in the third quarter of 2009 and better-than-expected jobless claims were reported. Following the news, Alcoa shares were up 9% and the volume reached 44.5M on October 29. In expectation of the report, shares had slipped 6.4% on October 28 with a volume of 53.6M.

On December 2, Alcoa gained 5.7%, 6.6% from December 1 close, and volume reached 49.4M.

Alcoa shares added 8.2% on December 11 after an upbeat note from JP Morgan Chase, who said that strength in aluminium prices had led them to up their already bullish price target on Alcoa. On the day, the volume reached 75.2M.

On December 21, Alcoa shares rallied 7.9% on the news that the company would go into a joint venture with a Saudi Arabian mining company to develop an integrated aluminium industry in the Kingdom of Saudi Arabia. The volume reached 60.9M traded shares. In addition to this news, options expired on December 18 with Alcoa reaching 29.9M.

Finally, a bunch of negative news was reported on January 11, 2010, which was followed by volume rising to 76.4M on January 11, and 155.9M on January 12. After-hour reports of January 11 posted lower-than-expected fourth quarter earnings (profit of 0.01USD per share versus the expected 0.06USD). Huge expectations on the news release reflected in large January 11 volume and a rise in price. Not to forget that AA closing price of January 5 was 16.13USD on a moderate volume, while the January 11 close was 17.45USD. However, after the news, January 12 opened at 16.12USD, 7.6% lower than January 11 close and lost an additional 3.7% during the day. Alcoa thus lost 11.1% from the January 11 close to the January 12 close.

Kraft Foods (NYSE: KFT)

On January 12, 2009, Kraft Foods rose 2.7% on a volume of 13.8M. No special news was reported before or within the day.

No special news related to Kraft Foods was reported around January 21, 2009, despite the volume of 23.9M being significantly above the usual, and the price did not exhibit any special shift in any direction.

17.5M Kraft Foods shares were traded on January 30 and Kraft lost 4%. No special news was reported before or within the day. However, its earnings report was approaching.

Before the open of February 4, Kraft Foods released a negative fourth quarter earnings report that missed consensus expectations by 0.01USD per share and revenues by 4.6% and trimmed its outlook for 2009 (EPS down to 1.88USD from earlier guidance of 2.00USD). As said, the company was hit by restructuring costs, inventory reductions at grocery retailers,

and market-share losses after it raised prices. The price sank from the February 3 close price of 28.74USD to 26.09USD; February 4 opened on the news, which was followed by a huge volume of 26.4M on February 4 and 14.2M on February 5. However, stock prices remained steady in these two days.

Kraft Foods rose 2.8% on February 12 with a volume of 18.1M shares. However, no special news was reported in the day.

On February 26, Kraft Foods lost 5.1% in a day on a volume of 11.6M. Kraft Foods volume exceeded 17.6M the day before with no major price shift perceived. No special news was reported in these days.

On March 18, 19.9M Kraft Foods shares were traded and the price sank 3.9% within the trading day.

On March 30, 15.4M Kraft Foods shares were traded and the price sank 3.5% in the day. However, March 31 saw an upwards correction of 2.1% on a volume of 14.6M.

Before the open of May 5, there was news that Kraft Foods cut costs and beat first quarter profit forecasts; nevertheless a 6.5% year-over-year drop in revenues led to a 5.4% price shift from the May 4 close to the May 5 open, and the stock sank an additional 1.4% on May 5 with a volume of 28.9M. During the day of May 5, shares topped at 26.44USD, which was 4.6% above its closing price of 25.22USD. The company said they had increased profits by bringing prices in line with higher commodity costs, eliminating underperforming product lines, and cutting 1.1 billion USD in annual expenses. Increased trading activities continued for the next three days, but no major price shifts were perceived. In the report, Kraft Foods backed its financial outlook for the year, saying their profit margin would benefit from cutting less profitable brands and marketing investments in faster-growing products.

On July 1, Kraft Foods rose 4.3% on a volume of 16.3M. No special news was reported in the day.

On July 22, Citigroup analysts upgraded Kraft Foods from hold (neutral) to buy and put the price target as 32USD. Following the news, volume increased, reaching 10.2M on July 22, 13.3M on July 23, and 12.2M on July 24. Kraft Foods stock turned bullish.

In the after-the-close report of August 4, Kraft Foods announced slightly better-than-expected second quarter earnings, beating expectations by 0.02USD per share. Kraft Foods reported an 11% rise in quarterly profit, boosted by increased demand for their products. The market was undisturbed by the news; volume was slightly higher and the price remained leveled.

There was no news from the company until the weekend of September 6-7, when Kraft Foods proposed a take-over purchase of Cadbury. The bid of Kraft Foods was rejected by the board of Cadbury on September 8, saying that the proposal "fundamentally undervalues" the company and its prospects. A move expected to force Kraft Foods to raise its offer price by at least 8 billion USD sank Kraft Foods shares by 6.2%, from 28.10USD of September 4 close to 26.36USD September 8 open. September 8 saw a huge volume of 43.2M traded shares and the price remained even to the opening level. Consequently, the volumes were above 10M until October 2.

In October, options expired on October 16. Kraft Foods shares reached a volume of 19M and rose 3.3%.

On November 3, 2009, after the close, Kraft Foods reported that their third quarter earnings had beaten the consensus by 0.07USD, while revenues were lower than expected. In a longer report the next day, they announced that operating income was up 38.7% year-over-year, while the adjusted EPS of at least 1.97USD, up from an earlier forecast of 1.93USD. Kraft's CEO, Irene Rosenfeld, said they were interested in acquiring Cadbury, but that a "disciplined approach" would be maintained. This led to an increase in volume to 28.9M on November 4, and a price drop from 27.54USD on November 3, to 26.67USD on November 4.

On November 16, 17.5M Kraft Foods shares were traded, and the price jumped 2.7% from the Friday close. In November, options expired on November 20 and the volume of Kraft Foods reached 11.4M with a rise in the prices.

In December, options expired on December 18. The volume reached 13M with prices going up.

January 2010 saw two peaks in the Kraft Foods stock that were propelled by the Cadbury deal. On January 5, Kraft Foods sold its North American pizza business to Nestle and used the proceeds from the 3.7 billion USD all-cash deal to improve the cash portion of its offer for Cadbury. On the same day, Warren Buffett, the largest Kraft Foods shareholder, voted against the proposed deal, saying in the news release, "Kraft stock, at its current price of 27USD is a very expensive "currency" to be used in the transaction." The day saw a huge 37.2M in volume and a price shift of 3.2% in early trading and 4.9% from the January 4 close price. January 6 was another extremely high trading day for Kraft Foods with a volume of 40.8M. Although such huge volumes continued into March 2010, January 19 should be considered a separate event as it was the day when Cadbury accepted the offer. The day saw a volume of 53M and a closing price of 29.41USD. Next two days were again high trading days with volumes of more than 29M per day, but the price sank slightly to 28.78USD and 28.24USD. However, on January 15, American billionaire, William Ackman, said his fund acquired 2% of Kraft Foods stocks worth 950 million USD and shared the view with Warren Buffett in a statement that Kraft Foods shares were undervalued, for which he proposed larger portion of cash in the deal.

Microsoft (NYSE: MSFT)

On January 7, 2009, 72.7M Microsoft shares were traded and the price sank 6% from the January 6 close.

In January 2009, options expired on January 16 and the volume reached 79.6M. On Monday, January 20, shares were down 6.2% on a volume of 89.9M as the second quarter earnings report was approaching.

Before the opening bell of January 22, Microsoft reported worse-than-expected second quarter earnings and significant contractions in gross margins and net income. Microsoft indicated that it could no longer offer quantitative revenue and earnings guidance for the balance of its fiscal year due to the volatility of market conditions going forward, as all they could do was to consider operating expenses. The first such move was the elimination of 5000 jobs over the next 18 months. The market strongly responded to the news, with volume

increasing to 222.4M on January 22, and 117M on January 23. Additionally, prices sank 6.9% from the January 21 close to the January 22 open and an additional 5.2% during the day. Shares of Microsoft traded down as much as 11% in the wake of the report.

Microsoft stocks rose 3.8% on a volume of 86.9M on February 3. A positive trend continued from the day before. Before the market open of February 3, Microsoft patched its Xbox 360's HDMI issues and a new version of Windows 7. No other news was reported on the day.

Options expired on February 20 and volume reached 69.4M. On Monday, shares were down 4.4%.

On February 24, Google pledged to support the EU Commission's case against Microsoft over allegations of anti-competitive behavior on the internet-browser market. The same day, Microsoft CEO, Steve Ballmer, made the trek to Wall Street to provide analysts with Microsoft annual strategic plans, in which he highlighted the need for cost management and increased R&D activities. On that day volume reached 122.7M and 105.9M on February 25.

On March 10, 95.2M Microsoft shares were traded, and its price rose 8.8% from the March 9 close.

March 20 was highly traded with Microsoft reaching 81.7M. Following that day, Monday saw a huge increase in price, 7.4%. Options expired on March 20. Steve Ballmer gave a speech on Microsoft prospects on the same day.

On March 31, Microsoft rose 5.1% from the March 30 close on a volume of 92.1M shares. April 1 was another highly traded day with 96.4M shares traded and the price shift of 5.1%. April 2 saw a volume of 99.1M, but the price remained steady.

Options expired on April 17. Volume reached 61.4M and MSFT lost some percents. However, Monday saw a drop in price as the earnings announcement was approaching.

Following the April 23, 2009 closing bell, Microsoft announced its third quarter earnings results, which met consensus expectations but slightly missed revenue expectations. On this day, many more companies reported their earnings for the March quarter, and the better-than-expected results were considered the first signs that the crises was over and poured some optimism onto the markets. Shares rallied in the wake of the report, gaining 10.5% from the April 23 close (from 18.92USD to 20.91USD), and continued slightly below 20USD in the subsequent days. This was a time when the stock market rallied around the news that companies' losses were lower than expected. The volume of MSFT reached 168.5M.

Options expired on May 15 and Microsoft reached a volume of 61.3M traded stocks with prices remaining steady.

On June 19, analysts at Goldman Sachs added Microsoft to their conviction buy list and put the rate on buy. They also raised its price target of the stock to 29USD. Analysts at Goldman saw the potential for the company's earnings based on a combination of better revenue drivers, improved expense management, and sizeable cash balances. This led the stocks to gain 3.1% in the midmorning trade from the June 18 close of 23.50USD to 24.23USD. June 19 ended at 24.07USD on a volume of 115.5M traded shares. Options expired on June 19.

After the closing bell of July 23, Microsoft released a fourth quarter earnings report, which failed to impress investors. Microsoft reported a 17% fall in sales, far short of analysts' forecasts, although earnings per share managed to be in line with the forecasts. Microsoft lost 7.6% from the July 23 closing price of 25.56USD to the July 24 open of 23.61USD. The stock reached the day low of 22.81USD and ended at 23.45USD on a volume of 215.1M. The optimism was up the day before (July 23), when stocks rose 2.5% on the volume of 106.1M. However, July 22 was also the date when Microsoft announced the release of Windows 7 to manufacturing.

Options expired on August 21, and Microsoft was highly traded, reaching a volume of 69M. Shares were up 2% within the day and 3.1% from Thursday closing's price.

In September, options expired on September 18 and Microsoft was again heavily traded, reaching a volume of 68M. The day did not affect the prices.

On October 1, 76M Microsoft shares were traded, and the price sank 3.3% from September 30 close. Stocks tumbled after a bigger-than-expected rise in weekly jobless claims and a weaker-than-expected reading on manufacturing sparked worries about the pace of the economic recovery.

On October 15, 65.6M Microsoft shares were traded with the price increasing by 3.1% during the trading day. No special news was reported in the day.

Before the open of October 23, Microsoft released a better-than-expected first quarter earnings and revenue report. Both well surpassed the expectations, beating earnings consensus expectations by 0.08USD per share. Microsoft was also gliding past revenue estimates, even though they were still down 14.2% year-over-year. On the opening bell, shares were up 9.8% from the close price of the day before. Yet, it lost 4% during the day on a volume of 281.8M. October 26 was still a high volume day (124.1M), in which MSFT gained 2%. In addition, Windows 7 reached general retail availability on October 22, the news having been announced and confirmed on June 2, 2009.

On December 18, the Dow Jones reported that the EU Commission settled with Microsoft over the browser antitrust case. In exchange for a legally binding commitment from Microsoft to start marketing its rivals' browsers alongside its own Internet Explorer, the Commission agreed to abandon its case against Microsoft without a fine; the being whether Microsoft was illegally abusing its dominance in the Internet browser market. Following the news, the price shifted 1.7% in a day on the volume of 94.1M. News was awaited from December 8. A positive bullish trend continued to December 29. Options also expired on December 18.

ExxonMobil (NYSE: XOM)

On January 6, 2009, 41.9M Exxon Mobil shares were traded, and the price declined 2.2% during the trading day. Following this decline, shares declined an additional 2.6% on January 7. There was a debate on January 5, whether Exxon Mobil should acquire another oil company.

On January 15, faced with the plunge in oil prices and a decline in domestic oil production, senior Venezuelan officials had begun soliciting bids from some foreign oil companies.

Venezuelan president, Hugo Chavez, nationalized oil fields of foreign oil companies in 2007. Venezuela is among the countries with the largest oil reserves in the world. January 15 was also the third Friday of the month, the time when options expired. Following both news reports, ExxonMobil shares rose 2.6% during January 15 on a volume of 55.6M and additional 1.9% in January 16 on a volume of 45.5M.

Before the market open of January 30, ExxonMobil reported 0.1USD higher than expected fourth quarter earnings, despite a 27.4% year-over-year decrease in revenues and a sharply lower quarterly earnings due to the steep drop in the price of crude oil. Following the news, the market-opening price of 78.25USD was 1.6% above the January 29 close. However, it fell by 2.3% during the day on the volume of 51.9M.

Options expired on February 20. Shares started 1.7% below the Thursday close and the volume reached 42.9M.

Before the market open of February 23, Deutsche Bank (its Tokyo-based unit Deutsche Securities) lifted Exxon Mobil grade to buy from hold and raised the target price to 80USD from 70USD. On February 24, Exxon Mobil reached a volume of 48.9M and the price soared 4%. However, February 24 ended at the same level as the February 23 open.

On February 27, 64.9M ExxonMobil shares were traded and the price sank 4.3% from the day before close (2.7% intraday). Shares fell 4.4% the next day, March 2, on a volume of 54.8M. On February 27, it was reported that the ExxonMobil pension deficit, which was the highest among the US blue chip companies in 2007, more than doubled in 2008 to above 15 billion USD.

In an analyst presentation published on March 5, ExxonMobil Chairman and CEO, Rex Tillerson, outlined how the company's disciplined business approach would continue to pay off. One of the points was the plan to spend about 3 more billion USD on capital outlays in 2009 to bring major projects on line and to meet long-term goals. It was planned that increased investments would raise its total production about 2-3% a year over the next five years. Tillerson also noted that the company would remain a marginal player in renewable energy businesses as long as they relied on tax subsidies to become profitable. On a volume of 50.2M, shares lost 5.3% from March 4, and gained 2.9% by the March 6 close on a volume of 47.1M. I consider this positive news, because Exxon Mobil shares gained 8.3% until the March 10 close on high volumes exceeding 45M per day.

In March, options expired on March 20, and the volume reached 67.3M. Shares lost 3.7% during the day.

On March 23, Brent crude oil prices climbed to a four-month high of 52.35USD a barrel, or a 6.2% increase from the Friday, March 20 price of 49.29USD. Oil stocks had gone along for the ride, with ExxonMobil adding 6.7% from the Friday close price, and the volume reached 51.7M.

In April, options expired on April 17. Shares lost 1.6% on a volume of 32.6M.

Before the market open of April 30, Exxon Mobil announced they had missed first quarter earnings forecast by 0.03USD. The report included sharply lower revenues and net profit due to a slowdown in global markets and a weaker demand for oil. On the volume of 35.1M, the

market responded with a decrease in XOM of 2.9% in the day. However, the following days corrected the price close to the April 29 closing level.

In May, options expired on May 15. Shares were not largely affected by the event, as volume reached 26.7M.

On June 19, Exxon Mobil lost 1.1% on a volume of 42.8M traded shares as oil slid more than a dollar a barrel and gasoline tumbled on speculation that supplies of the motor fuel would climb as refineries bolstered output. A barrel was traded at 69.55USD on June 19, well below 72.04USD from the week before. In the succeeding weeks, a barrel slipped below 60USD. Options expired on June 19.

Exxon Mobil shares rose 3.4% from the July 14 close to the July 15 close on the daily volume of 29.7M shares. On July 14, Exxon Mobil announced an alliance with a leading biotech company, Synthetic Genomics, founded by Craig Venter, to research and develop next-generation biofuels from photosynthetic algae.

In a report that was released before the market open of July 30, ExxonMobil announced sharply lower second-quarter earnings, missing estimated consensus earnings by 0.18USD. Lower revenues were also reported, down by 46.1% year-over-year. The global withering impact of a recession on oil prices and demand dragged down profits of oil companies. The opening price of XOM sank 1.6% from the July 29 closing price.

On August 18, PetroChina signed a liquefied natural gas import deal with Exxon Mobil worth an estimated AUD50 billion over the next 20 years from the Gordon project in Australia. August 19 it jumped 2.9% on a volume of 28.4M. In addition to the news, options in August expired on August 21, and the daily volume reached 26.2M. Monday, August 24, saw a 2% increase in the price. On August 19, crude oil prices surged after the US government's weekly report showed a surprise drop in supplies.

September 18 was the third Friday in September, and the volume reached 43.2M. Prices were not shaped by much.

Before the market opened on October 29, Exxon Mobil reported third quarter earnings of 0.98USD per share, 0.05USD lower than the First Call consensus of 1.03USD per share, as lower commodity prices and weak product margins had taken a toll on the bottom line. Following the news, the day started at 1.7% below the close price of October 28, while the day ended 1.9% above the opening price on a volume of 30M. Exxon Mobil shares rose 2.2% on October 27, when the company announced that the earnings report would be released in two days.

On December 14, Exxon Mobil announced an agreement to acquire XTO Energy, a US company involved with natural gas business. An all-stock transaction valued at 41 billion USD was announced with a 25% premium to XTO stockholders. The reaction of the market was huge. The volume reached to 91.5M and the stock sank 4.3% from the previous day close. ExxonMobil shares continued to be highly traded for the rest of the week.

In December, options expired on December 18. The volume was huge, reaching 63M, while prices remain even.

Finally, Exxon Mobil shares dropped 2.1% on January 21, 2010, on a volume of 39.1M and 1.8% from the January 19 close to the January 20 close on a January 20 volume of 34.6M.

Citigroup (NYSE: C)

Before the market open of January 16, 2009, Citigroup reported worse than expected earnings, with an actual loss of 1.72USD per share, which was 0.41USD above consensus expectations. The news followed the January 14 news that Citigroup was selling its stake in the Smith Barney brokerage business to Morgan Stanley, which had done little to inspire confidence since it was being viewed more as a forced sale in a bid to boost the bank's capital position. The reaction from the market was huge. In just four trading days the stock went down from the January 13 closing price of 5.90USD to just 2.80USD, the closing price of January 20, being a 52.5% decline. Trading volumes jumped significantly in both cases, reaching 513.9M on January 14 and 634.8M on January 15. After the loss, Citigroup announced that they would realign into two units. Options expired on January 16.

On a January 27 afternoon, Citigroup CEO Vikram Pandit downplayed the notion that Citigroup or any other major financial institution would be taken over by the US government. Following the news, the stock rose 18.6% on January 28 on a volume of 376M.

Options expired on February 20, and Citigroup ended at 1.95USD and a volume of 617.7M. This was 22.3% below the Thursday closing price of 2.51USD. However, the stock gained 21% over night to the February 21 open.

Before the market open of February 27, Citigroup announced that they had reached a deal with the US government under which the government could have control of as much as 36% of the bank. As part of the agreement, Citigroup said they would suspend dividends on both its common stock and preferred shares. Following the news, shares started at 1.56USD, a drop by 36.6% from the day before close of 2.46USD. February 27 reached a huge volume of 1868.2M and was followed by 1078M on March 2 and additional decrease in the price for 20% to a day close at 1.20USD.

On March 10, Citigroup shares rose sharply on the bank CEO's comment that the company was profitable in the first two months of 2009 and on his remarks on its capital strength. On the day, volume reached 1115.1M and the price went up 38.1%.

On March 16, as expected, Citigroup announced several new directors to its board, in accord with an agreement with the US government in exchange for a financial injection. Although expected, the news strengthened the commitments between the two parties. Volume reached 1475.8M and the price was up 30.9% from the day before close. High volumes continued for the next three days.

On March 19, Citigroup sank 27.4% within the day on the news that it had filed a registration statement with the Securities and Exchange Commission (SEC) in connection with the proposed offer of its common stock in exchange for publicly held convertible and non-convertible preferred and trust preferred securities. This day Citigroup also received approval to proceed the exchange from the New York Stock Exchange (NYSE). Besides, options expired on March 20. On Monday, March 23, shares started 26.3% above the Friday close.

Ahead of the FASB (the Financial Accounts Standards Board) April 2 vote on a proposal to give banks more leeway on how they should apply mark-to-market accounting standards, Citigroup shares gained 10.8% from the April 1 close to the April 2 open. Credit default swaps insuring Citigroup's debt jumped over 700 basis points in the intraday trading of April 1. April 2 saw a 7.7% decrease in its price on a volume of 525.9M traded shares.

On April 13, Citigroup was up 20.3% on a volume of 834.7M, and April 14 opened at 4.22USD, 11.1% above the April 13 close. It ended at 4.01USD per share on a volume of 1222.3M traded stocks. Citigroup stock boosted on large earnings expectations ahead of Friday's quarterly results release, after Goldman Sachs reported better-than-expected quarterly profit as a surge in trading revenue outweighed asset write-downs. Thus, a 2.46 million call options (call options give buying rights to the shares) and a 1.11 million put options (put options give selling rights to the shares) were traded on April 14, relating to bullish and bearish bets on the stock.

In the news before the open of April 17, Citigroup reported a 0.16USD lower-than-expected first quarter loss per share, as they beat the consensus forecast that expected a loss of 0.34USD per share. Following the news, shares were up in the premarket trading, yet the market closing price was down by 12% from the day's opening, and volume was 1115.3M. Options also expired on this day.

Citigroup shares rose 20% on April 21 on a volume of 709.9M. Citigroup held an annual shareholder meeting on April 21.

On May 6, it was announced that Citigroup and some other banks were short on capital. It was speculated that Citigroup's requirement for deeper reserves to offset potential losses over the coming two years would be about 5 billion USD. In the afternoon, Tim Geithner, the US secretary of finance, said, "All Americans should be confident that these institutions are going to be viable institutions going forward." Citigroup stock rallied after the news, gaining 10% during the day on the volume of 867M. This was 16.6% higher than May 5 close.

The long-awaited results of stress tests for two banks, Citigroup and Bank of America, were publicly released on May 7, and the US government determined that Citigroup should raise an additional 5.5 billion USD. During May 7, Citigroup shares sank 13% on a volume of 1032.4M. However, May 8 started 10% above the May 7 close, after the May 7 afternoon press release of Ben Bernanke and Tim Geithner on financial health. It was said that the bank was short 5.5 billion USD in capital. However, Citigroup executives said the bank could easily cover the shortfall. It is worth mentioning that in expectation of the stress tests, Citigroup shares gained 30% from the May 1 close to the May 6 close on moderate volumes.

Before the market open of July 17, Citigroup astonished the markets on the second quarter earnings report with a profit of 0.49USD per share, exceeding consensus earnings forecasts by 0.86USD per share. However, this included a gain from the Smith Barney sale, which was not anticipated in the consensus forecast. Yet, managed revenue without the sale was slightly below the consensus. The market responded with a volume well below the average. Options expired on July 17.

Before the market open of July 28, Dow Jones reported that Citigroup would issue a 1.25 billion EUR 10-year bond at a spread of around 385 basis points over mid swaps, and within the trading day they also reported that Citigroup had priced a 1.75 billion EUR, 7.375% bond

due 2019 in a self-led deal. The day ended in a 10% increase in the price on a volume of 1037.5M. The three days that followed were also high volume and high volatility days.

August 5 was another high volume day for Citigroup. Before the opening bell, Citigroup announced that it had delayed the disclosure of its second quarter account settlement for the fiscal year ending December 2009, as it required a longer time to confirm the account settlement numerical value. More importantly, as the trading day proceeded Reuters reported that Citigroup launched its 2.5 billion USD five-year unsecured notes at 380 basis points over US Treasuries. August 5 saw a huge volume of 2674.5M and was followed by two more high-volume days. On August 7, Citigroup also started the sale of its Japanese telemarketer Bellsystem24, a deal expected to be worth 1.5 billion USD.

Before the market open of August 14, it was reported that Citigroup was upgraded to Buy from Underperform at Bank of America and that the old price target of 2.50USD per share had been raised up to 5.75USD. The reasons cited were stabilization of some credit quality and the removal of the supply overhang of all the new stocks. On the news, Citigroup shares were up 2.5% in pre-market trading, but ended back at the level of the August 13 close. Volume was 1121.6M.

Options expired on August 21. Citigroup shares were highly traded, reaching a volume of 1366.8M and a rise of 4.9% from the August 20 close. Monday, August 24, was another highly traded day, with a volume of 1202.3M. High volumes continued until August 27 and after.

Before the market open of August 27, it was reported that hedge-fund manager John Paulson had been quietly buying shares of Citigroup in the past weeks and reached stock holdings of 2%. Following the news, shares were up 2.2% in pre-market trading and gained an additional 6.8% during the day on a volume of 1216M. Following the news, August 28 was another high-volume day, 1360M, in which Citigroup shares gained another 3.6% from the August 27 close.

On September 15, Citigroup announced they were working on a plan to reduce the US government's 34% stake in the bank that could include a multi-billion equity sale. In the afternoon, Dow Jones reported that Citigroup had launched a combined 5 billion USD debt offering on September 12, 2009. On September 16, Citigroup announced that they anticipated entirely divesting their stake in Morgan Stanley Smith Barney LLC over time. On September 17 during the trading day, Citigroup launched a 2-billion USD five-year senior notes at a spread of 325 basis points over Treasuries. Following this news, volumes reacted sharply, ranging from 1154.9M to 1318.9M. The stock sank from 4.52USD (September 14 close) to 4.12USD (September 15 close), a decrease of 8.8%. Options expired on September 18 and the volume reached 1250.7M with the price losing 4.5% in a day.

Before the open of October 15, Citigroup announced 0.11USD smaller loss per share than expected for the third quarter. However, Citigroup was still rocked by steep credit losses worth 8 billion USD. The market did not react as sharply as it did a couple of times before on the news related to Citigroup's future. Better than expected results were inferior to the Goldman Sachs strong earnings performance, which glided past consensus earnings estimates with ease. Following the news, the volume of Citigroup reached 834.1M, while the price was almost even to the October 14 close. Options expired on October 16, but the volume of 411M traded shares was an average one.

Citigroup was highly traded in the period of December 14-18. On December 14, Citigroup announced they had reached an agreement with the US government on the 20 billion USD TARP repayment. Waiting for the US Treasury press report, 1191.1M of Citigroup shares were traded on December 16. Later in the day, the US Treasury announced a delay in the plan to sell its 5 billion USD Citigroup stocks after the two events occurred. First, a stock that the bank offered to potential buyers attracted weak demand and was priced at a much lower-than-expected 3.15USD per share; and secondly, a 17 billion USD new-stock deal to repay 20 billion USD TARP money. The US Treasury agreed not to sell the stock for 90 days, and the next day prolonged the period to 12 months. The market response was huge, 3772.6M in volume, and a drop in December 17 opening price to the expected price of 3.15USD. On December 18, 2813.7M shares were traded and the price shifted from 3.26USD to 3.40USD. This was close to 3.45 USD of December 16 close. Options expired on December 18.

Finally, before the market open of January 19, 2010, Citigroup posted a 7.6 billion USD loss in the fourth quarter, 0.33USD per share, which was in line with the estimated consensus earnings. In a press conference regarding the report release, Vikram Pandit, Citigroup CEO, also said that loan performance outside of the United States looked strong, adding to investors' perception that the bank was recovering. Markets saw this news with approval and the price shifted 6% in the day on the volume of 807.9M.

8.4 Results and discussion

The analysis contains the average-game and the endgame proportion of unsuspicious and suspicious agents with given portfolios. In all cases, the results are averaged over 30 independent repetitions of the game. The endgame and the average-game results relate to the same games. The endgame results present the average proportion of agents per portfolio of 30 independent repetitions in $t = 264$, while average-game results present the average proportion of agents per portfolio over all 264 time periods and over all 30 repetitions. As to the news, the more diversified a portfolio is, the more the news is likely to relate to it, but this is not the rule. Because most of the news was related to C, portfolios containing it were related to the most news. The market portfolio S31 is related to every news event.

Unsuspicious agents

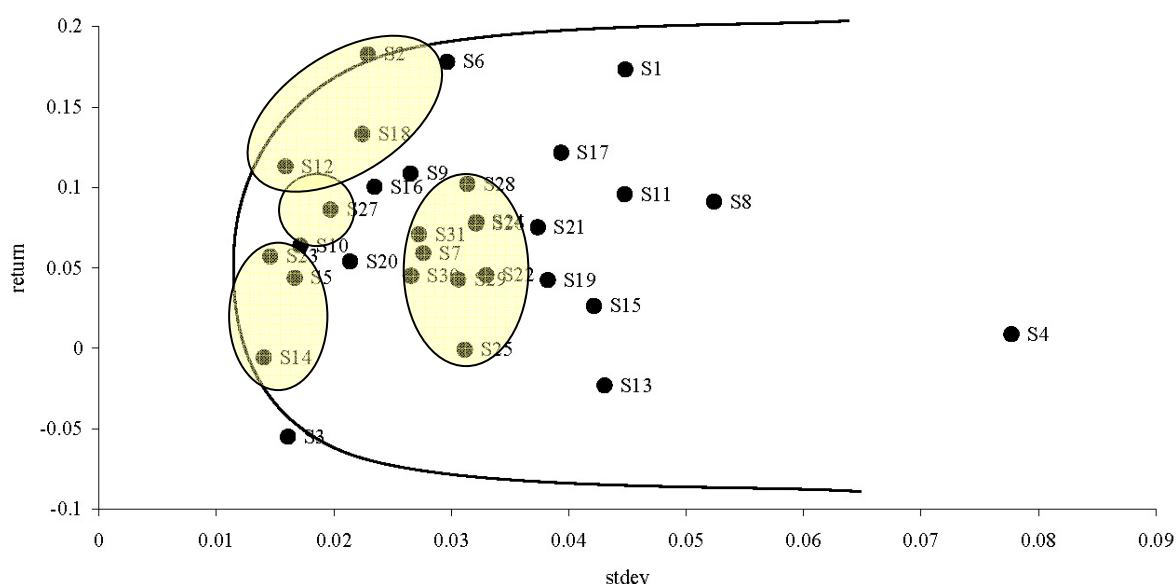
Table 8.2: Proportion of unsuspicious agents per portfolio in the average-game (AVG) and the endgame (END) settings

	AVG	END	S11	0.88	0.85	S22	2.67	1.62
S1	0.68	1.94	S12	7.63	10.43	S23	7.20	3.54
S2	3.71	8.04	S13	0.85	0.12	S24	5.51	6.62
S3	0.69	0.12	S14	3.97	0.51	S25	4.98	1.53
S4	0.84	0.27	S15	2.68	1.33	S26	2.94	3.22
S5	11.86	3.77	S16	0.94	1.12	S27	3.23	4.53
S6	2.33	6.55	S17	1.66	3.63	S28	3.06	6.98
S7	0.73	0.85	S18	2.93	7.65	S29	5.15	3.66
S8	0.80	1.11	S19	1.05	0.65	S30	8.73	5.01
S9	1.52	3.56	S20	2.07	1.23	S31	5.09	5.40
S10	1.90	0.75	S21	1.76	3.44			

As Table 8.2 reports, the winning average-game portfolios of unsuspecting agents were S5 (11.86%), S30 (8.73%), S12 (7.63%), and S23 (7.20%), while the winning endgame portfolios were S12 (10.43%), S2 (8.04%), S18 (7.65%), S28 (6.98%), S24 (6.62%), and S6 (6.55%).

The weighted beta of 0.822 in the average-game setting and 0.874 in the endgame setting indicate that the unsuspecting agents prefer low-risk portfolios. This low-risk preference is reflected by the five most-desired portfolios with the weighted beta of 0.597, accounting for 40.9% of all agents in the average-game setting.²⁸ This group of the most-desired portfolios includes some of the lowest beta portfolios: S5 (0.314), S12 (0.433), S23 (0.426). On the other hand, the ten least-desired portfolios account for 8.98% of all agents. This is much more than in the “no-news” framework of Chapter 6. Again, the least-desired portfolios are high-risk portfolios with a weighted beta of 1.246 in the average-game setting. Figure 8.1a displays portfolios as to their risk (X-axis) and return (Y-axis). I grouped the most-desired portfolios into colored ellipses.

Figure 8.1a: Clusters of unsuspecting agents in the average-game setting

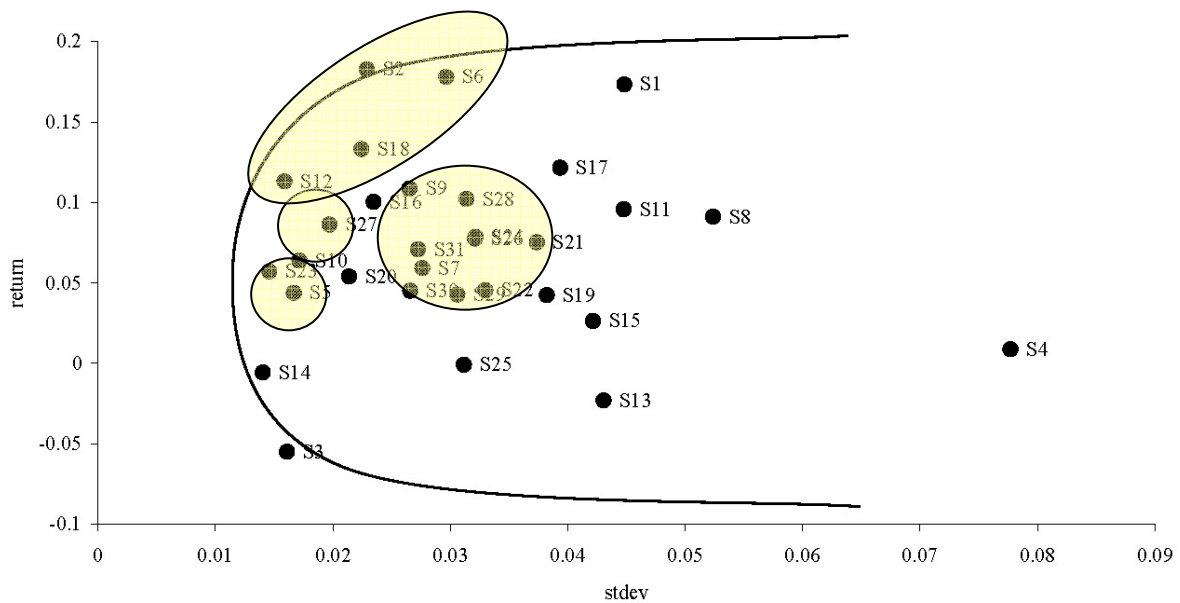


As displayed in the figure, two groups of portfolios seem to be the winners in the average-game setting. As in Chapter 6, the first group consists of portfolios S2, S18, S12, S27, S23, S5 and S14, which are portfolios from the efficient frontier or from its closest neighborhood. The second group is represented by highly diversified portfolios S31, S30, S29, S25, S24 and S26. These portfolios exhibit moderate returns and risk levels and were among the least desired in the basic framework of Chapter 6.

As in the average-game setting, the endgame portfolios can also be grouped into two clusters (Figure 8.1b): portfolios from the efficient frontier and the group of highly diversified portfolios. Portfolios from the former are S12 (10.43%), S2 (8.04%), S18 (7.65%), S6 (6.55%), S5 (3.77%), and S23 (3.54%), while portfolios from the latter are S28 (6.98%), S31 (5.40%), S30 (5.01%), S27 (4.53%), S29 (3.66%), and S21 (3.44%). They are represented by colored ellipses in the figure.

²⁸ This is half the proportion of unsuspecting agent selections in the “no-news” setting, where 84.75% of all chose the first five portfolios.

Figure 8.1b: Clusters of unsuspicious agents in the endgame setting



The endgame portfolios of unsuspecting agents are slightly riskier than the average-game portfolios with the weighted beta of 0.874. This is also true for the five most-desired portfolios, whose weighted beta is 0.748, while the weighted beta of the ten least-desired portfolios reached “only” 1.139.

The final impression is that in the “news-setting” agents selected their portfolios much less synchronously than they did in the “no-news” setting of Chapter 6, as 6.35% of all agents ended the games with one of the ten least-desired portfolios on average, while 39.7% of agents ended the games with the one of the five most desired.

Suspicious agents

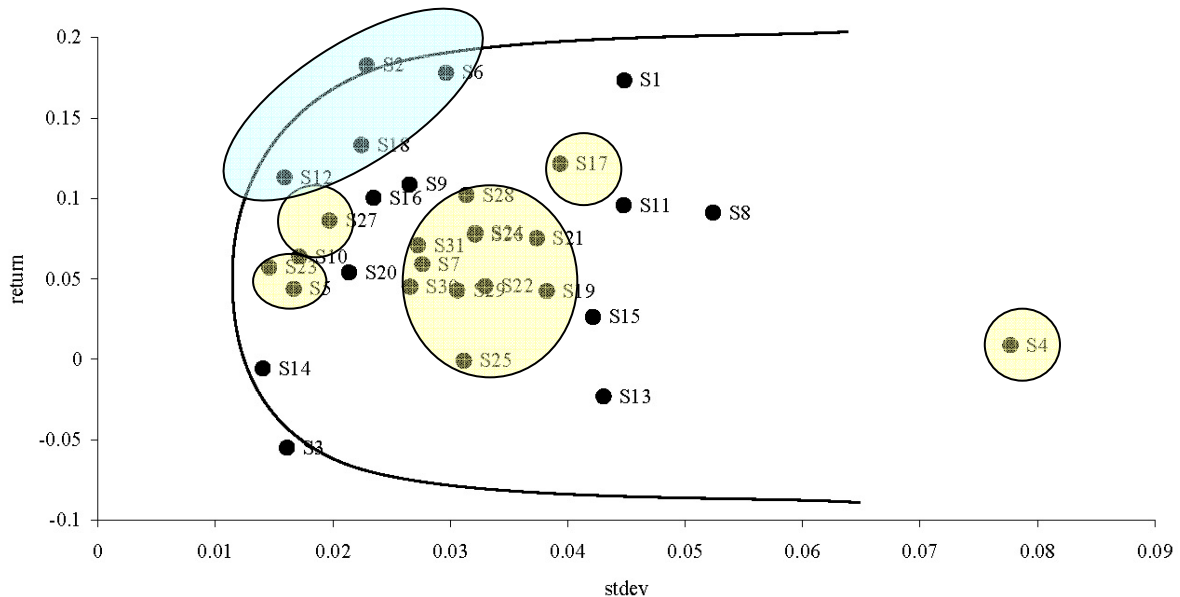
I now turn to suspicious agents. Note that the assumption of the model is that suspicious agents behave suspiciously only with regard to returns and not to news. Therefore, when news comes they always choose a portfolio that is subject to better news. In this respect, they behave as unsuspicious agents.

Table 8.3: Proportion of suspicious agents per portfolio in the average-game (AVG) and the endgame (END) settings

	AVG	END	S11	1.99	2.14	S22	4.61	1.69
S1	0.76	1.94	S12	2.47	3.18	S23	2.94	1.19
S2	1.91	3.87	S13	2.41	0.24	S24	5.52	7.61
S3	0.70	0.12	S14	1.38	0.27	S25	4.32	0.66
S4	4.03	1.14	S15	3.90	2.07	S26	4.21	3.28
S5	3.68	0.36	S16	1.55	2.16	S27	4.57	5.66
S6	1.53	4.24	S17	3.74	8.80	S28	3.56	7.43
S7	0.73	0.38	S18	1.51	4.08	S29	5.06	3.08
S8	2.41	4.87	S19	3.95	2.46	S30	8.71	4.19
S9	2.72	5.30	S20	2.10	1.59	S31	7.19	6.52
S10	1.06	0.49	S21	4.81	9.01			

Table 8.3 demonstrates that the winning average-game portfolios of suspicious agents were highly diversified portfolios S30 (8.71%), S31 (7.19%), S24 (5.52%), and S29 (5.06%), while the winning endgame portfolios were S21 (9.01%), S17 (8.80%), S24 (7.61%), S28 (7.43%), and S31 (6.52%). The weighted beta of the average-game setting is 1.070 and 1.080 in the endgame. This means that moderate-to-high risk portfolios were preferred to low-risk portfolios.

Figure 8.2a: Clusters of suspicious agents in the average-game setting



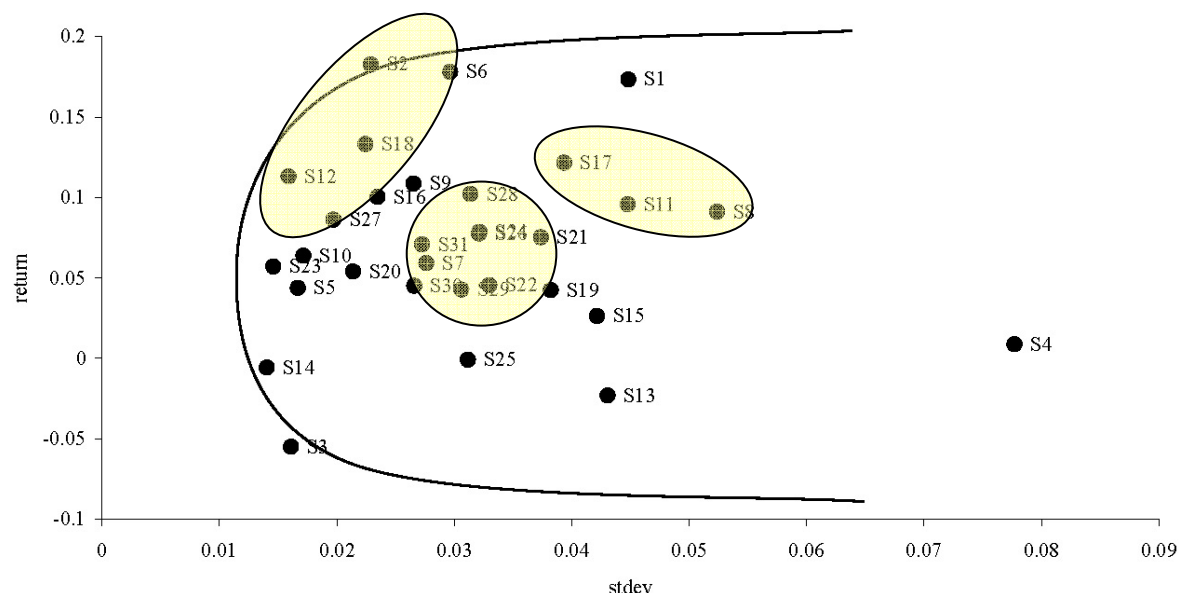
The five most-desired portfolios accounted for 31.3% of all suspicious agents in the average-game setting. Contrary to the unsuspicious agents, these are moderate-risk portfolios with the following reported betas: S30 (0.938), S31 (1), S24 (1.113), S29 (1.112), S21 (1.345); and the weighted beta of 1.074. On the other hand, the ten least-desired portfolios were low risk portfolios with a weighted beta of 0.800, accounting for 13.12% of all agents.

In the average-game setting, the selection of suspicious agents is highly dispersed. The blue ellipse contains four portfolios from the efficient frontier that were selected by a moderate proportion of agents: S2 (1.91%), S6 (1.53%), S12 (2.47%), and S18 (1.51%). The second group contains two portfolios from the efficient frontier, S5 (3.68%) and S23 (2.94%). The largest is the group of highly diversified portfolios that were also the most desirable: S31 (7.19%), S30 (8.71%), S29 (5.06%), S28 (3.56%), S24 (5.52%), S21 (4.81%), S22 (4.61%), S25 (4.32%); they are placed in the middle. The riskiest portfolio S4 was selected by 4.03% of suspicious agents in the average-game setting.

Figure 8.2b displays the endgame proportion of unsuspicious agents. I made three clusters from their average endgame selections. The first contains four portfolios from the efficient frontier, S2 (3.87%), S6 (4.24%), S12 (3.12%), and S18 (4.08%), along with S27 (5.66%), which is close to them. The second consists of portfolios S17 (8.80%), and S8 (4.87%), along with S11 (2.14%), which lies between them. The largest is the group of highly diversified portfolios S28 (7.43%), S31 (6.52%), S24 (7.61%), S30 (4.19%), S21 (9.01%), and S26 (3.28%). Yet, the riskiest portfolio S4 ended with just 1.14% of all suspicious agents, while S1 was selected by only 1.94% of them. After the final iteration, the five most-desired portfolios were chosen by

39.4% of suspicious agents on average, while the ten least-desired portfolios were chosen by 6.43% of them on average.

Figure 8.2b: Clusters of suspicious agents in the endgame setting



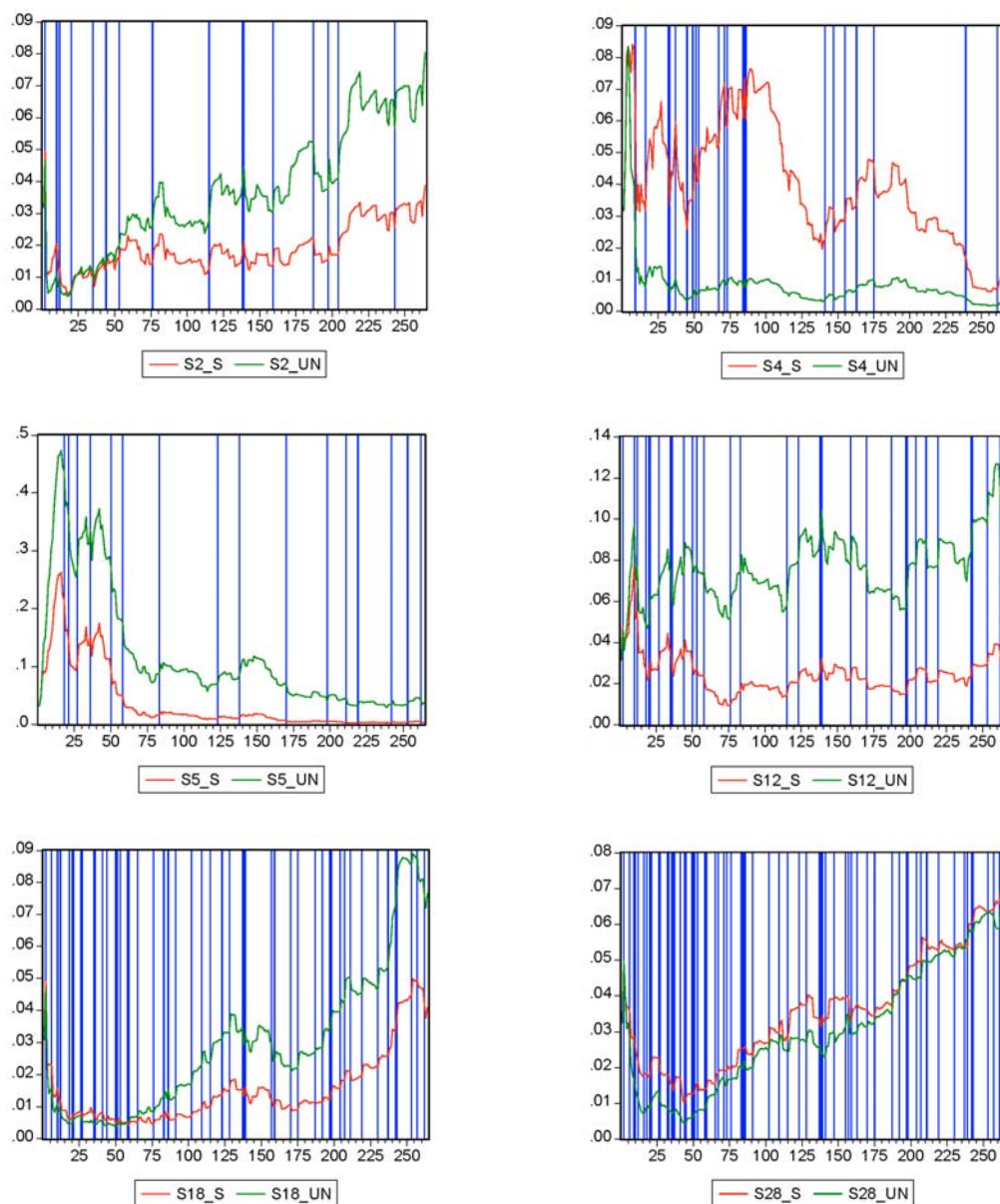
Discussion

Because news conveys information to agents, one would expect that an announcement's impact on the market's valuation of a firm's equity would depend on the magnitude of the unexpected component of the announcement (MacKinlay 1997). Because agents in the model always choose a portfolio that is the subject of better news, this might in turn lead to a higher desirability for portfolios that are subject to a higher number of positive news events. This is generally true but is not the rule, because while agents do withdraw from portfolios that exhibit poor returns over time, they also select them when expecting or hearing an announcement of positive news. To illustrate the argument: when agents expect a positive news announcement, such as an earnings report, they increase the demand for such stocks and portfolios and thus shift the price upward. This makes such stocks and portfolios more desirable to others and leads to an increase in the proportion of agents with such stocks and portfolios prior to the news announcement.

Until this point, the desirability of portfolios is spurred by returns in the expectation of positive news, while herding provokes overshooting. The report of positive news puts additional pressure on the price and extends overshooting due to herding. However, too high expectations turn the returns around, downplaying the effects of positive news and provoking herding in the opposite direction away from such portfolios, etc. The same intuition might be employed when portfolios are subject to negative news and positive post-event returns. In this case, a downward overshooting in the selection prior to the negative news leads to an increased desirability after positive returns follow, etc. Both phenomena are demonstrated in Figure 8.3, which displays the proportion of unsuspicious (UN, green line) and suspicious (S, red line) agents with selected portfolios over time. The blue vertical lines display the occurrence of news. A significant point here is that the effects of news are not

only direct but also indirect through the formation of expectations, which is reflected in the level of returns in the days, hours, and minutes prior to the news announcement as well as afterwards.

Figure 8.3: Proportion of unsuspecting (UN) and suspicious (S) agents with selected portfolio over time



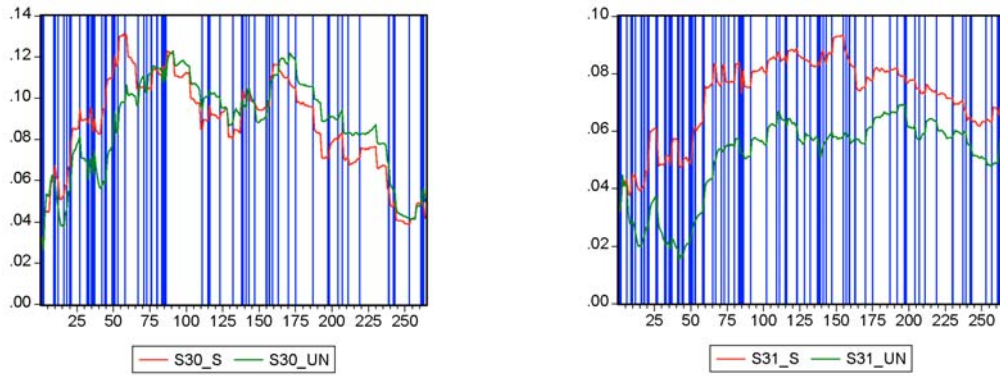


Table 8.4 brings an overview of the results. With a weighted beta of 1.080, the endgame portfolios of suspicious agents are slightly riskier than the average-game portfolios (1.070). However, they both are well above the weighted betas of unsuspecting agents (0.882/0.874). In the endgame setting, the five most-preferred portfolios: S21, S17, S24, S28 and S31, reach a weighted beta of 1.223, which is much higher than the corresponding beta of the average-game setting. Yet, the ten least-preferred portfolios of suspicious agents ended on a weighted beta of 0.969, which is below the endgame beta of the ten least-preferred portfolios of unsuspecting agents (1.139). According to the lambda values, both endgame selections barely meet the “rich get richer” pattern of $\lambda > 1$, while the average-game selections do not. There is no substantial densification in the upper or the lower decile of the selections, because portfolios are, to a certain extent, evenly distributed.

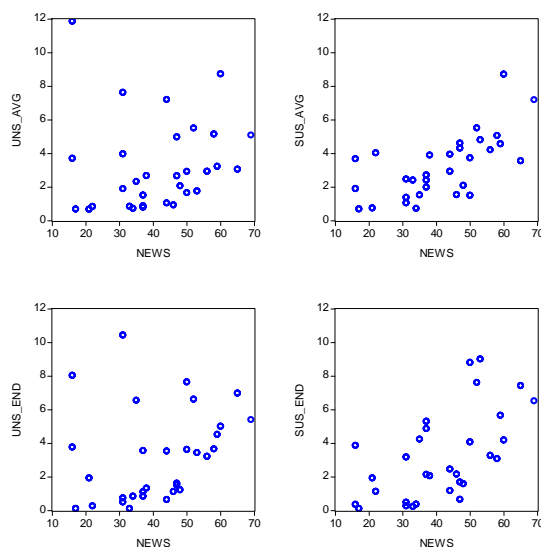
Table 8.4: Overview of results

	Unsuspicious agents		Suspicious agents	
	AVG	END	AVG	END
Proportion of agents				
Top 5 (%)	40.90	39.70	31.30	39.40
Least 10% (No./31)	11/31	13/31	9/31	12/31
Weighted beta				
Top 5	0.597	0.784	1.074	1.223
Least 10	1.246	1.139	0.800	0.969
Lambda				
	0.910	1.150	0.670	1.110

In addition, Figure 8.4 plots the unsuspecting and suspicious agents’ average-game and endgame selection (Y-axes) against the number of non-zero news that were reported per individual portfolio (X-axes). Figures on the left (right) relate to the unsuspecting (suspicious) agents and the upper (bottom) figures to the average-game (endgame) decisions. After some “outliers” are excluded, the figure shows positive correlation patterns between the number of news events and the selection of portfolios in all four cases; the proportion of agents with a given portfolio generally increases with the number of news events per portfolio. This conclusion is in the spirit of Barber and Odean (2008); that being in the news is a good thing, and that preferences determine choices after attention has determined the choice set. Recall that agents prefer high-yield portfolios. While the relationship is pretty straight in the setting of suspicious agents, there are some highly desired portfolios in the settings of unsuspecting agents that were subject to a small number of reported news. As regards the setting of unsuspecting agents, the introduction of news brings a restructuring of

the winning portfolios into two groups: portfolios of the “outliers” from the efficient frontier, and highly diversified portfolios.

Figure 8.4: Scatter graphs of unsuspecting and suspicious agents' average-game and endgame selections against the number of news-events



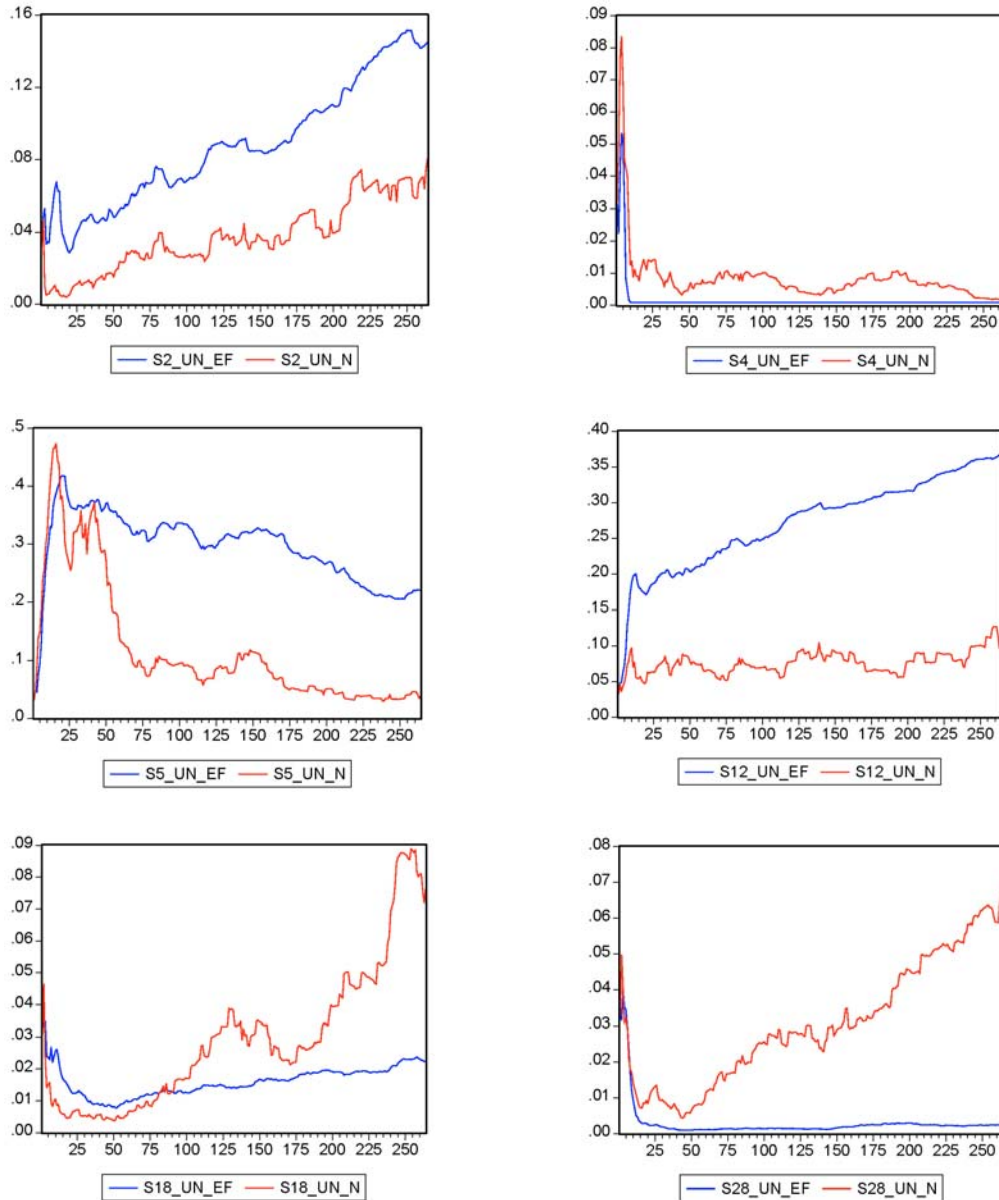
As in Chapter 6, the choice for the efficient frontier portfolios was stimulated primarily by the returns of portfolios, while that for the group of diversified portfolios was due mostly to the number of reported news events. I should acknowledge that the selection process is made up of two components: one due to news, and the other due to a change in returns. However, when both news and returns are given, agents first consider news and only then returns. In addition, much more of the news is related to highly diversified portfolios. Hence, this is not to say that the efficient frontier portfolios are not as highly desired as they were in the Chapter 6, but rather that their lower proportion is due to the increased desirability of the news-related highly diversified portfolios. However, the amount of news does not guarantee a portfolio of being selected. One such is S4 (Citigroup) to which much of news was related, but was selected by only 0.84% of unsuspecting agents in the average-game setting and only 0.27% in the endgame setting. Unsuspecting agents were very eager to avoid portfolios that were subject to negative news or portfolios that were subject to positive news regarding which high pre-news expectations produced an after-news bearish correction.

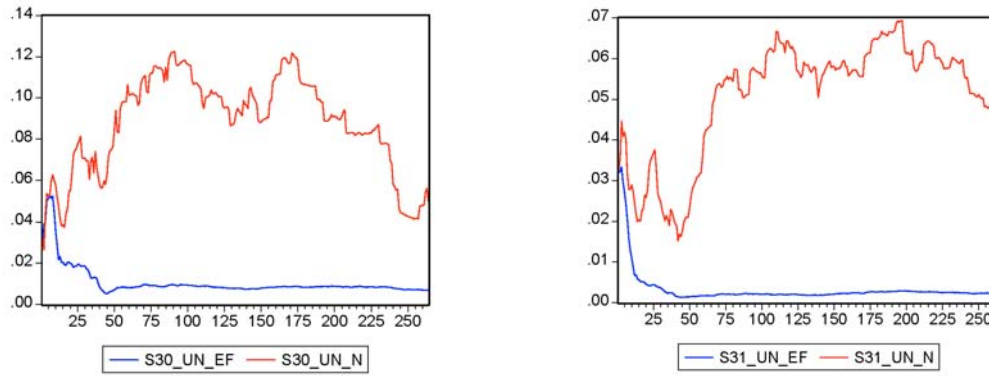
In the “no-news” settings of Chapter 6, unsuspecting and suspicious agents selected their portfolios very similarly because they were capable of distinguishing winners from losers. Here, the selections of both cohorts are similar due to the amount of news. Namely, all agents in the model considered news unsuspectingly. This is especially true for highly diversified portfolios, to which much of the news related. Thence, a great similarity is found between unsuspecting and suspicious agents in the selection of highly diversified portfolios, which is most specifically obvious in the last three plots of Figure 8.3.

Figure 8.5 displays the plots of the game developments of unsuspecting agents in the efficient frontier setting (blue line) versus that in the news-game setting (red line) for selected portfolios. Two features can be perceived from the figures. One relates to the efficient frontier portfolios that were highly desired in the no-news setting. These portfolios remain desired in the games with news. The second relates to highly diversified portfolios, which

were mostly avoided in the no-news setting but were desired in the news setting. News-related agents are much more inclined towards changing their portfolios. In particular, positive (negative) news events attract agents' attention and promote word-of-mouth enthusiasm, expectations about the prices, and higher (lower) demands for stocks, all of which leads to the rise (fall) in the prices. S4 was not a desired portfolio in any of the cases of unsuspicious agents, despite it being subject to many positive and negative news announcements and extreme returns. It was highly avoided, indeed.

Figure 8.5: Proportion of unsuspicious agents (UN) with selected portfolio under the efficient frontier setting (EF) and the news setting (N) over time





Although it is obvious that stock prices respond to news events, it is difficult to identify significant news events and match particular events to particular changes in stock prices, especially in the light of the enormous number of different news events, whose effects are usually highly dispersed throughout the period prior and after the news announcements. Thus, it is not only a question how news-events affect to the value of a firm, but foremost how they affect to agents' perceptions, expectations and their responses. Historical perspective is full of evidence that news events were often followed by the "excess" reaction by the people, including professional brokers (Kindleberger and Aliber 2011). Additional issue in this respect might be that the daily interval may be too long, since many events can take place in a 24-hour period. Fair (2002) found that most large moves in high-frequency S&P500 returns were identified with U.S. macroeconomic news announcements.

In the games, I consider news events and stock returns as two separate variables, but I do make an implicit assumption that they are related. Implicitly, I also consider the over- and underreactions to news events, as well as the expectations building prior to news announcements. It is just that agents do not know the reasons for price shifts that occur prior and after an announcement. However, even if agents were capable of predicting the quality of information, every opportunity that offers just the slightest chance for speculation is used in that way, even by fully informed agents (Ben-Porath (1997) offers a survey on the backward induction game with speculation). Such opportunities arise when one just thinks that others do not possess all the relevant information, or when one just thinks that others think that other thinks (and so on) that one does not possess all the relevant information or builds different expectations. Therefore, agents are either convinced that they will be able to find someone who will buy shares at a higher price in the future (Scheinkman and Xiong 2003), or they are incapable of temporarily coordinating their selling strategies (Abreu and Brunnermeier 2003). In real markets, news flows are stochastic in both quantity and quality, yet unpredictability is also the response of market participants.

Chapter IX

Concluding comments

9.1 Conclusion

The dissertation examines portfolio selection and relates it to the games on networks. The main interest of the research has been to understand portfolio choices of interacting agents under a variety of circumstances when prices are uncertain. A fundamental methodological premise of the dissertation is that information-sharing is essential in agents' decision-making, while interaction of bounded rational agents leads to complex collective behavior.

Methodology

Network-based approach, which is applied in the dissertation, represents a new approach for modeling economic phenomena. It provides a useful multidisciplinary tool for exploring models that are mathematically intractable. Examples of such issues are path dependency, the effects of adaptive versus rational behavior, the consequences of heterogeneity among agents, etc. It is built on three critical pieces: agents, rules and securities. The network of agents represents an infrastructure which agents use to interact locally with each other, transmit information and make decisions. I use an undirected network, in which a mutual consent is needed to form and maintain the link between the two agents.

Dissertation is rooted in a methodological individualism. In the model, agents regularly make decisions upon a four-stage process that starts with the observation of past returns of one's portfolio, continues through an agent selection and a comparison of the two portfolios, and ends in a decision. Once agents make their decisions, new returns are reported and the process repeats.

In the dissertation agents are not omniscient individuals. Agents have incomplete knowledge on asset prices, they have friends with whom they, more or less regularly, share their knowledge, they also communicate with people they meet occasionally, read newspapers and books, gather information, and also have some luck when making decisions. In addition, agents are able to use their reason, to learn, build expectations and adjust their behavior to market moves. Agents are price-taking individuals who make decisions autonomously.

All these features represent a behavioral aspect which, implicitly or explicitly, is included in the model. The notion of behavioral finance is on the psychology of agents' decision-making. Research in cognitive science has provided many arguments to disbelieve in agents' capabilities to making even good, let alone optimal decisions. Behavioral studies suggest that agents deviate from the standard model in three respects: nonstandard preferences, nonstandard beliefs, and nonstandard decision making. In addition, economic agents collaborate with one another, while their decisions are influenced by the behavior of others. Given the subjective nature of information and the agents' cognitive imperfections, selection is the outcome of agents' preferences within constraints, such as the circumstances, limited and asymmetric knowledge, expectations, dynamics on the capital markets and luck; a synthesis between human cognition and social networks.

In the model, agents incorporate a naïve form of reinforcement learning, which has been extensively used in the “cheap-talk” or “asking around” communication games of social learning. An agent who applies reinforcement learning asks another agent what strategy he used and how well it did, and then simply restructures his own portfolio into the one of another agent if such portfolio seems better. Face-to-face conversation is important for sharing such sensitive information as it is one’s portfolio, when knowing that group conversation pools information very poorly and that individuals do not reveal their private information to unknown individuals (Stasser et al. 1989). Following this strategy, agents tend to possess portfolios that have performed well in the past. Unavoidable consequence of imitation is herding, which is one the most generally recognized phenomena in financial markets and has been highlighted by many. In the dissertation, herding is very strong when agents perfectly rebalance their portfolios, always choosing the alternative that performed best in the past. Such is the case with unsuspicious agents, contrary to the sluggishness of suspicious agents. The introduction of liquidity agents, i.e. highly conservative or loyal agents who never change their initial portfolios, not even in the face of new evidence, into the model serves as a cushion to prevent perfect herding that would end in a synchronized solution. The games have demonstrated that imitation leads to a power law distribution. Namely, copying process reflects the behavior of preferential linking models with agents giving preference to profitable alternatives.

Additional aspect of agents’ behaviorism is modeled through the level of agent’s suspiciousness. Specifically, agents’ selections are obstructed by the level of their suspiciousness. Suspicious agents are prone to making poor decisions, be they intentional or accidental. Agents can make errors in their selection or get confused or simply do not trust their friends or even make intentional mistakes. Technically, the concept of suspiciousness is solved by the random number generator. Whatever its reasons, suspiciousness becomes highly significant and also relevant when the difference in the values of two portfolios is very small, while its stochastic nature makes the course of the selection process over time even more unpredictable.

In the dissertation, complexity of the portfolio selection over time is not induced by a complex model, but by interaction of bounded rational agents who regularly make decisions upon very simple behavioral rules. Starting from an initially specified system state and the rules of conduct, the large number of bounded rational agents is constantly engaged in local interactions, thus producing a behavior of the entire group that goes far beyond equilibrium closed-form solutions of non-interacting or representative agents. As argued by Tesfatsion (2006), the only way to analyze a complex system is to run it and let it evolve over time.

By using very simple behavioral rules and local interaction, the dissertation applies a positive decision analysis, addressing the question of which portfolios are selected and not which portfolios should be selected. Tversky and Kahneman (1986) argue that normative approaches are doomed to failure, because people routinely make choices that are impossible to justify on normative grounds, in that they violate dominance or invariance. In the dissertation, agents’ decisions are not considered as right or wrong, but as decisions that bring them lower or higher payoffs. This represents a methodological novelty that this dissertation adds into the portfolio selection literature, which has mostly been normative or related to asset pricing. By applying an interaction-based approach, I am not stuck in equilibrium, but do not exclude it in the long run, either.

Simulations

I conduct two sorts of simulation games: two-asset games and multiple-asset games.

Two-asset games are good to start with, but they represent a huge simplification of the entire complexity which agents face in reality. Agent-based models of financial markets have often been criticized for having only two assets, a risky and a riskless asset. The number of alternatives significantly increases the extent of an agent's problem. In all settings, games are run for several times and average results are reported. Due to the stochastic nature of agents' decision-making, repetitions of the games do not necessarily duplicate their history, despite an unchanged learning algorithm and unchanged circumstances. Despite the synchronization tendencies, conditions in the markets change faster than information propagates around the network. In addition, there is a very small probability that all the events needed to get to identical developments will replicate as the games are repeated; with an increased number of alternatives this small probability approaches zero.

a) Two-asset games

The questions within the setting of the two-asset games (Chapter 5) were the following: how do agents select between risky and riskless portfolios; how do agents select between two risky alternatives; and what is the effect of a one-time shock on portfolio selection.

The games have shown that when agents, be they unsuspicious or suspicious, choose between risky and riskless assets and a combination of the two, risk is highly pronounced. Agents choose mixed portfolios when both returns and risk are high, or when the returns of risky securities lie in the neighborhood of riskless returns. As returns fall below the lower bound of this neighborhood, agents take riskless alternatives for any levels of risk. In mixed portfolios riskless securities serve as a security cushion for high risk, while risky securities make the zero-return riskless portfolios more profitable. On the other hand, positive returns as such do not imply the selection of risky alternatives. As the risk increases, agents start to retract from risky portfolios, although a mathematical solution would make risky portfolios a better alternative. Obviously, risk is considered a negative factor. An initial proportion of agents with different types of portfolios affects the agents' final decisions in the extreme cases. I use heat-map visualizations to present phase-transitions between selections of different alternatives.

In the games of two risky stocks, unsuspicious agents were able to choose a winning alternative unanimously, while suspicious agents were not. These games were simulated on real data of stock returns of two financial corporations. The solution of unsuspicious agents appeared to reflect the effect of what might be called unfavorable comparable initial conditions. As the initial proportion of agents with the favorable alternative was decreasing, unsuspicious agents were unable to select a winning alternative unanimously. In addition, selections of unsuspicious agents were highly consistent, while the selections of suspicious agents were not. I use a simple consistency test; I plot single game developments to the game development averaged over all 20 repetitions.

The games with a one-time shock have demonstrated that shocks affect the agents' selections in the short run but not over the long run unless the magnitude is very large. The effects of a shock on the ultra-long run depend on the extent to which a shock changes agents' behavior, the post-shock activities, and the extent of herding. As expected, a shock resulted in the

move from portfolios that were hit by a negative shock into other portfolios, while these moves were positively correlated with the magnitude of the shock. Subsequent favorable returns of a portfolio that was hit by a shock can alleviate the negative consequences of the shock, although the recovery was slow. In connection with the unfavorable initial proportion of agents with the alternatives that were hit by a shock, the shock can also have long run consequences. Especially unsuspicious agents are very sensitive to the shock, while highly suspicious agents do not even perceive it.

b) Multiple-asset games

In the multiple-asset games of Chapters 6-8, I extend the level of a problem and bring it closer to reality. Multiple-asset games are run under three different features: the arbitrarily chosen time span (Chapter 6); the bull and the bear trends (Chapter 7); and in the same arbitrarily chosen time span as before but with the presence of news events (Chapter 8).

These games are repeated 30 times, while the average-game selections and the endgame selections of the same game realizations are examined. Endgame results present the average proportion of agents per portfolio of 30 independent repetitions in the last time period, while average-game results present the average proportion of agents per portfolio over all time periods and over all 30 repetitions. The two separate analyses are required because of the time-dependent nature of the portfolio selection process, for which the endgame decisions might not adequately reflect game developments.

In the games of Chapter 6, I examine the efficient frontier hypothesis of Harry Markowitz (1952a) in an interaction-based environment where portfolio selection is a perpetual activity. The hypothesis says that agents choose portfolios that maximize their return given the risk, or minimize the risk for the given return. The principal question here was not whether agents prefer such portfolios but whether they are capable to reach them in an uncertain future. In addition, two different measures were used to test the consistency in selection: the coefficient of variation and Monte Carlo. A consistently chosen portfolio should exhibit a small variability in its holdings in each time period over independent repetitions of the games. The additional question of Chapter 7 was whether agents invest differently in good times of a bull trend than in bad times, represented by a bear trend.

The games have demonstrated that agents are capable of investing according to the efficient frontier hypothesis and that they behave in a risk-averse manner. Again, agents consider risk as a negative factor, which they try to avoid. The average-game and the endgame selections of unsuspicious agents were highly synchronized with the five most desired portfolios being selected by 84.75 percent of agents in an average-game setting and 86.40 percent of them in an endgame setting. A slightly more dispersed selection of suspicious agents is a consequence of their slight failure to perform a "winner takes all" behavior, even though they also identify the same "winners" as unsuspicious agents do. This conclusion was supported in both bull and bear markets, with the exception that agents take on more risk in the bull market. The last conclusion is not surprising. Behavioral studies find that agents are less willing to take risk in a domain of losses that is characterized by a bear market. Highly preferred portfolios are two-asset portfolios with an additional stock added to the most desired one. Additional stocks either sufficiently reduce the risk of a dominant single asset or improve its profitability or both, thereby making it more desirable. In a bear market, synchronization was huge, as the five (two) most desired portfolios were chosen by

95.67 (80.09%) percent of all unsuspecting agents and 83.35 (53.48%) percent of all suspicious agents in the endgame setting.

Although the behavior of agents is more risk averse in a bear market, the selection of portfolios S13 and S22 could signify the presence of a reflection effect, i.e. risk seeking in the domain of losses, the phenomena that is then followed by loss recognition which leads agents to retract from such alternatives. When looking at the figures (Table 7.3a and 7.3b), the two portfolios were relatively largely possessed in an average-game setting, but ended on liquidity agents in the endgame. Both effects were present only with the unsuspecting agents. A reflection effect is a highly important outcome of these simulation games, because it presents the pattern that there is a small proportion of agents within the group, who try to ride on the risk or are trapped inside the risk until the risk transforms into a loss which agents recognize and respond appropriately. The model is thus able to single out this phenomenon as an anomaly, which has been documented as such (see Hirshleifer (2001) for a discussion).

Consistency tests have demonstrated that unsuspecting agents were much more consistent in their selections than suspicious agents. In addition, the most consistently chosen portfolios were the most desired and the least desired portfolios. We could say that the latter were consistently avoided. Again, this conclusion was supported also in bull and bear markets.

In the last part of the dissertation I extend the baseline model of Chapter 6 by introducing news events directly into the agents' decision making functions. Agents thus decided according to returns and news. Therefore, all the differences in the conclusions as to the baseline scenario go to the news part. I use real data on both returns and news. I used a rule of thumb to extract the news and assumed that significant events should induce price and volume shifts. This same rule was also used by Barber and Odean (2008). Following the results, the news events have contributed to the portfolio desirability. News events provoke a shift into portfolios that are subject to positive news and away from those that are subject to negative news. Because agents react not only to news but also to the returns that follow the news, negative returns that follow positive news may turn agents away from such portfolios, while positive returns that follow negative news may make such portfolios more desirable. This means that price reactions to news events are crucial for the behavior of market participants with over- and underreaction spurring movements in the opposite direction. In the presence of news and returns, two groups of portfolios seemed to be the winners. As before, the first group consisted of the efficient frontier portfolios or portfolios from its closest neighborhood. The second group was stimulated by the number of non-negative news and was comprised of highly diversified portfolios.

9.2 Future work

The model I use is simple, intuitive and plausible enough – some might even call it kinky-dinky – but it is by no means exhaustive and can be extended in many directions.

Despite the apparent simplicity of the problem which financial agents face, some open questions of how to approach to portfolio selection in an interaction-based setting still remain. For instance, how to model asset returns, how to return predictability and expectations building, how to best present agent's problem, how to model agents' reasoning and learning procedures, how to model agents' reputation in opinion sharing, how to assess and evaluate the news, how to consider a delay between the opportunity being noticed and

trades being executed, how to select the appropriate network, etc. A more sophisticated model would also consider derivatives, such as options, futures, swaps and others sophisticated instruments, which are used for managing credit and financial risks. Then, it would also consider timing (synchronous versus asynchronous trading), duration, bid-ask spreads, trading volumes, short selling, hedging strategies, opinion mining, and taxes in relation to different types of securities being subject to different tax rates, etc.

The future of finance theory will to a great extent depend on how successful researchers will be in grounding it on a psychological evidence about how people consider uncertainty and how they behave under different circumstances when they are faced with uncertainty. A specification of how agents form expectations is a crucial component of any model of financial markets. Simon (1997) has argued that the future challenge for economists relates to the question of how to “receive new kinds of research training, much of it borrowed from cognitive psychology and organization theory,” and that they “must learn how to obtain data about beliefs, attitudes, and expectations.” In such games, learning is important as it determines the ways in which agents acquire information, process data and make decisions. As argued by Roth and Erev (1995), this is not just about the learning about the structure of the game, but also about the behavior of other agents. In addition, a theory should be parsimonious, should explain a range of anomalous patterns in different contexts and generate new empirical implications (Daniel et al. 1998).

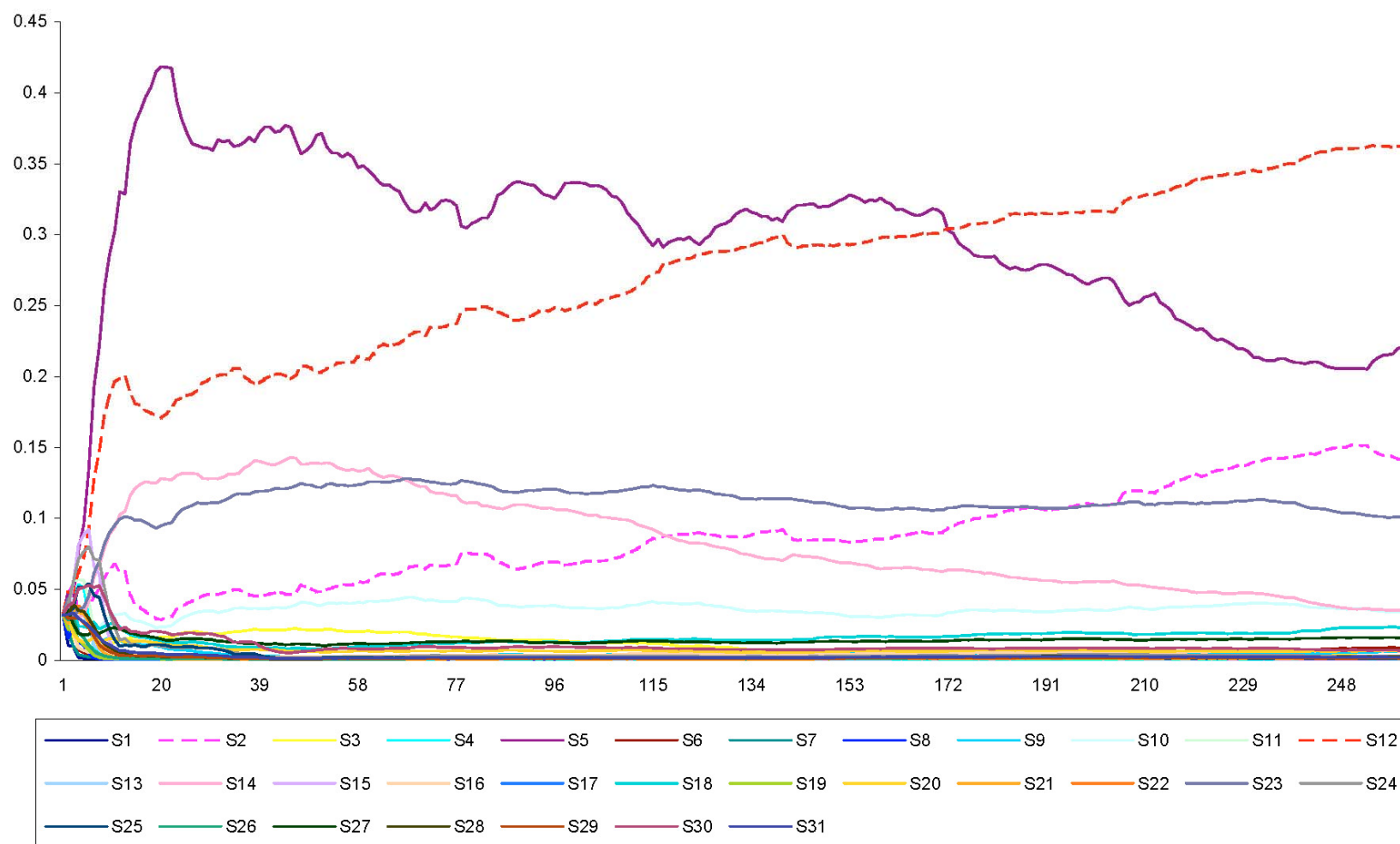
A survey of Pang and Lee (2008) covers some techniques and approaches in a new research field of opinion mining and sentiment analysis. This could bring some new insights on how to give information an economic value and benefit from it.

There is no doubt that the games on social networks will be an important part of future research in finance as they represent an appropriate instrument for conducting different kinds of agent-based experiments that are based on interaction. As argued by Dorogovtsev and Mendes (2003), “the world of networks is our inevitable future.” In addition, social networks are very robust and applicable to include ideas from behavioral science.

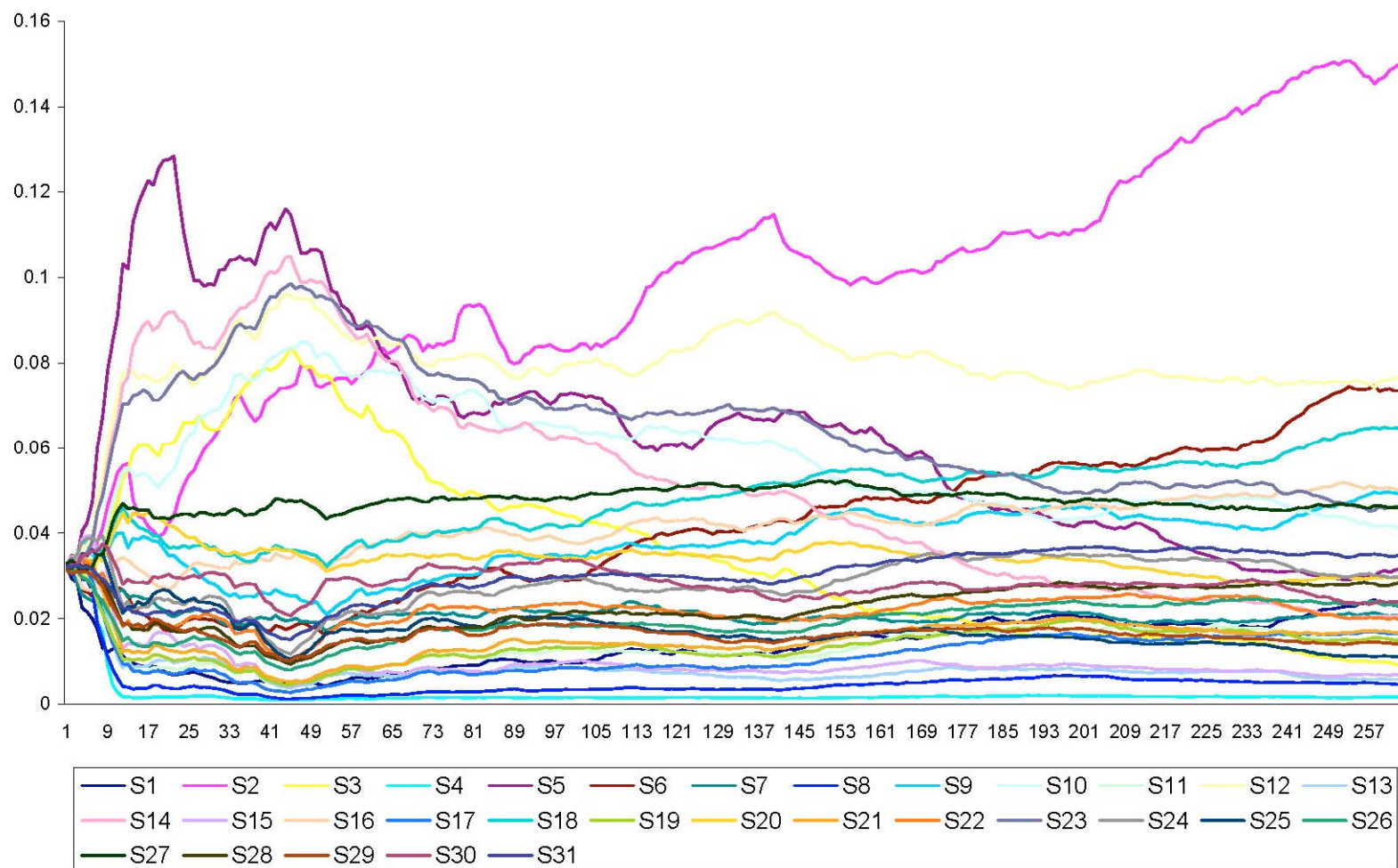
On this trail for better models, the good news is that hardware and software solutions develop very fast, and that newly developed simulation techniques could allow for this data translation. However, we should not be overly optimistic. The bad news is that no matter how good all these improvements are and will be in the future, given the capacity of people to communicate, think and adapt, human action will always be a couple steps ahead of the conceivable capabilities of researchers and financial economists to model and understand it. However, a good researcher will try to do his best.

Appendices

Appendix 1: Simulation time-path, efficient frontier setting, $\kappa = 0.01$



Appendix 2: Simulation time-path, efficient frontier setting, $\kappa = 0.1$



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UNIVERZA V LJUBLJANI
EKONOMSKA FAKULTETA

Doktorska disertacija

SIMULIRANJE PORTFELJEV Z UPORABO
OMREŽNIH MODELOV
– razširjeni povzetek –

Matjaž Steinbacher

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KAZALO

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1 UVOD

Disertacija je v prihodnost usmerjena in na simulacijah temelječa raziskava, ki proučuje izbor portfeljev v negotovem svetu trgov kapitala. Osrednji motiv raziskave je skušati razumeti, katere portfelje v razmerah negotovosti in pod različnimi okoliščinami izbirajo agenti, ki se nahajajo v medsebojni interakciji. Da bi dobil odgovore na zastavljena vprašanja, sem izvedel vrsto simulacij, ki temeljijo na preprostih vedenjskih pravilih in interakciji med agenti.

Finančni trgi so inherentno povezani z vprašanji, ki vključujejo čas in negotovost. Z vrednostnimi papirji se trguje v času nič, ki je gotovo, medtem ko so donosi realizirani v času 1, ki je negotovo (Arrow 1963, Milgrom in Stokey 1982, Mandelbrot 1963, Campbell, Lo in MacKinlay 1998). Velik del te negotovosti je povezan z informacijsko neučinkovitostjo, ki je prisotna tudi v dobro delujočem okolju kapitalskih trgov. Kot poudarita Grossman in Stiglitz (1980), pa je tudi okolje, ki je informacijsko popolnoma učinkovito, še vedno lahko neučinkovito z vidika pričakovanj; ljudje si na podlagi istih informacij namreč utegnejo ustvariti različna pričakovanja (glej tudi Ben-Porath 1997). Neučinkovitost z vidika pričakovanj gradi na izhodišču, da so posameznikove umske sposobnosti redka dobrina. Torej, četudi bi trije investitorji opazovali iste napovedi, bi še vedno obstajala verjetnost, da bodo med seboj trgovali.

Negotovost na trgih je eden osrednjih razlogov za to, da si agenti oblikujejo portfelj, ki je sestavljen iz različnih, po možnosti nekoreliranih, enot premoženja, četudi niti popolna diverzifikacija ne more povsem odpraviti tveganja. Približno v četrtem stoletju je rabin Issac bar Aha predlagal sledeče investicijsko pravilo: "Ljudje bi svoje premoženje morali razdeliti na tri dele: tretjino v zemljo, tretjino v trgovino in tretjino na dosegu roke." Leta 1952 je Harry Markowitz (1952a, 1959) objavil prispevek na temo izbora portfeljev, v katerem je vprašanje izbora portfelja proučeval glede na odnos med donosom in tveganjem ter podal optimalno pravilo, skladno s katerim bi naj agenti oblikovali svoje portfelje glede na raven tveganja. Prvi nadgradnji Markowitzeve teorije učinkovite meje sta bili CAPM (Sharpe 1964, Lintner 1965a, b) in APT (Ross 1976).

Merton (1969, 1971), Brennan, Schwartz in Lagnado (1997), Barberis (2000) in Liu (2007) proučujejo vprašanje izbora portfeljev kot multiperiodni odločitveni problem v negotovem svetu. Barberis je pokazal, da agenti večji del svojega premoženja namenjajo v delnice, v kolikor so cene delnic predvidljive. Wachter (2003) je pokazala, da v kolikor se pripravljenost agentov, da ne sprejemajo tveganjih izbir, približuje neskončno, potem je optimalni portfelj sestavljen zgolj iz dolgoročnih obveznic. Constantinides (1986) in Lo et al. (2004) proučujeta izbor portfelja v odnosu do transakcijskih stroškov in pokažeta, da se agenti na visoke transakcijske stroške odzovejo z zmanjšanjem pogostosti in obsega trgovanja. Xia (2001) je pokazala, da lahko agenti, ki zanemarjajo priložnosti, ki jim jih ponuja časovna komponenta, utrpijo velike oportunitetne stroške, kar daje predvidljivosti donosov, četudi gre za tvegano početje, ekonomsko vrednost. Cocco (2005) proučuje učinke nakupa stanovanj na portfeljske odločitve posameznikov in ugotavlja, da so ti občutni, saj nakup stanovanj občutno zniža finančne zmožnosti ljudi.

Skupaj z obsežnostjo ravnovesnih modelov izbora portfeljev so se pojavljale različne tehnike za razreševanje teh optimizacijskih problemov. Nekatero novejšo tehniko vsebujejo metodo nevronske mreže (Fernandez in Gomez 2007), metodo simuliranega ohlajanja (Crama in Schyns 2003). Chang et al. (2000) primerjajo rezultate več različnih metod: tabu search, genetični algoritem in simulirano ohlajanje. Cura (2009) uporabi metodo swarm, Doerner et al. (2004) uporabijo metodo kolonije mravel (t. i. ant colony optimization). Četudi so ti

ravnovesni modeli dokaj intuitivni in so podali tudi nekatere odgovore glede izbora portfeljev v posameznih okoliščinah, pa imajo bore malo skupnega s turbulentnim okoljem, o katerem vsakodnevno beremo v časopisu, kot sta se izrazila LeRoy in Werner (2001). Glavna kritika zoper te modele se nanaša na to, da ti ne upoštevajo finančnega okolja kot kompleksen in prilagodljiv sistem, ki je sestavljen iz množice majhnih agentov, za katere je značilno nestandardno vedenje in ki so neprenehoma vpleteni v medsebojno interakcijo, iz česar nastajajo globalne posledice (Sornette 2004). V bistvu je edini način, kako modelirati takšne sisteme ta, da jih spustimo, da se v času odvijajo sami (Tesfatsion 2006). Končno, ravnovesni modeli praviloma sistematično izključujejo ekstremne vrednosti, navkljub vsem učinkom, ki jih takšne vrednosti lahko imajo. Dejansko pa se finančni trgi vseskozi prehajajo med obdobjem relativnega miru in obdobjem relativnih pretresov.

Vedenjski pristop k financam, oziroma ACE (*Agent-Based Computational Economics*) finance, vsebuje velik del te mikrostrukture, ki v ravnovesnih modelih ni prisotna (Rabin 1998, Hirshleifer 2001, Barberis in Thaler 2003 in DellaVigna 2009). Kot pravi DellaVigna, posamezniki odstopajo od standardnega modela v treh vidikih: preferenc, prepričanj in sprejemanja odločitev. Razvoj ACE je potekal v dveh smereh, ki sta med seboj povezani: vedenjski in interakciji. Kot poudarita Simon (1955), Kahneman in Tversky (1979) in literatura s področja psihologije, lahko že majhne spremembe pri dojetanju problema pri posameznikih drastično vplivajo na njihove odločitve. Drugi vidik se nanaša na interakcijo med posamezniki in zajema vprašanje sprejemanja informacij in njihove uporabe. Osnovna predpostavka teh modelov je, da imajo posamezni agenti nepopolne in asimetrične informacije; da pripadajo posameznim skupinam, znotraj katere komunicirajo; da se v času učijo in kopirajo vedenje od drugih; da včasih sprejemajo dobre in včasih slabe odločitve. Posamezniki, ki med seboj komunicirajo in si izmenjujejo informacije, s tem privedejo do pojava črednega nagona. Čredni nagon je neizbežna posledica imitiranja in je verjetno ena najpomembnejših značilnosti finančnih trgov (Bikhchandani et al. 1992, Banerjee 1992, Lux 1995, Shiller 1995, 2002, Scharfstein in Stein 1990).

V tem času je nastalo ogromno modelov ACE. Eden prvih je Schellingov (1971) model segregacije, ki so ga kasneje nadgradili Fagiolo et al. (2007). ACE modeli v financah začenjajo z Zeemanom (1974) in Garmanom (1976). Epstein in Axtell (1996) analizirata številne različne družbene pojave. Drugi modeli so še: Arifovic (1996), Brock in Hommes (1998), Brock in LeBaron (1996), Cont in Bouchaud (2000), Raberto et al. (2001), Stauffer in Sornette (1999), Lux in Marchesi (1999), Palmer et al. (1994), Johnson (2002), Caldarelli et al. (1997), Sharpe (2007), Kim in Markowitz (1989), Jacobs et al. (2004), Frijns et al. (2008), Dieci in Westerhoff (2010). Preis et al. (2006) in Rosu (2009) predstavijo na agentih temelječ model knjige naročil (t. i. order book), kjer agenti podajajo svoje nakupne in prodajne zahteve. Ti modeli so praviloma osredotočeni na izbor portfelja v povezavi z modeliranjem cen vrednostnih papirjev.

Na podlagi teh dognanj iz različnih področij je disertacija aplikacija vedenjske in na agentih temelječe dinamične stohastične omrežne igre, kjer agenti simultano sprejemajo odločitve. Disertacija vključuje agente in njihove preference, vrednostne funkcije, povezave med agenti in množico potencialnih odločitev za vsakega posameznega agenta. Četudi je uporaba omrežnih modelov redka, pa omrežno proučevanje pojavov ni novost. Pastor-Satorras in Vespignani (2001) ter Chakrabarti et al. (2008) uporabijo omrežje za proučevanje širjenja virusov. Calvo-Armengol in Jackson (2004) uporabijo omrežni pristop pri proučevanju trga dela. Allen in Gale (2000) uporabita finančna omrežja za proučevanje kreditnega krča. Leitner (2005) predstavi omrežni model, kjer je učinkovitost posameznih projektov odvisna od uspešnosti projektov povezanih oseb. Cohen et al. (2008) uporabijo omrežne modele za

proučevanje prenosa informacij na trgih vrednostnih papirjev. Bramoulle in Kranton (2007) analizirata omrežja v povezavi z javnimi dobrinami. Jackson in Yariv (2007) in Galeotti et al. (2010) predstavita omrežno igro, v kateri agenti sprejemajo odločitve, pri tem pa ne vedo natančno, kakšne so izbire njihovih sosedov oziroma, kdo so njihovi sosedi. Szabo in Fath (2007) in Jackson (2010) predstavita pregled nekaterih evolucijskih omrežnih iger.

Osnovna ideja, na kateri je zgrajena disertacija, prihaja od Markowitza, ki oblikovanje portfelja opredeli kot dvofazni postopek zbiranja informacij in oblikovanja pričakovanj, ki se zaključi z izborom portfelja (Markowitz 1952a). Za razliko od Markowitzevega koncepta je disertacija zgrajena na štirifaznem procesu izbora: opazovanje donosov, izbor enega od povezanih agentov, primerjava portfeljev in izbor. V modelu se agenti odločajo za izbor posameznega portfelja v vsakem časovnem obdobju, in to na podlagi pretekle donosnosti portfelja, ki ga imajo, oziroma portfelja, ki ga ima agent, s katerim primerjajo svoj portfelj.

V disertaciji uporabim omrežje, ki je podobno tistemu, kot ga predlagata Watts in Strogatz (1998). V takšnem omrežju agenti ne komunicirajo z vsemi posamezniki v omrežju, ampak le s tistimi, ki jim zaupajo. Pri tem jim omrežje služi kot infrastruktura za komunikacijo z drugimi agenti. V disertaciji se informacije med agenti po omrežju pretakajo po principu osebne komunikacije "od ust do ust" (Ellison in Fudenberg 1995, Shiller 2002, Hong et al. 2004, 2005). V okolju, za katerega je značilno pretakanje informacij, se agenti ne odločajo samo na podlagi svojega znanja in izkušenj, ampak tudi na podlagi znanja in izkušenj vseh drugih posameznikov v omrežju. V modelu predpostavljam, da agenti sprejemajo odločitve na podlagi uspešnosti njihovih preteklih odločitev in tudi uspešnosti odločitev tistih agentov, s katerimi so neposredno povezani. Implicitno to pomeni, da se agenti, četudi z rahlim zamikom, odločajo na podlagi pretekle uspešnosti vseh agentov v okolju. Mehanizem učenja je tako podoben t. i. metodi ocenjevanega učenja (ang. *reinforcement learning*). Gre za vrsto učenja, ki temelji na opazovanju preteklih realizacij dogodkov, pri čemer agenti v času uporabljajo tiste izbire, ki so se v preteklosti izkazale za delujoče in opuščajo tiste, ki se niso (Fudenberg in Levine 1998, Hart in Mas-Colell 2000, Hart 2005). V kolikor delujoče odločitve niso njihove, jih preprosto prekopirajo od svojih kolegov (Roth in Erev 1995, Erev in Roth 1998, Camerer in Ho 1999). Grinblatt et al. (1995) so pokazali, da se na tak način vedejo vzajemni skladi, kar DeLong et al. (1990a) definirajo kot strategija "pozitivnih povratnih informacij." Agenti tako nenehno spreminjajo svoje portfelje, kar pa ne velja za likvidnostne agente. Likvidnostni agenti ne spreminjajo svojih izhodiščnih portfeljev. Njihova vključitev v model sledi ideji, da v populaciji obstaja majhen del pasivnih investitorjev. Cohen (2009) predstavi model lojalnosti, s katerim pojasni pojav, ko portfelji ljudi vsebujejo vrednostne papirje podjetij, v katerih so zaposleni.

Pomemben element disertacije predstavljajo t. i. nezaupljivi agenti. Odločitev za njihovo vključitev v model je zelo intuitivna. Ko agenti komunicirajo med seboj, je težko meriti, kako močna je takšna medosebna komunikacija. Prav tako je težko meriti, koliko so ljudje pri tem iskreni in si med seboj zaupajo. Glavna značilnost nezaupljivih agentov je, da obstaja neničelna verjetnost, da med primerjanimi alternativami ne bodo izbrali tiste, ki se zdi boljša. Nekateri razlogi za takšno odklonsko vedenje se lahko nanašajo na nezaupanje do drugih agentov, do katerega pride na povsem individualni ravni, nezaupljivost do podatkov, bodisi posamezni agenti smatrajo, da je razlika med dvema primerjanima alternativama tako majhna, da zamenjava ni smiselna. Nezaupljivost se prav tako lahko nanaša na prisotnost "napak" v procesu odločanja (Selten 1975, Tversky in Kahneman 1974). Napake v samem izboru so lahko tudi posledica zmede (DellaVigna 2009). Uvedba nezaupljivosti postane še posebej pomembna v primerih, ko so si vrednosti različnih primerjanih portfeljev med seboj

zelo podobne. V takšnih primerih je povsem racionalno pričakovati, da se bodo agenti odločali tudi za navidez slabše alternative.

Temeljna metodološka premisa disertacije je, da interakcija med agenti pripelje do zelo kompleksnega vedenja na makro ravni, ki bistveno presega ravnovesne matematične rešitve modelov reprezentativnih agentov (Simon 1955a, Aumann in Myerson 1988, Schelling 1978, Smith 1976, Axelrod 1984, Epstein in Axtell 1996, Tesfatsion 2006, Hommes 2006, LeBaron 2006, Duffy 2006). Pri izgradnji te kompleksnosti sta pomembni predvsem sledeči dve značilnosti. Najprej gre za učinke nepopolnih informacij, ki so razlog za negotovost na trgih ter z njim povezana pojava črednega nagona in informacijske kaskade (Hayek 1937, 1945, Keynes 1936, Banerjee 1992, 1993, Lux 1995, Scharfstein in Stein 1990, Bikhchandani et al. 1992, 1998, Cont in Bouchaud 2000, Shiller 2002). Druga pa je povzročena z ravno (ne)zaupljivosti. Ta povzroči, da se vedenje posameznih agentov približuje hevrističnemu, še posebej v primerih, ko so razlike v negotovih alternativah izredno majhne (Kahneman in Tversky 1979, Rubinstein 1998, Heath in Tversky 1991, Hirshleifer 2001).

V disertaciji so obravnavana številna pomembna vprašanja v zvezi s tem, kako agenti, ki se nahajajo v medsebojni interakciji, pod različnimi okoliščinami izbirajo portfelje.

Q1: Kako agenti izbirajo med tveganimi in netveganimi portfelji? (Poglavje 5)

Simulacije začnem s preprostim primerom, kjer imajo agenti na voljo en tvegan in en netvegani vrednostni papir, izberejo pa lahko tudi kombinacijo med njima. Gre za aplikacijo sila preprostega primera, kot so ga predstavili Tobin (1958), Arrow (1965) in Pratt (1964). V bistvu je v literaturi, ki se vprašanja izbora portfeljev loteva z uporabo matematičnega instrumentarija iskanja ravnovesne točke, takšna aplikacija še vedno najpogostejša. Splošna ugotovitev raznih študij je, da agenti pri izboru portfeljev upoštevajo donose in tveganje, pri čemer so zelo dovzetni na premijo za tveganje. Takšni pa so v splošnem tudi zaključki vedenjskega pristopa.

V teh igrah sem osredotočen na vprašanje, na kakšen način pričakovani donosi in raven tveganja vplivajo na izbor portfeljev. Natančneje, v igrah me zanima, kako se odločitve agentov spreminjajo s spremembami pričakovanega donosa tveganega vrednostnega papirja in variance. Za vsako perturbacijo po posameznih spremenljivkah igre ponovim 20-krat, portfelje, ki jih agenti izberejo v zadnji iteraciji v $t=10.000$ pa povprečim in prikažem na vročinskem grafu.

Rezultati iger pokažejo, da je, izbor tveganih portfeljev pozitivno koreliran s povprečnim donosom tveganega vrednostnega papirja in negativno z njegovo varianco. Ob tem se še pokaže, da se agenti odločajo za mešane portfelje, kadar sta tako pričakovani donos in varianca visoka, oziroma, kadar se donosi tveganega vrednostnega papirja nahajajo v okolici netveganega donosa. Četudi se agenti izogibajo negativnim donosom, v kolikor lahko izberejo netvegano alternativo z ničelnim donosom, pa je varianca tveganega vrednostnega papirja tista spremenljivka, ki ustvarja možnosti za dosego pozitivnega donosa. V tem primeru se mešani portfelji izkažejo kot ustrezna izbira med tveganimi in netveganimi donosi in varianco. Tudi varianca, kot mera za tveganje, ne prispeva k temu, da bi se agenti v medvedjem trendu odločali za tvegane portfelje. Izhodiščni delež agentov s posameznim portfeljem vpliva na končne odločitve agentov, še posebej v limitnih pogojih.

Q2: Kako se agenti odločajo med dvema tveganima vrednostnima papirjema? (Poglavje 5)

V naslednjih igrah razširim osnovni okvir in se lotim primera, kjer se agenti odločajo med dvema tveganima vrednostnima papirjema dveh finančnih korporacij (CreditSuisse in

Citigroup) in kombinacijo med njima. V tem delu uporabim dejanske dnevne donose za obe korporaciji, ob tem pa ne analiziram le končnih odločitev agentov, ampak tudi njihov razvoj v času. Na tak način lahko spremljam, kako so se odločitve agentov spreminjale glede na spreminjanje donosov.

V teh igrah se zelo jasno prikaže ena glavnih značilnosti trgov kapitala – čredni nagon, ki privede do sinhronizacije v odločitvah agentov (Bala in Goyal 1998). Čredni nagon se še posebej pokaže v okolju zaupljivih agentov, ki so zelo občutljivi na vsakršno majhno razliko v primerjanih portfeljih. Posledično so tudi njihove odločitve zelo konsistentne, saj pride do sinhronizacije v zelo zgodnjih fazah posameznih iger. Na drugi strani so nezaupljivi agenti mnogo manj občutljivi na razlike v portfeljih, zaradi česar njihovi izbori niso konsistentni. V teh igrah je konsistentnost merjena kot razmerje med korelacijskim koeficientom posamrnih iger glede na povprečje vseh iger. Tudi v teh igrah se pokaže, da izhodiščni delež agentov s posameznim portfeljem vpliva na končne odločitve agentov.

Q3: Kakšen je učinek enkratnega šoka na izbor portfeljev? (Poglavje 5)

V zadnjem delu poglavja 5 v igre dveh tveganih vrednostnih papirjev vključim enkratni šok. Kot poudari Sornette (2009), so ekstremni dogodki ena od najprepoznavnejših lastnosti naravnih in družbenih ved, ki pogosto vodijo do velikih izgub. Šoki so še posebej relevantni tudi v ekonomiji in poznani v finančnem svetu. Označimo jih lahko kot nenadne in občutne spremembe v cenah vrednostnih papirjev v katerokoli smer, zaradi česar spreminjajo okolje, v katerem agenti sprejemajo odločitve (Merton 1969, 1971). De Bondt in Thaler (1985) pokažeta, da agenti pogosto prekomerno reagirajo na takšne dramatične dogodke in nepričakovane novice. Vprašanje, ki si ga zastavljam v tem delu, je, kako občutljivi so agenti na enkraten šok različnih jakosti. Te igre vključujejo likvidnostne agente.

Skladno z nekaterimi ugotovitvami (Binmore in Samuelson 1994, Binmore et al. 1995 in Kandori et al. 1993) se tudi v igrah pokaže, da je kratkoročni učinek šoka neizbežen; še posebej močan šok. V igrah se agenti premaknejo stran od alternativ, ki jih je prizadel negativni šok in jih zamenjajo s tistimi, ki niso bile prizadete, oziroma so bile prizadete v manjši meri, pri čemer so premiki pozitivno korelirani z jakostjo šoka. Šoki manjših jakosti ne povzročijo dolgoročnih posledic. Učinki šoka so še posebej vidni v okolju zaupljivih agentov. Učinki šoka na ultra dolgi rok so odvisni od ravni, do katere šok spremeni vedenje agentov, donosov, ki sledijo šoku in jakosti črednega nagona. V igrah je okrevanje po šoku bilo zelo počasno.

Q4: Ali so agenti sposobni izbirati portfelje skladno s teorijo učinkovite meje? (Poglavja 6-8)

V poglavjih 6-8 razširim osnovni okvir in se lotim analize iger mnogoterih vrednostnih papirjev. Četudi so zelo uporabne, pa so igre dveh vrednostnih papirjev preveč preproste in premalo realistične. Uporaba več vrednostnih papirjev drastično poveča jakost problema izbora, saj se agenti nahajajo pred problemom iskanja ustreznih informacij (Barber in Odean 2008). Kot ugotavlja Merton (1987), bi naj ravno zaradi visokih stroškov iskanja, kot posledice množice potencialnih alternativ, agenti omejevali število vrednostnih papirjev v svojih portfeljih.

V teh igrah analiziram odločitve agentov glede na teorijo učinkovite meje. Teorija učinkovite meje govori, da agenti izbirajo takšne portfelje, ki maksimirajo njihov donos pri danem tveganju, oziroma minimirajo tveganje pri danem donosu (Markowitz 1952a). Vprašanje, ki me zanima, ni, ali agenti preferirajo portfelje iz učinkovite meje, ampak, ali so jih v stohastičnem okolju sposobni tudi realizirati. V teh igrah ponovno uporabim likvidnostne

agente. Kot v vseh prejšnjih primerih, tako imajo tudi tukaj agenti omejeno vedenje o donosih vrednostnih papirjev. V analizi sta povprečna vrednost in varianca uporabljena kot končna podatka, ne kot izhodiščna. V vseh primerih uporabim dejanske podatke. Glede na izbrane portfelje lahko še ocenim, kakšen je odnos agentov do tveganja.

Glede na rezultate simulacij se pokaže, da bolj kot so tvegani posamezni portfelji, večja je verjetnost, da se jim bodo agenti izogibali. Zaupljivi agenti so v mnogo večji meri sposobni izbrati zmagovalne in nezaželene portfelje kot nezaupljivi agenti, medtem ko so pri izboru tudi bolj konsistentni. V vseh primerih se pokaže, da so manj diverzificirani portfelji mnogo bolj zaželeni od bolj diverzificiranih. Konsistentnost v izboru ocenim z uporabo dveh metod: koeficientom variacije in z metodo Monte Carlo. Odločitve zaupljivih agentov so mnogo bolj sinhronizirane od odločitev nezazupljivih agentov.

Q5: Ali v "dobrih" časih agenti investirajo drugače kot v "slabih" časih? (Poglavje 7)

Skladno z intuicijo Kahnemana in Tverskega (1979) je moj naslednji cilj testirati, ali so izbrani portfelji agentov drugačni v obdobjih, ko cene vrednostnih papirjev rastejo, kot pa v obdobjih medvedjega trenda. Vprašanje bistveno presega sporočilnost variance kot mere za tveganje, kajti v bikovskem trendu se varianca nanaša na variranje cen v trendu naraščajočih cen, medtem ko se v medvedjem trendu nanaša na variranje cen v obdobju padajočih cen. Teorija vedenjskih financ pravi, da so vrednostne funkcije agentov konveksne za izgube in konkavne za donose (Tversky in Kahneman 1991). Fama in Schwert (1977) pokažeta, da so v času medvedjega trenda zahtevani donosi na tvegane vrednostne papirje višji. Ob tem pa Barberis et al. (2001) dodajo, da so v medvedjem trendu agenti manj naklonjeni posedovanju tveganih vrednostnih papirjev, saj se najprej začno zavedati tveganja, nato pa ga tudi ovrednotiti.

Rezultati simulacij so skladni s pričakovanji in pokažejo, da so v medvedjem trendu agenti mnogo bolj občutljivi na varianco, kot pa v trendu rasti. Rezultati še pokažejo, da so v medvedjem trendu odločitve agentov zelo sinhronizirane, kar se kaže v zelo doslednem sledenju koncepta "zmagovalec prejme vse". V bikovskem trendu se utegnejo agenti odmakniti od izbora portfeljev iz učinkovite meje in pri danem donosu izbrati tudi bolj tvegane alternative iz bližnje okolice portfeljev iz učinkovite meje. Ponovno se pokaže, da so zaupljivi agenti pri svojih odločitvah mnogo bolj konsistentni kot nezaupljivi agenti, ob tem pa imajo tudi mnogo večje zmožnosti izbora zmagovalnih portfeljev.

Q6: Kako novice vplivajo na izbor portfeljev? (Poglavje 8)

V zadnjem delu disertacije se lotim vprašanja, na kakšen način novice, ki se nanašajo na posamezune vrednostne papirje, vplivajo na izbor portfeljev. V prejšnjih poglavjih so bile novice upoštevane posredno preko cen vrednostnih papirjev, tokrat pa so neposredno.

Chen et al. (1986) poudarijo, da so cene vrednostnih papirjev sistematično predmet nenehnih novic o delovanju gospodarstva. Kandel in Pearson (1995) ugotovita, da javne objave privedejo do skoka v cenah in trgovalnih količinah. Kot poudari Fair (2002), je večina velikih skokov borznih cen delnic S&P500 bila povezana z objavami ameriških makroekonomskih podatkov. Bernanke et al. (2005) analizirajo učinke nepričakovanih sprememb ključne obrestne mere FEDa na cene vrednostnih papirjev in pokažejo, da je nepričakovano znižanje ključne obrestne mere za 25 bazičnih točk privedlo do dviga indeksa S&P500 za 1,3 odstotka. Boyd et al. (2005) proučujejo učinke borznega dogajanja glede na objave podatkov o nezaposlenosti. Barber in Odean (2008) pojasnita, da pomembne novice drastično vplivajo na odločitve investitorjev.

Za agenta so novice, ki prihajajo v nerednih intervalih, podobne večkratnim šokom. Novice so lahko pozitivne, nevtralne ali negativne. Novice, ki prihajajo v nerednih intervalih, povzročijo premike iz portfeljev, ki so predmet negativnih novic, v portfelje, ki so predmet pozitivnih novic. Ker pa v modelu agenti ne reagirajo samo na posamezne novice, ampak tudi na donose, ki sledijo posameznim novicam, lahko negativni donosi, ki sledijo pozitivnim novicam, odvrnejo agente od posedovanja takšnih portfeljev, medtem ko lahko pozitivni donosi, ki sledijo negativnim novicam, povišajo privlačnost takšnih portfeljev. To pomeni, da so za privlačnost posameznih portfeljev ključni cenovni odzivi na objavo posameznih novic.

Pri analizi vpliva novic na izbor portfeljev uporabim dejanske podatke za donose in novice. Pri evalvaciji novic uporabim preprosto in intuitivno pravilo. Predpostavim, da objava pomembnih novic povzroči skok v trgovanih volumnih in cenah vrednostnih papirjev; omenjeno pravilo uporabita tudi Barber in Odean.

V prisotnosti novic in donosov se kot zmagovalni pokažeta dve skupini portfeljev. Kot v predhodnih igrah gre za portfelje iz učinkovite meje, oziroma iz njene ožje okolice. Drugo skupino pa tvorijo močno diverzificirani portfelji, katerih izbor je bil stimuliran s številom objavljenih nenegativnih novic.

Glavni prispevek disertacije je metodološki, saj disertacija izhaja iz metodološkega individualizma. Pri tem je finančni sistem obravnavan kot kompleksen sistem, ki izbor portfelja proučuje preko interakcije med posamezniki, ob tem pa vsebuje elemente psihologije. Izbor portfeljev do sedaj še ni bil proučevan na tak način. Tudi sicer so igre na družbenih omrežjih dokaj redke, četudi finančni trgi ponujajo ogromno možnosti za njihovo aplikacijo (Bonabeau 2002). Na agentih-temelječ pristop mi omogoča, da analiziram vedenjske vzorce agentov ob različnih okoliščinah in za velik spekter parametrov. Zmožnost ponavljanja iger mi omogoča, da ocenim konsistentnost izbora. Ker proces učenja ne sledi strogo določeni proceduri, tudi ponovitve iger ne privedejo do istih rezultatov, četudi uporabljamo nespremenjen algoritem učenja (Vriend 2000). Disertacija tako predstavlja nov pristop, ki ni uporaben samo za proučevanje izbora portfeljev, ampak tudi za proučevanje številnih drugih vprašanj iz področja financ.

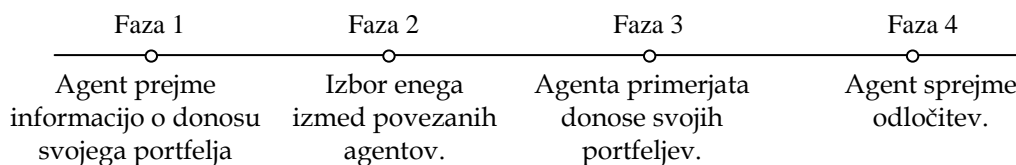
Novost je tudi vključitev nezaupljivih in likvidnostnih agentov. Z uporabo nezaupljivih agentov dodam v sistem agentovega odločanja psihološki vidik. Obenem lahko tudi primerjam odločitve zaupljivih agentov z odločitvami nezaupljivih agentov, in to tako glede samega izbora portfeljev, kot tudi ravni konsistentnosti izbora. Likvidnostni agenti so zelo pomembni v modelu, saj preprečujejo, da bi manj donosne alternative izpadle iz nabora potencialnih odločitev, četudi so manj donosne le za kratek čas. Na nek način so ti agenti podobni konzervativnim bodisi lojalnim investitorjem bodisi predstavljajo oblikovalce trga. V igrah s simuliranimi donosi je uporabljena Levyjeva porazdelitev, ki predpostavlja, da ekstremni dogodki niso tako redki (Mandelbrot 1963, Fama 1965, Sornette 2009). V igrah mnogoterih vrednostnih papirjev uporabim dejanske podatke, kar pomeni, da ta del disertacije vsebuje vse specifične oblikovanja cen vrednostnih papirjev.

2 MODEL

Gre za model v diskretnem času, ki teče na intervalu $t = \{1, 2, \dots, T\}$ in z diskretnimi stanji, ki je sestavljen iz treh kritičnih elementov: agentov, odločitvenih pravil in vrednostnih papirjev.

V modelu so agenti med seboj povezani v družbeno omrežje in v vsakem časovnem obdobju t sprejmejo odločitev. Pri tem sledijo zelo preprostim in intuitivnim odločitvenim pravilom, ki se izvajajo v štirih fazah (Slika 1).

Slika 1: Proces izbora portfelja



Na začetku vsakega obdobja t agenti opazujejo donosnosti svojih portfeljev v preteklem obdobju $t-1$ (Faza 1). V drugi fazi procesa izbora agenti izberejo enega izmed agentov, s katerimi so neposredno povezani. Pri tem predpostavim, da je izbor agenta naključen. V tretji fazi oba agenta primerjata donosnosti svojih portfeljev v obdobju $t-1$. Ko je primerjava zaključena, sledi zadnja faza, ko se agent odloči, ali bo tudi v obdobju t nadaljeval s portfeljem, ki ga je imel v obdobju $t-1$, ali pa bo izbral portfelj svojega kolega. Po koncu zadnje faze se sistem prestavi v prvo fazo naslednjega obdobja in proces izbora se ponovi in traja vse do obdobja T . V kolikor ni navedeno drugače, se simulacije zaključijo v $T=10.000$. Čas trajanja simulacij z dejanskimi podatki je določen s številom realiziranih donosov.

2.1 Struktura odločitvenega procesa

Odločitveni proces je zgrajen na komunikaciji med posameznimi agenti, ki s svojimi povezavami tvorijo družbeno omrežje (Wasserman in Faust 1998, Chakrabarti in Faloutsos 2006, Jackson 2008).

Graf g je urejen par dveh razčlenjenih množic (V, E) , pri čemer $E = \{e_1, e_2, \dots, e_n\}$ predstavlja množico povezav med pari točk (i, j) , $V = \{v_1, v_2, \dots, v_n\}$ pa množico med seboj povezanih točk.

Graf predstavlja matematično reprezentacijo omrežja. V omrežju imajo posamezne točke neko vsebino, bodisi se nanje nanaša neka vrednost bodisi funkcija. V disertaciji uporabim neusmerjeno in povezano omrežje, podobno tistemu, kot ga predstavita Watts in Strogatz (1998). Glavni značilnosti takšnega omrežja sta, da za vsak par točk (i, j) obstaja pot od točke i do točke j , pri čemer je za vzpostavitev povezave med dvema agentoma potrebno obojestransko soglasje. Implicitno to pomeni, da je tudi pretok informacij obojestranski. Večina ekonomskih stanj sodi v tak okvir obojestranskega formiranja povezav. Osrednji značilnosti takšnega omrežja sta, da so povprečne poti med agenti zelo kratke, hkrati pa omrežje ohranja lokalno nakopičenost. Slednje pomeni, da obstaja velika verjetnost, da so ljudje, ki imajo skupne prijatelje, prijatelji tudi med seboj. Omrežja malega sveta združijo lastnosti urejenih in naključnih omrežij. Prve zagotavljajo lokalno nakopičenost, naključna omrežja pa s posamičnimi globalnimi povezavami zagotovijo učinek malega sveta. Takšne globalne povezave idejno slikajo prijateljstva, ki jih imajo posamezniki zunaj svojega lokalnega okolja, prispevajo pa k skrajšanju poti pretakanja informacij po omrežju (Milgram 1967).

V vsakem časovnem obdobju je na trgu prisotno konstantno število n agentov, ki so oštevilčeni z $i = 1, 2, 3, \dots, n$. V omrežju lahko agenti komunicirajo samo s tistimi agenti iz omrežja, s katerimi so neposredno povezani. V poglavju 5 je v omrežju prisotnih $n = 1000$ agentov, vsak med njimi pa je v izhodišču povezan s šestimi najbližjimi agenti v krogu, po tremi na vsako stran. V poglavjih 6-8 je v omrežju prisotnih $n = 5000$ agentov, vsak med njimi pa je v izhodišču povezan z desetimi najbližjimi agenti, po petimi na vsako stran. Razlog za omejeno število povezav izhaja iz omejenih sposobnosti posameznikov, da sklepajo prijateljstva, ki jih dejansko uporabljajo za izmenjavo informacij (Amaral et al. 2000). Kot predlagajo Watts in Strogatz ter Barrat in Weight (2000), je v omrežju vsaka povezava z naključno izbranim agentom iz omrežja prevezana z verjetnostjo $p = 0.1$. Obstoje večkratnih povezav med agenti ali povezav posameznih agentov s samo seboj ni dovoljen. Ko je omrežje zgrajeno, ostaja nespremenjeno do konca tekoče igre.

Agenti v času akumulirajo svoje donose, oziroma vrednost svojega premoženja, pri čemer rešujejo sledeči problem:

$$\max_W (E_t(W_{t+1})), \text{ pri čemer velja} \\ W_{t+1}(A_i) = W_t(A_i) \cdot [1 + R_t(\bullet)], W_0(A_i) = 1 \text{ in } q_t^i \geq 0 \quad (1).$$

W_t in W_{t+1} prikazujeta vrednosti portfelja posameznika i v času t in $t+1$, $R_t(\bullet)$ pa donos alternative (\bullet) v času t . V času $t=0$ je vrednost vseh portfeljev enaka ena. $q_t^i \geq 0$ zagotavlja, da skozi potek igre agenti ne morejo imeti kratkih pozicij, niti se ne morejo zadolževati. Agenti tudi ne morejo uporabljati izvedenih finančnih instrumentov, s katerimi bi lahko zavarovali svoje pozicije. V simulacijah upoštevamo zakon ene cene, kar pomeni, da je cena portfeljev enaka vrednosti enot premoženja, ki sestavljajo portfelj. Začetni portfelji so agentom podeljeni naključno z enako verjetnostjo. V kolikor $q_t^i \geq 0$ prikazuje delež vrednostnega papirja j v portfelju v času t , potem je donos portfelja enak tehtanemu povprečju donosov vrednostnih papirjev, ki sestavljajo posamezen portfelj $R_t^S = \sum_{j=1}^m q_t^j \cdot R_t^j$.

Pri tem velja, da je $\sum_{j=1}^m q_t^j = 1$.

Agenti dobijo podatke o donosih portfeljev, ki jih posedujejo, po koncu vsakega obstoječega časovnega obdobja. S tem se ponovno začne prva faza novega obdobja. Drugo fazo odločitvenega procesa predstavlja izbor enega izmed povezanih agentov. Implicitna predpostavka modela tako je, da agenti niso sposobni v vsakem obdobju kontaktirati večjega števila agentov. Ker predpostavim, da nihče med povezanimi agenti nima nekih posebnih sposobnosti, ki bi mu omogočale, da bi lahko sistematično premagoval trg, ima vsak agent enake možnosti, da je izbran. Po tem, ko agent primerja donosnost svojega portfelja s portfeljem izbranega agenta, se odloči, ali obdržati enak portfelj, ali na trgu kupiti portfelj izbranega agenta. Za agenta drugi portfelji niso dosegljivi, saj o njih nima informacij.

V odločitvenem procesu se agenti v času vsebolj nagibajo k posedovanju tistih portfeljev, ki so se v preteklosti izkazali za donosne (Roth in Erev 1995, Erev in Roth 1998). Gre za uporabo t. i. metode ocenjevanega učenja (ang. *reinforcement learning*), ki je bila pogosto proučevana v igrah posnemanja, ki temeljijo na vsakodnevnih komunikaciji med ljudmi in njihovem poizvedovanju.

Pomembna elementa modela sta vključitev ravni zaupljivosti med agenti in vključitev likvidnostnih agentov. Likvidnostni agenti so v model vključeni v simulacijah v poglavjih 6-8. Njihova glavna značilnost je ta, da skozi potek igre ne menjujejo svojega izhodiščnega portfelja, ne glede na njegovo donosnost v primerjavi z drugimi. Na tak način ohranjajo informacije o vseh portfeljih. Likvidnostne agente lahko označimo kot konzervativne ali zelo prepričane investitorje, ki so bodisi zadovoljni s svojimi portfelji bodisi imajo kakšne druge osebne razloge za svoj konzervativizem. Kot poudari Constantinides (1990), lahko navade ljudi drastično dvignejo premijo za posedovanje lastniških vrednostnih papirjev, kar utegne spodbujati njihov konzervativizem. V dejanskem svetu kapitalskih trgov niso samo konzervativni vlagatelji tisti, ki nastopajo kot likvidnostni agenti, ampak to vlogo igrajo tudi vzdrževalci trga. V poglavju 5.5 so likvidnostni agenti postavljeni s sledečih homogenih skupinah: $i = \{(100, 109), (200, 219), (400, 419), (600, 619), (970, 1000)\}$, v poglavjih 6-8 pa v $i = \{(700, 719), (1000, 1019), (1200, 1219), (1500, 1519), (2500, 2519), (3500, 3519), (4800, 4819)\}$. Likvidnostnim agentom so portfelji dodeljeni naključno pred začetkom posamične igre. Pri ponovitvah iger lahko likvidnostni agenti posedujejo različne portfelje. Četudi likvidnostni agenti skozi potek posamičnih iger ne spreminjajo svojih akcij, pa si z drugimi agenti izmenjujejo informacije o svojih portfeljih.

Druga značilnost modela je vpeljava t. i. ravni zaupljivosti. Glavna značilnost nezaupljivih agentov je, da obstaja neničelna verjetnost, da med primerjanimi alternativami ne bodo izbrali tiste, ki je v preteklem obdobju dosegla najvišjo vrednost. Raven zaupljivosti je v model postavljena kot eksogena spremenljivka, kar pomeni, da nas razlogi za pojav nezaupljivosti ne zanimajo. Raven nezaupljivosti, podana preko spremenljivke $\kappa \in (0, 1)$, pomeni osrednji element odločitvene funkcije. Ta je podana sledeče:

$$\wp = \left[1 + \exp\left(\left(W(A_i) - W(A_j)\right) / \kappa\right) \right]^{-1} \quad (2).$$

V vsakem časovnem obdobju t , agent i primerja vrednost svojega portfelja $W(i)$ z vrednostjo portfelja izbranega agenta j , $W(j)$. Delovanje odločitvenega procesa je sledeče. V kolikor je $ran > \wp$, agent i ohrani svoj portfelj, v nasprotnem primeru na trgu kupi portfelj agenta j . Parameter $ran \sim U(0, 1)$ predstavlja naključno število, generirano iz enakomerne IID porazdelitve. Kot izhaja iz (2), je odločitev agenta odvisna od razlike v vrednostih portfeljev obeh agentov, kot tudi od vrednosti parametra zaupljivosti. V splošnem velja, da nižja, kot je vrednost parametra κ , višja je verjetnost, da bo agent izbral donosnejši portfelj, in nasprotno. Skozi celotno poglavje 5 postavim vrednost $\kappa = 0.001$ za zaupljive agente in $\kappa = 0.5$ za nezaupljive. V poglavjih 6-8 postavim vrednost $\kappa = 0.01$ za zaupljive agente in $\kappa = 0.1$ za nezaupljive agente.

2.2 Podatki

V disertaciji so uporabljene tri vrste vrednostnih papirjev: netvegani, tvegani s simuliranimi vrednostmi donosov in tvegani z dejanskimi podatki. Pri simuliranih vrednostih uporabim Levyjevo stabilno porazdelitev; Mandelbrot (1963, 1967) je pokazal, da se cene vrednostnih papirjev ne gibljejo po Gaussovi porazdelitvi, kot se v ekonomskih modelih pogosto domneva, ampak da je njihovo gibanje mnogo bolj kompleksno. Pri dejanskih podatkih uporabim podatke zaključnih (P_t^C) in otvoritvenih (P_t^O) tečajev delnic iz New York Stock

Exchange (NYSE). Otvoritvena cena je cena, ki je bila dosežena pri prvi transakciji, medtem ko je zaključna cena zadnja cena delovnega dne newyorške borze. NYSE se odpre ob 9.30 po lokalnem času in se zapre ob 16.00 po lokalnem času. Donosi so nato izračunani kot relativna sprememba dnevnega tečaja $R_t = \frac{P_t^C - P_t^O}{P_t^O}$. V analizi bikovskega in medvedjega trenda

uporabim samo zaključne tečaje delnic, s čimer upoštevam tudi trgovanja izven uradnega delovnega časa. V mnogih primerih se otvoritveni tečaji po posameznih trgovalnih dneh bistveno razlikujejo od zaključnih tečajev.

V poglavjih 5.4 in 5.5 uporabim delnice dveh bančnih korporacij, Credit Suisse (NYSE: CS) in Citigroup (NYSE: C). V poglavjih 6-8 uporabim delnice petih korporacij iz petih različnih gospodarskih sektorjev: Citigroup (NYSE: C), KraftFoods (NYSE: KFT), Microsoft (NYSE: MSFT), Alcoa (NYSE: AA) in ExxonMobil (NYSE: XOM). V vseh primerih je vir podatkov finančni portal Yahoo!Finance, dosegljiv na finance.yahoo.com.

V modelu predpostavljam, da so vsi vrednostni papirji neskončno deljivi in popolnoma likvidni. Obe predpostavki sta potrebni, v kolikor želimo agentom zagotoviti, da lahko skladno s svojim prepričanjem poljubno spreminjajo svoje portfelje v času. Ko se agent odloči za prehod na portfelj svojega kolega, implicitno predpostavim, da agent proda vse odvečne delnice in na trgu kupi nove. Pri tem predpostavim okolje brez transakcijskih in drugih stroškov, ki bi bili povezani s trgovanjem in bi, v kolikor bi do njih prišlo, zniževali donosnost posameznih portfeljev. Kot poudarijo Constantinides (1986) in Lo et al. (2004), transakcijski stroški vplivajo tako na frekvenco trgovanja, kot tudi na volumen. V poglavjih 6-8 predpostavim, da so mešani portfelji vedno sestavljeni iz enakih deležev posameznih delnic, ki so vključene v portfelj.

3 REZULTATI SIMULACIJ

V igrah dveh vrednostnih papirjev je v okolju prisotnih $n=1.000$ agentov, ti pa izbirajo bodisi med portfeljem posameznega vrednostnega papirja, ali kombinacijo obeh. Rezultati simulacij se nanašajo na povprečne odločitve v dvajsetih med seboj neodvisnih realizacijah iger. V teh igrah nas zanimajo le končna stanja v $T=10.000$. V primeru simulacij dveh tveganih vrednostnih papirjev, delnic finančnih korporacij Credit Suisse in Citigroup, analiziram razvoj celotnih iger v času. Pri tem uporabim dejanske podatke o doseženih donosih. Tudi v tem primeru se rezultati nanašajo na povprečne razvoje iger dvajsetih med seboj neodvisnih ponovitev iger. Čas trajanja posameznih iger je pogojen z izborom podatkov in znaša $T=2457$.

V poglavjih 6-8 ocenjujem povprečne in končne odločitve agentov, pri čemer naredim 30 med seboj neodvisnih simulacij posameznih iger. V poglavjih 6 in 8 zajema celoten nabor podatkov obdobje od 2. januarja 2009 do 21. januarja 2010, tj. $T=264$. Medvedji trend zajema obdobje od 22. septembra 2008 do 13. marca 2009, tj. $T=120$. Bikovski trend se začne s koncem medvedjega trenda, 16. marca 2009, in se konča 11. januarja 2010, tj. $T=209$. 14. in 15. marec sta bila netrgovalna dneva.

Povprečne odločitve agentov se nanašajo na povprečje povprečne izbire agentov skozi celotno časovno obdobje, končne odločitve pa se nanašajo na povprečje končnih odločitev agentov. Analiza povprečnih iger daje informacijo o povprečni zaželenosti posameznih

portfeljev skozi celoten razvoj simulacij, medtem ko končne odločitve dajejo informacije o končni zaželenosti posameznih portfeljev. Oba pogleda se med seboj dopolnjujeta.

3.1 Igre dveh vrednostnih papirjev

V prvi igri agenti izbirajo med tveganim in netveganim vrednostnim papirjem ter kombinacijo med njima. Končne odločitve agentov prikažem na toplotnih grafikonih. Ti pokažejo deleže agentov s posameznimi portfelji glede na pare posameznih spremenljivk. V prvem primeru so prikazane odločitve agentov glede na μ in σ na intervalih $-0.05 \leq \mu \leq 0.05$ in $0 \leq \sigma \leq 0.2$. Pri spremenljivki μ uporabim korak dolžine 0.01 enote, pri spremenljivki σ pa korak dolžine 0.02 enote. Vrednosti drugih spremenljivk so konstantne in imajo sledeče vrednosti: $\alpha = 1.996$, $\beta = 0.2834$, $q_t^i = 0.5$. Začetna vrednost $u = 0.5$ se v času spreminja. Kot dopolnitev simuliram še učinke prvotnih preferenc agentov na njihove končne odločitve. To storim tako, da simuliram odločitve agentov glede na perturbacije σ in u ter μ in u . V vseh primerih znašata koraka po spremenljivki u 0.1 enote na intervalu $0 \leq u \leq 1$, enako kot v predhodnih simulacijah, pa znašata koraka pri 0.01 in 0.02 enote na intervalih $-0.05 \leq \mu \leq 0.05$ in $0 \leq \sigma \leq 0.2$.

Simulacije iger tveganega in netveganega vrednostnega papirja pokažejo, da donosnost in tveganje odločilno vplivata na izbor portfelja, pri čemer je še posebej poudarjen učinek donosnosti. Tvegani portfelj je izbran za pozitivne pričakovane donose tveganega vrednostnega papirja; donosnost netveganega vrednostnega papirja je skoraj nič. Kot prikazuje Tabela 1, je privlačnost tveganega portfelja v negativni korelaciji z varianco. V kolikor so pričakovani donosi tveganega vrednostnega papirja negativni, pa netvegani portfelj. S/MIX/B se nanašajo na tvegani/mešani/netvegani portfelj, UN in SUS predstavljata zaupljive in nezaupljive agente, MU predstavlja pričakovani donos tveganega vrednostnega papirja, SIGMA pa varianco. Oba koeficienta se nanašata na Levyjevo porazdelitveno funkcijo. Agenti se odločijo za mešani portfelj v dveh primerih. V prvem primeru takrat, kadar sta visoka tako pričakovana donosnost tveganega vrednostnega papirja, kot tudi njegova varianca. Visoka varianca pomeni pojav mnogo bolj ekstremnih dogodkov. Očitno se agenti skušajo za vsako ceno izogniti visokemu tveganju in iščejo varnost v razpršenosti. V drugem primeru pa se agenti odločijo za mešani portfelj takrat, ko se pričakovani donosi tveganega vrednostnega papirja nahajajo v okolici donosa netveganega vrednostnega papirja. Odločitev za netvegani portfelj je pogojena skoraj izključno s pričakovanim donosom tveganega vrednostnega papirja. Odločitve agentov so tako zelo močno podobne intuiciji teorije obetov.

Tabela 1: Koeficienti korelacije med spremenljivkami

	MU	SIGMA
S_UN	0.749	-0.346
S_SUS	0.717	-0.360
MIX_UN	0.326	0.521
MIX_SUS	0.330	0.433
B_UN	-0.915	0.026
B_SUS	-0.912	0.040

Pri simulacijah iger se pokaže učinek črednega nagona, kot posledica kopiranja portfeljev drugih. Čredni nagon povzroči, da manj donosne alternative v času postopoma izginjajo iz

spektra alternativ, saj jih uporablja vse manj agentov. Tako lahko že kratkoročna neuspešnost posameznih alternativ, ki bi na dolgi rok sicer utegnile biti donosne, eliminira takšne alternative iz spektra množice potencialnih. Kot odgovor na pojav črednega nagona v nadaljevanju v model vključim t. i. likvidnostne agente, ki v času ne spreminjajo svojih alternativ, s čimer ohranjajo informacije o vseh alternativah.

V drugem sklopu simuliram igre dveh tveganih vrednostnih papirjev, Credit Suisse in Citigroup. Za razliko od predhodnih iger se tukaj ne posvetim samo končnim izborom, ampak celotnemu razvoju odločitev agentov. Pri tem še analiziram, kakšna je konsistentnost izbire posameznih agentov. Pokaže se, da so zaupljivi agenti zelo konsistentni pri svojih izbirah, medtem ko nezaupljivi agenti niso.

V zadnjem delu šestega poglavja analiziram učinek enkratnega šoka na odločitve agentov. Pokaže se, da ima šok zelo velik kratkoročni učinek na odločitve zaupljivih agentov in se pokaže z zamikom enega časovnega obdobja po nastanku. Sam učinek šoka nato traja več obdobj, šele čez čas pa pride do postopnega umirjanja in vrnitve na stanje pred nastopom šoka. Po pričakovanju je učinek šoka bistveno bolj opazen takrat, ko manj agentov poseduje alternativo, ki je bila prizadeta s šokom. Nezaupljivi agenti šoka ne zaznajo.

3.2 Igre mnogoterih vrednostnih papirjev

Igre dveh vrednostnih papirjev predstavljajo ogromno poenostavitev problema, s katerim se agenti srečujejo v dejanskem svetu. Obstoj mnogo različnih vrst premoženja na različnih trgih daje agentom izjemno število možnosti za oblikovanje različnih portfeljev. Na primer, borzni indeks Dow Jones sestavlja 30 delnic, Standard&Poors500 je indeks 500 delnic, medtem ko NASDAQ vsebuje več kot 3800 delnic. V večini držav sveta obstajajo borze vrednostnih papirjev, poleg tega obstajajo še trgi valut, obveznic in drugih vrst dolga, blaga, izvedenih finančnih instrumentov in drugi trgi.

V kolikor si agenti izmed n vrednostnih papirjev, ki so jim na voljo, oblikujejo portfelj iz enakih delov i vrednostnih papirjev, potem si lahko oblikujejo $K(n) = \sum_{i=1}^n \binom{n}{i} = 2^n - 1$

različnih portfeljev. Na tak način obstoj dveh vrednostnih papirjev daje možnost oblikovanja treh portfeljev, treh vrednostnih papirjev 7 različnih portfeljev, pet vrednostnih papirjev 31 portfeljev in tako naprej. 32.767 različnih portfeljev je mogoče oblikovati, kadar je na trgu prisotnih 15 različnih vrednostnih papirjev. Število portfeljev narašča s faktorjem $2 + 1$. V dejanskem svetu se število možnosti približuje neskončno, saj si lahko agenti oblikujejo portfelje iz različnih deležev posameznih enot premoženja. V nadaljevanju analiziram stanje, kjer je $n = 5$.

V prvih igrah uporabim časovni interval, ki ne vsebuje kakšnega posebnega trenda. Skladno z rezultati lahko potrdim veljavnost hipoteze o učinkoviti meji, pri čemer se še izkaže, da so agenti pri svojih odločitvah zelo nenaklonjeni tveganim portfeljem. Izbrani portfelji so namreč zelo nakopičeni okrog učinkovite meje in okolice točke bifurkacije. Podrobnejši rezultati so navedeni v Tabeli 2, iz katere še izhaja, da so izbire zaupljivih agentov zelo skoncentrirane okrog majhnega števila t. i. zmagovalnih portfeljev, kar še posebej velja za njihove končne odločitve.

Tabela 2: Pregled rezultatov

	Zaupljivi agenti		Nezaupljivi agenti	
	Povprečne	Končne	Povprečne	Končne
Delež agentov				
Top 5 (%)	84.75	86.40	36.41	41.60
1. decil (št./31)	24/31	25/31	10/31	11/31
Tehtana beta	0.459	0.467	0.731	0.778
Top 5	0.396	0.419	0.451	0.637
Najslabših 10	1.450	1.424	1.391	1.280
Lambda	1.826	2.030	0.838	0.945

Opomba: za posamezne portfelje so koeficienti beta izračunani kot $\beta_i = \frac{\sigma_i}{\sigma_M} \rho_{i,M}$, pri čemer

$\rho_{i,M}$ označuje korelacijo portfelja i s tržnim portfeljem. V modelu predstavlja portfelj S31 tržni portfelj, saj pomeni najvišjo možno mero diversifikacije. Ker S31 predstavlja tržni portfelj, njegova varianca predstavlja tržno tveganje σ_M . β koeficient portfelja i izračunamo preko metode OLS, pri čemer uporabimo sledečo enačbo: $R_{i,t} = \alpha_i + \beta_i R_{M,t} + \varepsilon_{i,t}$, kjer je $E(\varepsilon_{i,t}) = 0$ in $Var(\varepsilon_{i,t}) = \sigma_i^2$. Ko imamo ocenjene beta koeficiente za posamezne

portfelje, izračunamo vrednost tehtanega beta koeficienta kot $\bar{\beta}_W = \frac{1}{N} \sum_{i=1}^N \beta_i h_i$, pri čemer h_i predstavlja delež agentov s posameznim portfeljem i in kjer je $\sum_{i=1}^N h_i = 1$. Za izračun tehtane

bête podvzorca, kjer velja $\sum_{i=1}^N h_i \neq \sum_{i=1}^N q_i$, je treba delež izbranih portfeljev, za katere

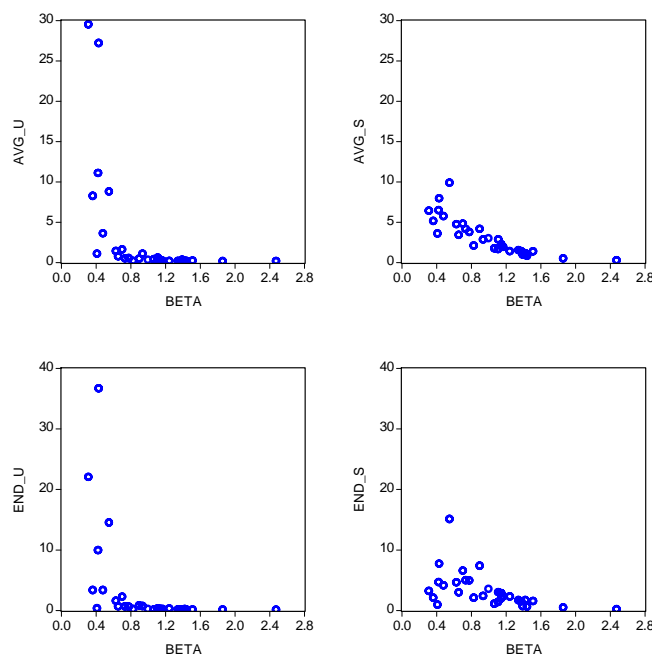
ocenjujemo vrednost beta normalizirati na zahtevani pogoj $\sum_{i=1}^N h_i = 1$.

V kolikor x predstavlja naključno spremenljivko in λ pozitivno konstanto, potem je porazdelitev slučajne spremenljivke potenčna, če in samo če je njena verjetnostna funkcija porazdelitve oblike $f(x) \propto x^{-\lambda}$.

Vrednost koeficienta lambda se nanaša na koeficient potenčne porazdelitve (ang. *power law*). V kolikor velja $\lambda > 1$, govorimo o konceptu "bogati postajajo bogatejši." Porazdelitev slučajne spremenljivke je potenčna, v kolikor pogostost pojava upada skladno z obratno potenčno stopnjo, medtem ko se velikost pojava povišuje. Oziroma, ko vrednost, ki jo nekdo ima, raste z vrednostjo, ki jo je predhodno že imel (Lotka 1926, Simon 1955b). V disertaciji je lambda uporabljena za rangiranje izbranih portfeljev in kaže raven sinhronizacije izbranih portfeljev. Vrednosti potenčnih eksponentov so izračunane z uporabo metode OLS.

Podrobnejši rezultati so prikazani na Sliki 2, ki prikazuje deleže agentov z izbranimi portfelji (Y-os) glede na vrednosti beta koeficientov portfeljev (X-os). Sliki na levi (desni) strani se nanašata na zaupljive (nezaupljive) agente, zgornji (spodnji) sliki pa na povprečne povprečne (končne) odločitve 30 med seboj neodvisnih ponovitev iger.

Slika 2: Razsevni diagrami odločitev agentov glede na beta vrednosti portfeljev



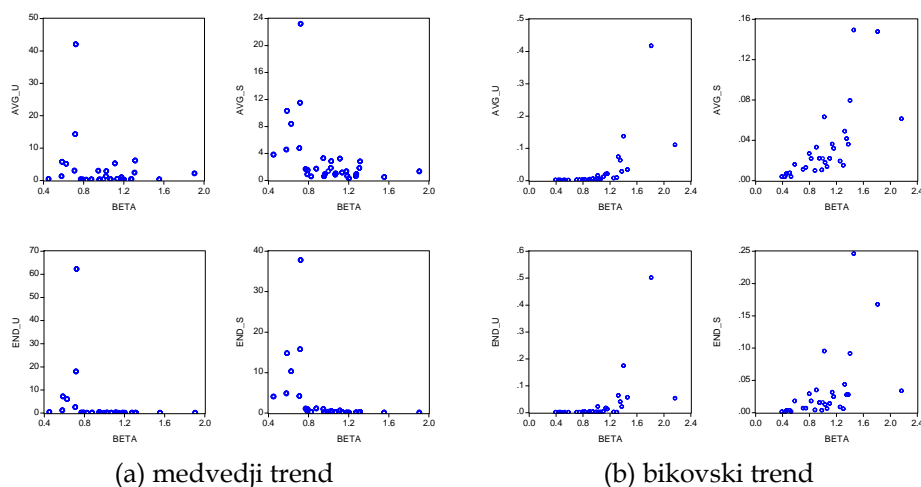
Skladno z rezultati lahko združimo odločitve agentov v tri sklope: prvi sklop sestavljajo portfelji, ki jih izbere več kot 5% agentov, drugi sklop sestavljajo portfelji, ki jih izbere med 1.5% in 5% agentov, tretji sklop pa sestavljajo portfelji, ki jih izbere manj kot 1.5% agentov. To so praviloma portfelji, ki jih posedujejo zgolj likvidnostni agenti. V prvem sklopu najpogostejše izbranih portfeljev so portfelji iz učinkovite meje. Izbrane skupine so negativno korelirane z varianco portfeljev. V okolju zaupljivih agentov je prehod iz skupine najbolj zaželenih portfeljev v skupino najmanj zaželenih portfeljev zelo oster, medtem ko je pri nezaupljivih agentih mnogo bolj postopen. Skladno z vrednostmi lambda je očitno, da pri nezaupljivih agentih ne pride do sinhronizacije odločitev, medtem ko pri zaupljivih agentih pride do aplikacije koncepta "zmagovalec pobere vse."

Za analizo konsistentnosti uporabim dve metodi: koeficient variacije in metodo Monte Carlo. Izkaže se, da so najbolj konsistentno izbrani portfelji tisti, ki se nahajajo na učinkoviti meji in tisti, ki so bili najmanj zaželeni portfelji. V obeh primerih gre za t. i. zmagovalce in poražence, torej portfelje, ki so si jih agenti konsistentno izbirali in tiste, ki so se jim agenti konsistentno izogibali.

3.3 Bikovski in medvedji trend

Četudi se je pokazalo, da agenti preferirajo manj tvegane portfelje, pa se postavlja vprašanje, kako posamezni trendi vplivajo na njihove odločitve. Kahneman in Tversky (1979) sta v svojem prispevku o teoriji obetov pokazala, da je odnos ljudi do sprejemanja tveganih odločitev odvisen od tega, ali gre za negativne ali pozitivne obete. Skladno s to intuicijo je moj naslednji cilj testirati hipotezo, da so v obdobjih naraščajočih cen vrednostnih papirjev agenti pripravljeni sprejemati bolj tvegane portfelje kot pa v obdobjih medvedjega trenda. Vprašanje bistveno presega sporočilnost variance kot mere za tveganje, kajti v bikovskem trendu se varianca nanaša na variranje cen v trendu naraščajočih cen, medtem ko se v medvedjem trendu nanaša na variranje cen v obdobju padajočih cen.

Slika 3: Razsevni diagrami odločitev agentov glede na beta vrednosti portfeljev v medvedjem in bikovskem trendu



Rezultati so prikazani na Sliki 3, ki prikazuje deleže agentov z izbranimi portfelji (Y-os) glede na vrednosti beta koeficientov portfeljev (X-os), in Tabeli 3. V obeh primerih se slike, ki se nahajajo na levi (desni) strani, nanašajo na zaupljive (nezaupljive) agente, medtem ko se slike, ki se nahajajo zgoraj (spodaj) nanašajo na povprečne (končne) igre.

Tabela 3: Pregledna tabela rezultatov v medvedjem in bikovskem trendu

	Zaupljivi agenti		Nezaupljivi agenti	
	Povprečne	Končne	Povprečne	Končne
Medvedji trend				
Delež agentov				
Top 5 (%)	73.23	95.67	57.90	83.35
1. decil (št./31)	21/31	28/31	13/31	25/31
Tehtana beta	0.842	0.714	0.808	0.696
Top 5	0.789	0.706	0.684	0.679
Najslabših 10	1.487	1.160	1.088	1.257
Lambda	1.672	2.017	1.885	2.037
Bikovski trend				
Delež agentov				
Top 5 (%)	80.00	84.83	50.01	64.38
1. decil (št./31)	23/31	25/31	12/31	17/31
Tehtana beta	1.600	1.610	1.317	1.346
Top 5	1.712	1.692	1.587	1.471
Najslabših 10	0.600	0.674	0.677	0.841
Lambda	1.820	2.088	1.077	1.883

Rezultati simulacij potrjujejo testirano hipotezo, da se agenti v času rasti borznih tečajev vedejo drugače, kot pa v primeru njihovega padanja in da so v primeru bikovskega trenda

pripravljeni prevzeti več tveganja. V medvedjem trendu so tehtane vrednosti beta koeficientov mnogo nižje od tistih v bikovskem trendu. Povprečne vrednosti koeficienta, višje od ena, povedo, da so agenti pogosteje izbirali nadpovprečno tvegane portfelje. V medvedjem trendu so odločitve agentov nekoliko bolj sinhronizirane kot pa v bikovskem. V obeh primerih so agenti zelo konsistentni pri svojih odločitvah, kar je, glede na visoko stopnjo sinhronizacije, skladno s pričakovanji. Koncentracija odločitev je še posebej opazna v končnih odločitvah medvedjega trenda, kjer so samo štirje od 31ih portfeljev končali z več kot 5% zaupljivimi agenti. Ti portfelji so S3 (62.19%), S10 (17.90%), S14 (7.14%) in S23 (5.97%). Med ostalimi pa samo S2 (2.47%) in S12 (1.11%) nista končala pri likvidnostnih agentih. Četudi nezaupljivi agenti svojih izbir niso koncentrirali v tolikšni meri kot zaupljivi agenti, pa so kljub temu bili v veliki meri sposobni identificirati iste zmagovalce kot zaupljivi agenti.

Ponovno se je pokazalo, da so bili med vsemi portfelji najpogosteje izbrani portfelji iz učinkovite meje oziroma iz njene bližnje okolice. Poleg tega je v medvedjem trendu opazna privlačnost portfeljev S13 in S22, ki ne ležita na učinkoviti meji, ampak na notranjem delu namišljene hiperbole. Njun izbor lahko pojasnimo preko pojava t. i. iskanja tveganja, kadar so obeti negativni, kot pojasni Markowitz (1952b). To pomeni, da posamezni agenti skušajo doseči višje donose z uporabo tveganja.

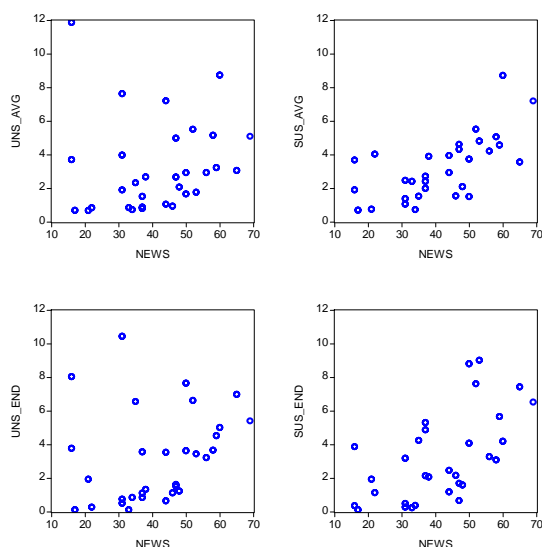
Testi konsistentnosti pokažejo, da so bili najbolj konsistentno izbrani bodisi najbolj zaželeni portfelji bodisi najmanj zaželeni portfelji. Med vsemi so bili najmanj konsistentno izbrani tisti portfelji, pri katerih imetja se med povprečnimi in končnimi igrami bistveno razlikujejo. Najmanj konsistentno izbrani portfelji pa so bili bodisi tisti, ki niso končali samo pri likvidnostnih agentih, bodisi tisti, ki med preostalimi niso bili posebej zaželeni. Če primerjamo obe skupini agentov, vidimo, da so zaupljivi agenti mnogo bolj konsistentni pri svojih odločitvah, kot nezaupljivi agenti. Vedenje agentov je bilo bolj konsistentno v medvedjem trendu.

3.4 Model z novicami

Nazadnje simuliram še model, kjer se agenti ne odločajo samo na podlagi objavljenih donosov delnic, kot v predhodnih simulacijah, ampak tudi na podlagi objavljenih novic. Gre za *ceteris paribus* nadgradnjo simulacij iz poglavja 6, z razliko, da tukaj vključim še novice kot dodatno spremenljivko.

V modelu z novicami se postopek izbire od osnovnega modela razlikuje le v tem, da agenta med seboj ne primerjata le donosov, ampak tudi novice. Pri tem velja pravilo, da agent vedno izbere portfelj, za katerega je objavljena boljša novica. V kolikor za nek portfelj ni objave novic, potem je vrednost novice postavljena na nič. Izmed dveh primerjanih portfeljev agenti vedno izberejo tistega, za katerega je objavljena boljša novica. Zaželenost portfeljev pa ni odvisna samo od objavljenih novic, ampak tudi od vsakokratnih donosov. Četudi lahko objava večjega števila pozitivnih novic poveča privlačnost posameznih portfeljev, pa se lahko agenti distancirajo od portfeljev, katerih donosi v času niso ustrezno visoki. To še posebej velja v luči prevelikega ali premajhnega odziva na objavljene novice, ki se tudi na borznem trgu kaže preko dinamike cen.

Slika 4: Razsevni diagrami izbranih portfeljev glede na število objavljenih novic za posamezni portfelj



Ker novice pomenijo prenos informacij do agentov, MacKinlay (1997) poudari, da je učinek objave na ceno delnic odvisen od jakosti nepričakovane komponente novic. Vključitev novic privede do dveh skupin "zmagovalnih" portfeljev: prvo sestavljajo portfelji iz učinkovite meje, drugo pa portfelji z največjim številom objavljenih novic (Slika 4). Sliki na levi (desni) strani se nanašata na zaupljive (nezaupljive) agente, zgornji (spodnji) sliki pa na povprečne povprečne (končne) odločitve 30ih med seboj neodvisnih ponovitev iger.

Tabela 4: Pregledna tabela rezultatov v modelu z novicami

	Zaupljivi agenti		Nezaupljivi agenti	
	Povprečne	Končne	Povprečne	Končne
Delež agentov				
Top 5 (%)	40.90	39.70	31.30	39.40
1. decil (št./31)	11/31	13/31	9/31	12/31
Tehtana beta	0.882	0.874	1.070	1.080
Top 5	0.597	0.784	1.074	1.223
Najslabših 10	1.246	1.139	0.800	0.969
Lambda	0.910	1.150	0.670	1.110

V nasprotju s predhodnimi simulacijami pa v modelu z novicami ne pride do sinhronizacije odločitev (Tabela 4). To še posebej velja za povprečne odločitve nezaupljivih in zaupljivih agentov; v obeh primerih je $\lambda < 1$.

5 ZAKLJUČEK

Vprašanje, s katerim se na finančnih trgih srečujejo investitorji in ga tudi rešujejo, je, kako na učinkovit način upravljati s premoženjem. V tem procesu pomeni izbor portfelja izbiro med mnogimi stohastičnimi alternativami, ki so posameznim agentom na voljo v času. Disertacija je ilustracija vedenjske dinamične igre sočasnih potez igralcev v negotovem svetu trgov

kapitala. Model predstavlja aplikacijo socialnih omrežij v ekonomiji in vsebuje agente in njihove preference, vrednostne funkcije, povezave med agenti in nabor akcij za posameznega agenta. V modelu se vedenjske finance nanašajo na psihologijo izbora agentov. V igrah uporabim tako zaupljive, kot tudi nezaupljive agente.

Osrednji motiv disertacije je skušati razumeti, na kakšen način zaupljivi in do neke mere nezaupljivi agenti, ki se nahajajo v medsebojni interakciji, pod različnimi okoliščinami izbirajo svoje portfelje v razmerah negotovih cen vrednostnih papirjev. Temeljna metodološka značilnost disertacije je ta, da interakcija med agenti privede do kompleksnega vedenja celotne skupine, ki ga brez uporabe pristopa, ki vključuje interakcijo med agenti, ni mogoče pojasniti.

V prvem delu simulacij pokažem, na kakšen način donosi in raven tveganja posameznih portfeljev vplivajo na njihov izbor v preprosti igri z dvema vrednostnima papirjema. Simulacije izvedem v dveh različnih okoliščinah: najprej z netveganim in tveganim vrednostnim papirjem, nato še z dvema tveganimi vrednostnima papirjema. Rezultati pokažejo, pod katerimi okoliščinami se agenti odločijo za mešane portfelje tvegane in netvegane vrednostnega papirja. Simulacije še pokažejo, da je za nemoten potek izbora nujno potrebno zagotavljanje likvidnosti. Vključitev šoka v proces izbora pokaže, da v kolikor jakost šoka ni premočna, je njegov učinek zgolj kratkoročen.

V drugem delu razširim osnovni okvir in se lotim iger z mnogoterimi alternativami. Četudi imajo agenti v modelu omejeno vedenje o donosih vrednostnih papirjev, svoje portfelje pa izbirajo na podlagi realiziranih donosov, pa so portfelje kljub temu sposobni izbrati skladno s hipotezo učinkovite meje. Nekoliko bolj razpršeni izbor nezaupljivih agentov je posledica njihove nezmožnosti igranja načela "zmagovalec pobere vse," četudi so sposobni identificirati iste "zmagovalce" kot zaupljivi agenti. Omenjena ugotovitev je podprta tako v bikovskem kot tudi medvedjem trendu, četudi v bikovskem trendu agenti prevzemajo več tveganja, kar je skladno s teoretičnimi predvidevanji. Agenti ne preferirajo preveč razpršenih portfeljev, ampak portfelje dveh vrednostnih papirjev, ki so zgrajeni okrog najbolj zaželenega posamičnega vrednostnega papirja. Testi konsistentnosti, opravljeni s pomočjo koficienta variacije in metode Monte Carlo, pokažejo, da so najbolj konsistentno izbrani bodisi najbolj bodisi najmanj zaželeni portfelji. Ti testi še pokažejo, da so zaupljivi agenti bolj konsistentni pri svojih odločitvah kot nezaupljivi agenti. Simulacije z novicami so navrgle dve skupini zmagovalnih portfeljev: portfelje iz učinkovite meje oz. iz njene okolice, in diverzificirane portfelje, katerih izbor je pozitivno koreliran s številom objavljenih nenegativnih novic.