The Aging Investor: Insights from Neuroeconomics

Peter N. C. Mohr*
Hauke R. Heekeren*

BERLIN

ECONOMIC RISK

SFB 649

* Psychology of Emotion and Affective Neuroscience,
Freie Universität Berlin

The Aging Investor: Insights from Neuroeconomics

Peter N. C. Mohr[1]   **Hauke R. Heekeren**[1]

[1]Psychology of Emotion and Affective Neuroscience, Freie Universität Berlin

May 21, 2012

Abstract

Individuals in most industrialized countries have to make investment decisions throughout their adult life span to save for their retirement. These decisions substantially affect their living standards in old age. Research on cognitive aging has already demonstrated several changes in cognitive functions (e.g., processing speed) that likely influence investment decisions. This review brings together research on behavioral and neural aspects of financial decision making and aging to advance knowledge on age-related changes in financial decision making. The dopaminergic system plays a key role in financial decision making, both in financial decisions from description and financial decisions from experience. Importantly, both dopaminergic neuromodulation and financial decision making change during healthy aging. Especially when the parameters of the return distribution have to be learned from experience, older adults show a different and suboptimal choice behavior compared to younger adults. Based on these observations we suggest ways to circumvent the age-related bias in financial decision making to improve older adults' wealth.

Corresponding author:
Peter N. C. Mohr
Psychology of Emotion and Affective Neuroscience
Freie Universität Berlin
Habelschwerdter Allee 45, 14195 Berlin, Germany
peter.mohr@decision-neuroscience.eu

1 Introduction

In our everyday life we often have to make investment decisions. Especially retirement saving decisions have become more and more important in developed countries over the last years. Due to demographic changes the public pension systems are usually no longer able to ensure the living standard for older adults. Therefore everybody is recommended to invest in private retirement plans. Although we have to make investment decisions throughout our life and although these decisions can have important consequences (e.g., they can affect the living standard in old age) it is still not fully understood how individuals make investment decisions. It further remains unclear how investment decisions might change across the lifespan, influencing especially retirement saving decisions.

Theories of lifespan development posit that the gain-loss dynamics of fundamental developmental resources (e.g., cognitive, emotional, social, and financial resources) vary dynamically across the lifespan (Baltes et al. (1999), Carstensen (1995)). Individuals thus need to adaptively regulate their behaviors and actions throughout life for optimal development. During the process of aging, losses in different types of developmental resources gradually outweigh gains. For instance, the age-related decline of various cognitive processes underlying fluid intelligence has a steeper slope than the growth of crystallized intelligence over the same period (Li et al. (2004)). Fluid intelligence is the abilitry to think logically and solve problems in novel situations, independent of acquired knowledge. Crystallized intelligence is one's lifetime or intellectual achievement, as demonstrated largely through one's vocabulary and general knowledge. To age successfully it is therefore of particular importance for individuals in midlife and old age to adjust their preferences, decision strategies, and behaviors in different domains of life, including economical and financial practices,.

Traditional research on financial decision making (FDM) focused on observable choice behavior thereby neglecting the underlying processes. Technological and conceptual advances in the last two decades offered new methods to investigate these underlying processes. Especially, the advancement of functional magnetic resonance imaging (fMRI) offered a new tool that contributed significantly to the understanding of human cognition. The new field of neuroeconomics uses neuroscientific methods and

psychological concepts to investigate the underlying processes of economically relevant behavior, including risk processing and decision making under risk.

The aim of this review is to bring together research on behavioral and neural aspects of FDM and research on cognitive aging to advance knowledge on age-related changes in FDM. The remainder of this article is structured as follows: In the next section we begin with the behavioral basis of FDM followed by a section on age-related changes in FDM across the adult life span. In the following section we derive why and under which circumstances neuroeconomics can provide valuable new insights for research in business administration and economics. Afterwards we review in two sections the state of the art of the neural basis of FDM and age-related differences, respectively. We conclude with a section on implications for the practice and an outlook for future research.

2   Behavioral basis of FDM

The dominant model in FDM is the so-called Mean-Variance Model (MVM). The MVM is based on the idea of a risk premium (Markowitz (1952)). To be equally attractive, a risky investment (e.g., a stock) has to offer a higher expected value compared to a safe investment (e.g., a bond).

$$SV(X) = EV(x) - b \cdot V(x) \qquad (1)$$

The MVM proposes that the subjective value (SV) of a choice option is determined by the expected value of possible outcomes (EV) minus its standard deviation (SD) (or variance) linearly weighted with a factor b. This factor represents the risk attitude in the MVM and determines the risk premium. If b is positive, risk (measured as the SD) reduces the SV of a choice option and the individual is characterized as risk averse. Similarly, individuals can be described as risk neutral if b is equal to zero and as risk seeking if b is negative.

The MVM is highly related to Expected Utility Theory (EUT) and is therefore also regarded as a normative model of decision making under risk. For the special case of quadratic utility functions it can be shown analytically that the expected utility of a choice option can be re-described in the form of the MVM (d'Acremont/Bossaerts

(2008)). Furthermore, utility functions can be approximated by means of a second-order Taylor series expansion, that is the sum of an infinite number of statistical moments (e.g., expected value, variance, skewness, etc.) of the utility function (d'Acremont/Bossaerts (2008)). Taking the first two statistical moments (expected value and variance) results in a formulation of expected utility that is similar to the MVM.

The MVM belongs to the broader class of risk-return models that follow the intuitively appealing idea to trade off risk and return, reflecting positive and negative characteristics of the investment. Based on findings that perceived risk often does not simply correspond to the variance the psychological Risk-Return Model (PRRM) defines risk and return as subject-related variables (Weber/Johnson (2009a), Weber/Johnson (2009b)).

$$SV(X) = SER(x) - b \cdot PR(x) \qquad (2)$$

In the PRRM the SV of a choice option is defined by the difference between subjective expected return (SER) and weighted perceived risk (PR). Similar to the MVM the trade-off factor b reflects the risk attitude of the individual (in this case perceived risk attitude). Whereas observed risk attitudes are highly dependent on situational and contextual factors in EUT and MVM, perceived risk attitudes are constant within individuals for certain choice domains (Weber, et al., 2002; Weber & Milliman, 1997). In contrast, SER and PR are assumed to be prone to situational and contextual influences.

But not only these factors might influence perceptions of risk and return. In real-life investment decisions the return distribution is often unknown. (Subjective) Expected return and (perceived) risk can thus only be estimated from past performance data, assuming the past performance of the investment reflects the full return distribution. Another way to estimate expected return and risk is to update and learn them over time based on observed returns. Importantly recent research has shown, that decision making from description (i.e., based on a known return distribution) and decision making from experience (i.e., based on learned parameters of the return distribution) can differ significantly (Hertwig/Erev (2009), for review).

During decision making from experience, individuals learn and update expected return and risk based on their actual experiences (i.e., the returns they get). The learning and updating process can be described by reinforcement learning models (Rescorla/Wagner (1972)). Such a model generally assumes that after the decision has been made for one investment, a received return R(t) at time t is compared to the expected value of the investment's return EV(t), with the deviation d formalized as prediction error PE: $d(t) = R(t) - ER(t)$.

$$EV(t) = EV(t-1) + \alpha \cdot d(t-1) \qquad\qquad (3)$$

A reinforcement learning model assumes that learning is driven by these deviations; hence, a PE is used to update EV(t), allowing the optimization of reward predictions. A similar updating process was recently proposed for risk, also based on prediction errors (Preuschoff et al. (2008)). The so-called risk prediction error is defined as the deviation between the squared prediction error and the actual risk prediction.

3   Age-related differences in FDM

Economic preferences are usually quite stable in the short term. If you actually prefer, for example, an investment that offers a low expected return with low risk (e.g. a bond) over an investment that offers a high expected return with a high risk (e.g. a stock option), your preference will likely also hold next week or in a few months. It is, however, assumed that preferences change over the long run, that is, over the adult lifespan (Rogers (1994), Trostel/Taylor (2001)). Your actual preference for the first investment might thus change in five or ten years. Economic preferences are also influenced by situational, environmental, and biological factors. A new mother will likely have different preferences than she had a few years earlier. Similarly, a newly retired man may also have different financial considerations than before the retirement. Age is a descriptive variable for many changes that might cause changes in decision making in general and specifically in FDM over the adult life span.

One study that used data from a large representative sample found that age has a significant effect on the general willingness to take risks (Dohmen et al. (2011)). The applied scale was experimentally validated in a smaller sample. The general willingness

to take risks predicted actual choice behavior in a lottery game where subjects repeatedly had to choose between fixed outcomes and risky lotteries. Thus, the authors conclude that individuals get more risk averse over the adult lifespan.

Experimental studies on age-related differences in investment decisions can be broadly characterized by the two forms of decision making, namely decision making from description and decision making from experience.

Studies in which the parameters of the return distribution have to be learned (i.e. decision making from description) usually applied the Iowa Gambling Task (IGT) (Bechara et al. (1997)). In the IGT subjects have to choose repeatedly between four decks of cards without any knowledge about possible outcomes (i.e., reward magnitude and probability). Two of these card decks are "bad decks" and result on average in a loss. The other two decks ("good decks") have a positive expected return. The typical choice pattern of the IGT is to start with the bad decks, which have higher gains but also much higher losses compared to the good decks, and then switch to the good decks.

In one study that used the IGT, both younger and older subjects started with the typical pattern to choose the bad decks (Denburg et al. (2005)). Whereas the younger subjects then usually shifted towards the good decks, the older subjects did not demonstrate this shift, staying with the bad card decks. Obviously, they failed to correctly learn the expected return and variance of the card decks thereby showing an impaired ability to identify favorable choice alternatives in the long run. Two other studies also found that older adults perform less advantageously in the IGT compared to younger adults (Fein et al. (2007), Zamarian et al. (2008)). Zamarian et al. (2008) compared the performance of younger and older adults in the IGT with their performance in another task that, in contrast to the IGT, provides the subjects with full information about the return distribution (i.e. probabilities and magnitudes). As in other studies, older adults showed an impaired performance in the IGT compared to younger adults. In contrast, older adults showed similar choice behavior compared with younger adults in the other task, demonstrating their ability to make favorable decisions in decision making from description.

The observation that older adults have problems in decisions from experience but make similar choices in decisions from description was recently confirmed by an experimental study (Figner et al. (2009)) and a meta analysis (Mata et al. (2011)).

Importantly, it is not the risk attitude of individuals that changes with age, but their ability to learn relevant parameters of the return distribution. If learning lead to a greater number of risky choices, older individuals showed more risk averse behavior than younger adults. In contrast, if learning lead to risk avoidance behavior, older adults made more risky choices compared with younger adults.

4   Why Neuroeconomics?

Neuroeconomics seeks to integrate ideas from different disciplines that investigate decision making in general, namely economics, business administration, psychology and neuroscience (Kenning/Plassmann (2005), Sanfey et al. (2006)). In fact, neuroeconomics emerged when two lines of research met, that followed already interdisciplinary ideas – behavioral economics and cognitive neuroscience (Glimcher et al. (2009)). Behavioral economics aims to integrate ideas from psychology, business administration, and economics to provide a better understanding of economic behavior. Cognitive neuroscience, in contrast, aims to integrate ideas from psychology and neuroscience to investigate the biological substrates of cognition. Neuroeconomics consequently tries to ground economic behavior in neural mechanisms thereby gaining insights on the processes underlying economic decision making (Camerer (2007)). It can therefore be seen as a subfield of both behavioral economics and cognitive neuroscience. These two, however, constitute two different views on neuroeconomics. Behavioral economics aims to use neuroscientific methods as a tool to both test economic models of decision making and develop alternatives to classical revealed preference models (e.g., Expected Utilty Theory). Cognitive neuroscience in contrast uses economic models as a tool to test and develop algorithmic models of the neural hardware of choice.

But whereas the neuroeconomics approach, that is, investigating the neural processes underlying economic behavior, is widely accepted in psychology and neuroscience, it is met with more skepticism in economics and business administration and received substantial criticism especially from economics scholars (Gul/Pesendorfer (2008)). The main argument of these scholars is that evidence from neuroscience cannot falsify economic theories as they make no claims regarding the psychological and neurological processes involved in economic decision making. Following this argument

behavioral data are both necessary and sufficient to evaluate the validity of economic models. This is obviously correct, as economic models usually make "as if" statements. EUT for example proposes that individuals behave "as if" they would maximize their expected utility, implying that they behave "as if" a metric like utility would actually exist. The weakness of this argument is, however, that a variety of studies already provided behavioral data that questioned the predictive power of EUT (e.g., Allais (1953), Birnbaum (2008)).

The goal of neuroeconomics is, thus, not to falsify any model of individual decision making, as this has in most cases already been done (Clithero et al. (2008)). The role of neuroeconomics in decision sciences lies mostly in its potential to guide and constrain the development of new hypotheses and models. Without this guidance and these constraints, research has to test in its extreme all plausible influencing factors on economic decision making to form the basis for a comprehensive model. This is of course highly impractical. No collection of researchers can obtain all possible data about all possible behaviors. An understanding of the neural processes underlying economic decision making can indicate which possible factors are more likely and which are less likely to influence economic behavior. Neural and behavioral studies should interact to identify interesting phenomena, to suggest mechanisms that underlie those phenomena, and to map out the biological substrates that support those mechanisms.

Aside from generating new hypotheses neurobiological data can also introduce constraints. Psychological research has already turned to focus not only on predicting and explaining choices, that is, the outcome of a decision process, but tries to develop process models that include testable hypotheses regarding the underlying processes of decision making (e.g., Weber/Johnson (2009a), for review). By virtue of hypothesizing a series of psychological processes that precede decisions, process models make predictions about intermediate states of the decision maker, between the beginning and the end of the decision. Process models can, thus, improve model selection because they consider more variables and add multiple constraints. Following the same logic the neuroeconomics approach can add neurobiological constraints to models of decision making. In addition, neurobiological data can serve to test the biological plausibility of these models.

With respect to the relatively new field of research on age-related changes in economic decision making neuroeconomics can serve both functions, the generation of new hypotheses on age-related differences in choice behavior and a differential evaluation of the biological plausibility of assumed choice mechanisms.

5   Neural Basis of FDM

Economic decision making in general is heavily influenced by the modulation of different neurotransmitter systems (Doya (2008), for review). Neurotransmitters are chemicals that are used to relay, amplify, and modulate signals between neurons. Neural representations of reward and prediction error rely on the neurotransmitter dopamine. Research in monkeys demonstrated that the majority of midbrain dopamine neurons (75-80%) show rather homogeneous, phasic activations to unpredicted rewards (Schultz (2009)). The neuronal response thereby depends on the magnitude of the delivered reward (Tobler et al. (2005)). But when the monkeys have to learn stimulus reward associations, the dopamine response to the reward decreases gradually, and a response to the reward-predicting stimulus is observable. At the time of reward delivery dopamine no longer codes for the reward itself. In contrast, the dopamine response correlates with the prediction error, as modeled in reinforcement learning models (Schultz et al. (1997)). Similarly, activations of midbrain dopamine neurons shift from the time of reward delivery to the onset of the reward-predicting stimulus when the probability of being rewarded increases (Fiorillo et al. (2003)). But dopamine not only codes for reward delivery and prediction error, there is also a direct link between risk and dopamine release (Fiorillo et al. (2003), St Onge/Floresco (2009)). A substantial amount of midbrain dopamine neurons (ca. 1/3) in monkeys show a relatively slow, moderate activation that increases gradually between the reward-predicting stimulus and reward. This increase depends on the actual level of risk, demonstrating a relationship between dopaminergic neuromodulation and risk.

Due to ethical considerations it is not possible to investigate the relationship between the activity of dopamine neurons and investment behavior directly in humans. Several studies investigated, however, the effect of different genotypes, known to affect dopaminergic neuromodulation, on finacial decision making. These studies could

demonstrate an effect of dopamine on risk-taking behavior and the flexible learning of stimulus-reward associations (Krugel et al. (2009), Kuhnen/Chiao (2009)).

Several studies have also investigated the neural foundations of financial decision making in humans by using fMRI. The results of these studies reveal that both financial decision making from description and experience are highly complex processes that (a) are influenced by several factors and (b) recruit a network of different brain regions. Studies using simple gambles with discrete outcome distributions usually identified representations of reward magnitude and probability in ventral striatum (VST), ventromedial prefrontal cortex (VMPFC), and ventrolateral prefrontal cortex (VLPFC), brain regions heavily influenced by dopamine neurotransmission (Knutson et al. (2001), Knutson et al. (2005), Tobler et al. (2007)). Both reward magnitude and probability were, however, found to be nonlinearly represented in the VST. The decrease of ventral striatal activity for losses is steeper than the increase in activity for gains, reflecting loss aversion (Tom et al. (2007)). In addition probability-related activity in the VST follows an S-shaped function, overweighting probabilities near zero and underweighting probabilities near one (Hsu et al. (2009)).

Similar to their role in the processing of reward magnitude and probability, VST, VMPFC, and VLPFC were also found to code the expected and subjective value of simple gambles (Tobler et al. (2007), Tom et al. (2007), Rangel et al. (2008)). In addition to VST, VMPFC, and VLPFC, also the dorsolateral prefrontal cortex (DLPFC) might play an important role in valuing choice options. Compared with a control condition, application of repetitive transcranial magnetic stimulation (rTMS) to the right DLPFC (i.e. "switching" it off) decreases values assigned to the stimuli (Camus et al. (2009)).

The neural basis of risk was mainly investigated by comparing risky with save situations as well as correlating the fMRI blood oxygen level dependent (BOLD) signal with the degree of riskiness (e.g. measured by the variance of possible outcomes). Studies that followed this approach identified several brain regions as sensitive to the present degree of riskiness. These included the anterior insula (aINS), the VST, the midbrain, the medial prefrontal cortex (MPFC), and the DLPFC (Behrens et al. (2007), Huettel et al. (2005), Kuhnen/Knutson (2005), Preuschoff et al. (2006), Preuschoff et al. (2008), Rolls et al. (2008)). In a recent quantitative meta analysis we found support for

the role of the above mentioned brain regions in risk processing, but also evidence for the implication of the thalamus and the parietal cortex in risk processing (see Figure 1) (Mohr et al. (2010a)). Most importantly this meta analysis showed which brain regions process risk independent of a choice situation (aINS, DMPFC, and thalamus) and which brain regions only process risk if individuals have to make a decision (DLPFC and parietal cortex).
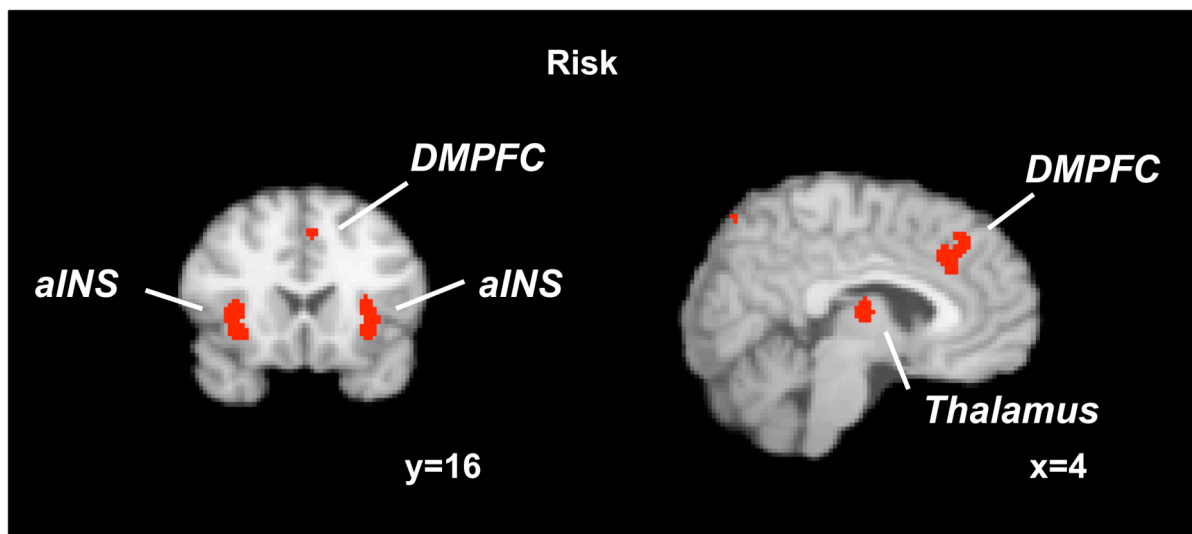

Figure 1. *Neural representations of risk.* Results from an ALE meta-analysis on risk Activated clusters included bilateral aINS, DMPFC, and Thalamus (adapted with permission from Mohr et al. (2010), Copyright *Journal of Neuroscience)*.

Some studies also investigated neural representations of risk and expected value simultaneously. One study found that the variance correlates with brain activity in the aINS and that both expected value and variance correlate with the BOLD signal in the VST (Preuschoff, et al., 2006). The variance-related BOLD response in the VST was, however, one second delayed. Another study that conducted two experiments with simple gambles found that both expected value and variance covary with brain activity in the ventrolateral prefrontal cortex (VLPFC) (Tobler et al. (2009)). All of the above mentioned studies used, however, simple gambles. Only one study so far, tried to mimic real-life financial decisions by using continuous outcome distributions that were described by past performance data (Mohr et al. (2010b)). The authors found

representations of (perceived) risk in the aINS and representations of (subjective) expected return in DLPFC, VLPFC, and DMPFC.

A separate line of research investigated the neural basis of reinforcement learning, thereby primarily focusing on the neural basis of the prediction error (Lee et al. (2012)). Several studies separately found neural representations of the prediction error in the VST (Abler et al. (2006), Li et al. (2006), McClure et al. (2003), Murray et al. (2008), O'Doherty et al. (2003), Rolls et al. (2008), Tobler et al. (2006)). In contrast only one study to date investigated the neural basis of the risk prediction error (Preuschoff et al. (2008)). The authors found that both risk and risk prediction error correlate significantly with the BOLD signal in the aINS.

6   Age-related differences in the neural basis of FDM

During the course of normal aging, dopaminergic systems undergo substantial decline (Mohr et al. (2010c), Brown/Ridderinkhof (2009), Mell et al. (2005), for review). Much of the work on the relationship between aging and dopamine neurotransmission has focused on the caudate and the putamen, two major nuclei in the striatal complex with dense dopaminergic innervation from the substantia nigra. Thus, the conditions for reliable analyses of dopamine biomarkers are particularly favorable in the striatum. There is strong evidence for age-related losses of pre- and postsynaptic biochemical markers of the nigrostriatal dopamine system. Regarding presynaptic mechanisms, both positron emission tomography (PET) and single photon emission computed tomography (SPECT) studies (Erixon-Lindroth et al. (2005), Mozley et al. (2001)) indicate marked age-related losses of the dopamine transporter in the striatum, with the average decline estimated to be 5-10% per decade from early to late adulthood. For postsynaptic mechanisms, molecular imaging work reveals age-related losses of both striatal D1 (Suhara et al. (1991), Wang et al. (1998)) and D2 (Antonini/Leenders (1993)) receptor densities of comparable magnitude, as found for the dopamine transporter.

A similar downward age trajectory is observed for the mesocortical and mesolimbic dopaminergic pathways. Thus, marked age-related losses in D2 receptor binding have been observed throughout the neocortex as well as in the hippocampus, the amygdala,

and the thalamus (Inoue et al. (2001), Kaasinen/Rinne (2002)). The fact that similar age patterns can be observed for the dopamine transporter and postsynaptic markers suggests that the expression of transporters and receptors may reflect adaptation of major components of the dopaminergic pathways. One possibility derived from work on knockout mice is that the loss of the dopamine transporter initially results in increased dopamine concentrations; increased dopamine levels may subsequently lead to down regulation of neurotransmission in postsynaptic neurons (Shinkai et al. (1997), Zhang et al. (1995)).

Various neurocomputational models have been proposed to link aging-related decline in dopaminergic neuromodulation to behaviorally observed cognitive deficits. One of these models relates weakened phasic activity of the mesencephalic dopamine system with aging-related deficits in detecting performance errors (Nieuwenhuis et al. (2002)). Another model focuses on capturing the effect of deficient dopaminergic neuromodulation on compromised prefrontal cortex functions, such as cognitive control (Braver et al. (2001)). A third model captures the effects of deficient neuromodulation on processing variability and the distinctiveness of memory and goal representations in more general terms (Li et al. (2001)).

To date several fMRI studies investigated the neural basis of age-related differences in FDM. The strongest link between age-related differences in behavior and neural processing lies in the domain of decision making from experience. One study used a probabilistic object reversal task, where stimulus-reward associations change after they have been properly learned, thereby mapping changing environments for example on the stock market. Younger participants in their study showed greater responses in the VST to reward cues after stimulus reward associations had been learned than older adults, indicating that younger adults have a clearer representation of the expected reward (Mell et al. (2009)). Another study compared the ability to learn stimulus-reward associations between younger and older adults (Schott et al. (2007)). Whereas young adults showed activations in the VST for stimuli that predicted monetary reward, healthy elderly subjects showed the opposite pattern, with an absent reward prediction response, but with activations to reward feedback itself. These results support behavioral results that indicate that older adults have deficits in learning from feedback in decisions from experience. The authors speculate that this might be caused

by a dopamine-dependent decrease of the signal-to-noise ratio in VST. This notion was supported by a study that found that more accurate representations of the expected value in VST and MPFC were positively correlated with the number of rational choices in an investment task (Samanez-Larkin et al. (2011)).

There is, however, also evidence for a reduced ability to form accurate reward expectations in decisions from description (Samanez-Larkin et al. (2007)). In contrast to learning studies where reward anticipation is generated through the repeated experience of reward, the authors used the monetary incentive delay task (Knutson et al. (2000)), where reward anticipation is induced by variations of the stimulus. The authors found evidence for intact striatal activation during gain anticipation with age, but report a relative reduction in activation during loss anticipation. This supports the finding from behavioral studies that report a reduced experience of negative emotions in older adults (Mather/Carstensen (2005)).

There is not only evidence for age-related changes in reward processing but also initial evidence for changes in brain systems related to risk perception and risk-taking behavior (Lee et al. (2008)). In a simple gambling task, in which subjects had to decide between a risky and a save investment, older adults chose the risky investment significantly less often. But when they chose the risky investment, they had a greater activation in the right insula compared to younger adults. This greater insula activity in older adults was interpreted as indicating that the risky option is perceived as more risky by elderly than by young adults, resulting in an increased avoidance of the risky investment.

In contrast to most studies that focus on the size of stimulus-related changes in the BOLD signal, a recent study investigated the relationship between the variability of the BOLD signal and age-related changes in an investment decision task (Samanez-Larkin et al. (2010)). The hypothesis was that older adults are impaired in decision making under risk because age-related declines in dopamine levels lead to noisier signal processing in the VST (see above) und thus to compromised value estimation during decision making. The authors found that the variability of the BOLD signal in the VST mediates the relationship between age and suboptimal investment decisions. Older adults showed a greater variability of the BOLD signal in the VST and chose the risky investment more frequently when the choice of the safe investment was optimal. These

results demonstrate that not only the size of the BOLD signal but also its variability can influence choice behavior (Mohr/Nagel (2010)).

7   Limitations, implications, and outlook

The dopaminergic system plays a key role in FDM, both in financial decisions from description and financial decisions from experience. Importantly, both dopaminergic neuromodulation and FDM change during healthy aging. Especially when the parameters of the return distribution have to be learned from experience, older adults have shown different choice behavior compared to younger adults. If learning lead to more risky choices, older individuals showed more risk averse behavior than younger adults. In contrast, if learning lead to risk avoidance behavior, older adults made more risky choices compared with younger adults. Given the functional role of dopamine in reinforcement learning, it was hypothesized that age-related changes in financial decision making from experience might be caused by age-related changes in dopaminergic neuromodulation. Support for this hypothesis comes from neuroeconomics studies on age-related changes in decision making from experience that identified differences in brain activity in the VST, a brain region known to be influenced by dopamine.

But dopamine does not only play a role in decision making from experience but also in decision making from description, in which actually no consistent age-related differences were observed. Most studies, however, investigated age-related differences in decision making from description only in the gain domain. Results from studies in the field of neuroeconomics suggest that reward processing in older adults is intact in the gain domain but not in the loss domain. Loss-related activity in the VST differs significantly between younger and older subjects. Consequently, based on these findings one might hypothesize that losses have different impact on perceptions of risk and return in older adults.

The present studies that investigated age-related changes in FDM and associated changes in neural processing, however, face several limitations. First, older individuals are much more willing to participate in experiments if they are highly educated and if their age-related decline in all domains (e.g., working memory) is limited. These individuals usually show only small or no differences compared to younger adults,

which might explain the null findings regarding decision making from description. To ensure the representativeness of the age-specific samples future studies could complement the experiments with questionnaires and psychological tests. Questions from large representative panel studies (e.g., the German Socio-Economic Panel (GSOEP)), for example, offer the opportunity to compare the experimental sample with the panel-sample in key questions related to the research question (e.g., willingness to take risks). Similarly standard psychological tests (e.g., for working memory capacity or processing speed) offer the opportunity to judge the representativeness of the specific age samples in important psychological variables known to decline with age.

Second, most experiments rely on the assumption that the same choice mechanism is used for simple and more complex decisions. Based on this assumption most experiments used simple gambles with discrete return distributions that are either provided in decisions from description or have to be learned in decisions from experience. Returns from most real-life investments, however, usually follow continuous return distributions which are much more complex than discrete return distributions with only few pairs of outcome magnitudes and probabilities. Given the known decline of cognitive functions like working memory and processing speed it might be questioned if artificially simple investments are the adequate objects to study age-related changes in FDM. Further, studies to date either fell into the domain of decision making from description or into the domain of decision making from experience. Real-life investment decision, however, usually does not fall in either of the two domains. The return distribution of real-life investments usually has to be inferred from past performance data. One might speculate that this process is more closely related to decision making from experience, but it still remains unclear if choice processes and strategies mimic those of decisions from experience using simple gambles. Future studies should investigate age-related changes in FDM with more ecologically valid stimuli to be able to control for possible age-related effects of complexity and information acquisition (learned from experience vs. inferred from past performance data).

The obvious limitations of the present studies on age-related differences in FDM also limit the implications for the practice that can be inferred from these studies. Consistent evidence from behavioral and neuroeconomics studies, however, suggests

that older adults have problems with learning relevant parameters of the return distribution. Decisions from experience most closely mimic decisions about investments that the investor already owns, as only in this case she can experience actual returns. Decisions regarding investments that the investor owns might thus differ from decisions between investments that she does not actually own. Especially older adults might have problems in correctly inferring expected return and risk of their own investments. Assuming that these investments appeared favorable when they were bought, older adults might stick too long with them. In this case it might be beneficial to advice them to rebuilt their portfolios in regular intervals, thereby using only past performance data and cloaking the names of the investments.

If one assumes that real-life investment decisions follow the same process like decisions from experience, older adults have in general problems with learning the correct expected return and risk of the investment. Depending on the return history this might lead to an over- or underestimation of expected return and risk. In this case, it seems reasonable to provide older investors directly with an estimate of these values to circumvent their impaired learning ability.

In sum, research on FDM across the adult life-span is only at its beginning. Studies from the field of neuroeconomics identified several differences in the neural processing of investment decisions between older and younger adults. Based on these results differences in choice behavior could be hypothesized and tested. Additional studies are, however, needed both in the behavioral domain and in the field of neuroeconomics. The first goal of these studies should be the investigation of age-related differences in more ecologically valid choice settings. When finding differences, research should focus on modulators of these differences (e.g., past performance data vs. summary statistics of past performance data) to define effective advice strategies to improve older investors' FDM.

Figures:
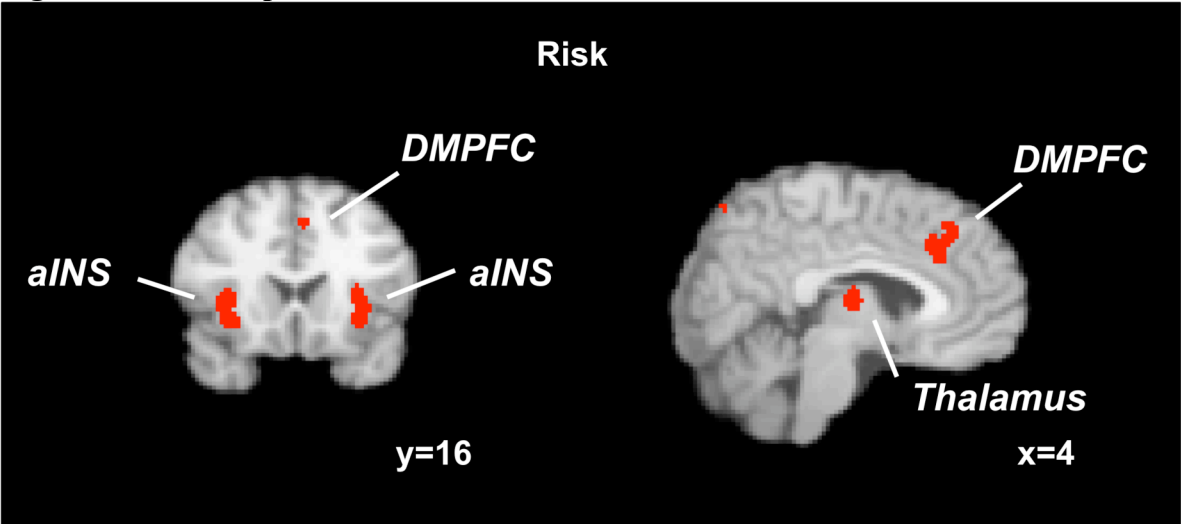
Figure 1. Neural representations of risk

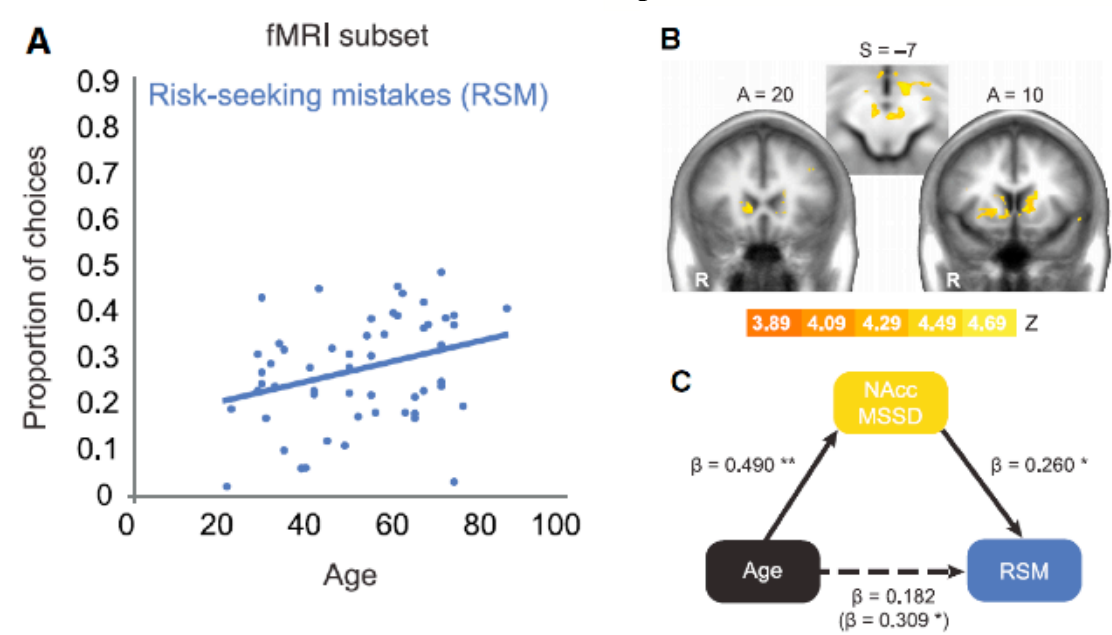**Figure 2. Variability in the VST mediates suboptimal FDM**

Figure Captions:

Figure 1: Results from an ALE meta-analysis on risk Activated clusters included bilateral aINS, DMPFC, and Thalamus (adapted with permission from Mohr et al. (2010), Copyright *Journal of Neuroscience)*.

Figure 1: A. The proportion of risk-seeking mistakes increases with age. **B.** The variability of the BOLD signal in the VST increases with age. **C.** The variability of the BOLD signal in the nucleus accumbens (NACC; part of the VST) mediates the relationship between age and the proportion of risk-seeking mistakes (adapted with permission from Samanez-Larkin et al., 2010, Copyright *Journal of Neuroscience)*.

References

Abler, B., H. Walter, S. Erk, H. Kammerer, and M. Spitzer, 2006, Prediction error as a linear function of reward probability is coded in human nucleus accumbens, *Neuroimage* 31, 790-5.

Allais, M., 1953, Le comportement de l'omme rationel devant le risque, critique des postulates et axiomes de l'école americaine, *Econometrica* 21, 503-546.

Antonini, A., and K. L. Leenders, 1993, Dopamine D2 receptors in normal human brain: effect of age measured by positron emission tomography (PET) and [11C]-raclopride, *Annals of the New York Academy of Sciences* 695, 81-5.

Baltes, P. B., U. M. Staudinger, and U. Lindenberger, 1999, Lifespan psychology: theory and application to intellectual functioning, *Annual Review of Psychology* 50, 471-507.

Bechara, A., H. Damasio, D. Tranel, and A. R. Damasio, 1997, Deciding advantageously before knowing the advantageous strategy, *Science* 275, 1293-5.

Behrens, T. E., M. W. Woolrich, M. E. Walton, and M. F. Rushworth, 2007, Learning the value of information in an uncertain world, *Nature Neuroscience* 10, 1214-21.

Birnbaum, M. H., 2008, New paradoxes of risky decision making, *Psychological Review* 115, 463-501.

Braver, T. S., D. M. Barch, B. A. Keys, C. S. Carter, J. D. Cohen, J. A. Kaye, J. S. Janowsky, S. F. Taylor, J. A. Yesavage, M. S. Mumenthaler, W. J. Jagust, and B. R. Reed, 2001, Context processing in older adults: evidence for a theory relating cognitive control to neurobiology in healthy aging, *Journal of Experimental Psychology: General* 130, 746-63.

Brown, S. B., and K. R. Ridderinkhof, 2009, Aging and the neuroeconomics of decision making: A review, *Cognitive, Affective, and Behavioral Neuroscience* 9, 365-79.

Camerer, C. F., 2007, Neuroeconomics: Using Neuroscience to Make Economic Predictions, *Economic Journal* 117, C26-C42.

Camus, M., N. Halelamien, H. Plassmann, S. Shimojo, J. O'Doherty, C. Camerer, and A. Rangel, 2009, Repetitive transcranial magnetic stimulation over the right dorsolateral prefrontal cortex decreases valuations during food choices, *European Journal of Neuroscince.*

Carstensen, L. L., 1995, Evidence for a life-span theory of socioemotional selectivity, *Current Directions in Psychological Science* 4, 151-156.

Clithero, J. A., D. Tankersley, and S. A. Huettel, 2008, Foundations of neuroeconomics: from philosophy to practice, *PLoS Biology* 6, e298.

d'Acremont, M., and P. Bossaerts, 2008, Neurobiological studies of risk assessment: A comparison of expected utility and mean-variance approaches, *Cognitive, Affective, and Behavioral Neuroscience* 8, 363-74.

Denburg, N. L., D. Tranel, and A. Bechara, 2005, The ability to decide advantageously declines prematurely in some normal older persons, *Neuropsychologia* 43, 1099-106.

Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp, and G. G. Wagner, 2011, Individual Risk Attitudes: Measurement, Determinants and Behavioral Consequences, *Journal of the European Economic Association* 9, 684–689.

Doya, K., 2008, Modulators of decision making, *Nat Neurosci* 11, 410-6.

Erixon-Lindroth, N., L. Farde, T. B. Wahlin, J. Sovago, C. Halldin, and L. Backman, 2005, The role of the striatal dopamine transporter in cognitive aging, *Psychiatry Research* 138, 1-12.

Fein, G., S. McGillivray, and P. Finn, 2007, Older adults make less advantageous decisions than younger adults: cognitive and psychological correlates, *Journal of the International Neuropsychological Society* 13, 480-9.

Figner, B., R. J. Mackinlay, F. Wilkening, and E. U. Weber, 2009, Affective and deliberative processes in risky choice: age differences in risk taking in the Columbia Card Task, *Journal of Experimental Psychology: Learning, Memomry, and Cognition* 35, 709-30.

Fiorillo, C. D., P. N. Tobler, and W. Schultz, 2003, Discrete coding of reward probability and uncertainty by dopamine neurons, *Science* 299, 1898-902.

Glimcher, P. W., C. F. Camerer, E. Fehr, and R. A. Poldrack, 2009, Introduction: A brief History of Neuroeconomcis, in P. W. Glimcher, C. F. Camerer, E. Fehr, and R. A. Poldrack, eds.: *Neuroeconomics. Decision Making and the Brain* (Elsevier, Lonson et al.).

Gul, F., and W. Pesendorfer, 2008, The case for mindless economics, in A. Caplin, and A. Schotter, eds.: *Foundation of positive and normative economics, methodologies of modern economics* (Oxford university Press, Oxford).

Hertwig, R., and I. Erev, 2009, The description-experience gap in risky choice, *Trends in Cognitive Science* 13, 517-23.

Hsu, M., I. Krajbich, C. Zhao, and C. F. Camerer, 2009, Neural response to reward anticipation under risk is nonlinear in probabilities, *Journal of Neuroscience* 29, 2231-7.

Huettel, S. A., A. W. Song, and G. McCarthy, 2005, Decisions under uncertainty: probabilistic context influences activation of prefrontal and parietal cortices, *Journal of Neuroscience* 25, 3304-11.

Inoue, M., T. Suhara, Y. Sudo, Y. Okubo, F. Yasuno, T. Kishimoto, K. Yoshikawa, and S. Tanada, 2001, Age-related reduction of extrastriatal dopamine D2 receptor measured by PET, *Life Science* 69, 1079-84.

Kaasinen, V., and J. O. Rinne, 2002, Functional imaging studies of dopamine system and cognition in normal aging and Parkinson's disease, *Neuroscience and Biobehavioral Reviews* 26, 785-93.

Kenning, P., and H. Plassmann, 2005, Neuroeconomics: an overview from an economic perspective, *Brain Research Bulletin* 67, 343-54.

Knutson, B., C. M. Adams, G. W. Fong, and D. Hommer, 2001, Anticipation of increasing monetary reward selectively recruits nucleus accumbens, *Journal of Neuroscience* 21, 1-5.

Knutson, B., J. Taylor, M. Kaufman, R. Peterson, and G. Glover, 2005, Distributed neural representation of expected value, *Journal of Neuroscience* 25, 4806-12.

Knutson, B., A. Westdorp, E. Kaiser, and D. Hommer, 2000, FMRI visualization of brain activity during a monetary incentive delay task., *Neuroimage* 12, 20-7.

Krugel, L. K., G. Biele, P. N. Mohr, S. C. Li, and H. R. Heekeren, 2009, Genetic variation in dopaminergic neuromodulation influences the ability to rapidly and flexibly adapt decisions, *Proceedings of the National Academy of Sciences of the United States of America* 106, 17951-6.

Kuhnen, C. M., and J. Y. Chiao, 2009, Genetic determinants of financial risk taking, *PLoS ONE* 4, e4362.

Kuhnen, C. M., and B. Knutson, 2005, The neural basis of financial risk taking, *Neuron* 47, 763-70.

Lee, T. M., A. W. Leung, P. T. Fox, J. H. Gao, and C. C. Chan, 2008, Age-related differences in neural activities during risk taking as revealed by functional MRI, *Social, Cognitive, and Affective Neuroscince* 3, 7-15.

Lee, D., H. Seo, and M. W. Jung, 2012, Neural Basis of Reinforcement Learning and Decision Making, *Annual Review of Neuroscience*.

Li, J., S. M. McClure, B. King-Casas, and P. R. Montague, 2006, Policy adjustment in a dynamic economic game, *PLoS One* 1, e103.

Li, S. C., U. Lindenberger, and S. Sikstrom, 2001, Aging cognition: from neuromodulation to representation, *Trends in Cognitive Science* 5, 479-486.

Li, S.-C., U. Lindenberger, B. Hommel, G. Aschersleben, W. Prinz, and P. B. Baltes, 2004, Transformations in couplings among intellectual abilities and constituent cognitive processes across the lifespan, *Psychological Science* 15, 155-163.

Markowitz, Harry, 1952, Portfolio Selection, *Journal of Finance* 7, 77-91.

Mata, R., A. K. Josef, G. R. Samanez-Larkin, and R. Hertwig, 2011, Age differences in risky choice: a meta-analysis, *Annals of the New York Academy of Sciences* 1235, 18-29.

Mather, M., and L. L. Carstensen, 2005, Aging and motivated cognition: the positivity effect in attention and memory, *Trends in Cognitive Science* 9, 496-502.

McClure, S. M., G. S. Berns, and P. R. Montague, 2003, Temporal prediction errors in a passive learning task activate human striatum, *Neuron* 38, 339-46.

Mell, T., H. R. Heekeren, A. Marschner, I. Wartenburger, A. Villringer, and F. M. Reischies, 2005, Effect of aging on stimulus-reward association learning, *Neuropsychologia* 43, 554-63.

Mell, T., I. Wartenburger, A. Marschner, A. Villringer, F. M. Reischies, and H. R. Heekeren, 2009, Altered Function of Ventral Striatum during Reward-Based Decision Making in Old Age, *Frontiers in Human Neuroscience* 3, 34.

Mohr, P. N. C., G. Biele, and H. R. Heekeren, 2010a, Neural processing of risk, *Journal of Neuroscience* 30, 6613-9.

Mohr, P. N. C., G. Biele, L. K. Krugel, S. C. Li, and H. R. Heekeren, 2010b, Neural foundations of risk-return trade-off in investment decisions, *Neuroimage* 49, 2556-2563.

Mohr, P. N. C., and I. E. Nagel, 2010, Variability in brain activity as an individual difference measure in neuroscience?, *Journal of Neuroscience* 30, 7755-7.

Mohr, P. N., S. C. Li, and H. R. Heekeren, 2010c, Neuroeconomics and aging: neuromodulation of economic decision making in old age, *Neuroscience and Biobehavioral Reviews* 34, 678-88.

Mozley, L. H., R. C. Gur, P. D. Mozley, and R. E. Gur, 2001, Striatal dopamine transporters and cognitive functioning in healthy men and women, *American Journal of Psychiatry* 158, 1492-1499.

Murray, G. K., P. R. Corlett, L. Clark, M. Pessiglione, A. D. Blackwell, G. Honey, P. B. Jones, E. T. Bullmore, T. W. Robbins, and P. C. Fletcher, 2008, Substantia nigra/ventral tegmental reward prediction error disruption in psychosis, *Molecular Psychiatry* 13, 239, 267-76.

Nieuwenhuis, S., K. R. Ridderinkhof, D. Talsma, M. G. Coles, C. B. Holroyd, A. Kok, and M. W. van der Molen, 2002, A computational account of altered error processing in older age: dopamine and the error-related negativity, *Cognitive, Affective, and Behavioral Neuroscience* 2, 19-36.

O'Doherty, J. P., P. Dayan, K. Friston, H. Critchley, and R. J. Dolan, 2003, Temporal difference models and reward-related learning in the human brain, *Neuron* 38, 329-37.

Preuschoff, K., P. Bossaerts, and S. R. Quartz, 2006, Neural differentiation of expected reward and risk in human subcortical structures, *Neuron* 51, 381-90.

Preuschoff, K., S. R. Quartz, and P. Bossaerts, 2008, Human insula activation reflects risk prediction errors as well as risk, *Jouranl of Neuroscience* 28, 2745-52.

Rangel, A., C. Camerer, and P. R. Montague, 2008, A framework for studying the neurobiology of value-based decision making, *Nature Review Neuroscience* 9, 545-56.

Rescorla, R. A., and A. R. Wagner, 1972, A theory of Pavlovian conditioning: variations in the effectiveness of reinforcement and nonreinforcement, in A. H. Black, and W. F. Prokasy, eds.: *Classical Conditioning II: Current Research and Theory* (Appleton Century Crofts, New York).

Rogers, A. R., 1994, Evolution of time preference by natural selection, *American Economic Review* 84, 460-481.

Rolls, E. T., C. McCabe, and J. Redoute, 2008, Expected value, reward outcome, and temporal difference error representations in a probabilistic decision task, *Cerebral Cortex* 18, 652-63.

Samanez-Larkin, G. R., S. E. Gibbs, K. Khanna, L. Nielsen, L. L. Carstensen, and B. Knutson, 2007, Anticipation of monetary gain but not loss in healthy older adults, *Nature Neuroscience* 10, 787-91.

Samanez-Larkin, G. R., C. M. Kuhnen, D. J. Yoo, and B. Knutson, 2010, Variability in Nucleus Accumbens Activity Mediates Age-Related Suboptimal Financial Risk Taking, *Journal of Neuroscience* 30, 1426-1434.

Samanez-Larkin, G. R., A. D. Wagner, and B. Knutson, 2011, Expected value information improves financial risk taking across the adult life span, *Social, Cognitive, and Affective Neuroscience* 6, 207-17.

Sanfey, A. G., G. Loewenstein, S. M. McClure, and J. D. Cohen, 2006, Neuroeconomics: cross-currents in research on decision-making, *Trends Cognitive Science* 10, 108-16.

Schott, B. H., L. Niehaus, B. C. Wittmann, H. Schutze, C. I. Seidenbecher, H. J. Heinze, and E. Duzel, 2007, Ageing and early-stage Parkinson's disease affect separable neural mechanisms of mesolimbic reward processing, *Brain* 130, 2412-24.

Schultz, W., 2009, Midbrain Dopamine Neurons: A Retina of the Reward System?, in P.W. Glimcher, C.F. Camerer, E. Fehr, and R.A. Poldrack, eds.: *Neuroeconomics. Decision Making and the Brain* (Elsevier, London et al.).

Schultz, W., P. Dayan, and P. R. Montague, 1997, A neural substrate of prediction and reward, *Science* 275, 1593-9.

Shinkai, T., L. Zhang, S. A. Mathias, and G. S. Roth, 1997, Dopamine induces apoptosis in cultured rat striatal neurons; possible mechanism of D2-dopamine receptor neuron loss during aging, *Journal of Neuroscience Research* 47, 393-9.

St Onge, J. R., and S. B. Floresco, 2009, Dopaminergic modulation of risk-based decision making, *Neuropsychopharmacology* 34, 681-97.

Suhara, T., H. Fukuda, O. Inoue, T. Itoh, K. Suzuki, T. Yamasaki, and Y. Tateno, 1991, Age-related changes in human D1 dopamine receptors measured by positron emission tomography, *Psychopharmacology (Berl)* 103, 41-5.

Tobler, P. N., G. I. Christopoulos, J. P. O'Doherty, R. J. Dolan, and W. Schultz, 2009, Risk-dependent reward value signal in human prefrontal cortex, *Proceedings of the National Academy of Sciences of the United States of America* 106, 7185-90.

Tobler, P. N., C. D. Fiorillo, and W. Schultz, 2005, Adaptive coding of reward value by dopamine neurons, *Science* 307, 1642-5.

Tobler, P. N., P. O'Doherty J, R. J. Dolan, and W. Schultz, 2006, Human neural learning depends on reward prediction errors in the blocking paradigm, *Journal of Neurophysiology* 95, 301-10.

Tobler, P. N., J. P. O'Doherty, R. J. Dolan, and W. Schultz, 2007, Reward value coding distinct from risk attitude-related uncertainty coding in human reward systems, *Journal of Neurophysiology* 97, 1621-32.

Tom, S. M., C. R. Fox, C. Trepel, and R. A. Poldrack, 2007, The neural basis of loss aversion in decision-making under risk, *Science* 315, 515-8.

Trostel, P. A., and G. A. Taylor, 2001, A theory of time preference, *Economic Inquiery* 39, 379-395.

Wang, Y., G. L. Chan, J. E. Holden, T. Dobko, E. Mak, M. Schulzer, J. M. Huser, B. J. Snow, T. J. Ruth, D. B. Calne, and A. J. Stoessl, 1998, Age-dependent decline of dopamine D1 receptors in human brain: a PET study, *Synapse* 30, 56-61.

Weber, E. U., and E. J. Johnson, 2009a, Mindful judgment and decision making, *Annual Revies of Psycholology* 60, 53-85.

Weber, E.U., and E.J. Johnson, 2009b, Decisions Under Uncertainty: Psychological, Economic, and Neuroeconomic Explanations of Risk Preference, in P.W. Glimcher, C.F. Camerer, E. Fehr, and R.A. Poldrack, eds.: *Neuroeconomics. Decision Making and the Brain* (Elsevier, London et al.).

Zamarian, L., H. Sinz, E. Bonatti, N. Gamboz, and M. Delazer, 2008, Normal aging affects decisions under ambiguity, but not decisions under risk, *Neuropsychology* 22, 645-57.

Zhang, L., A. Ravipati, J. Joseph, and G. S. Roth, 1995, Aging-related changes in rat striatal D2 receptor mRNA-containing neurons: a quantitative nonradioactive in situ hybridization study, *Journal of Neuroscience Neurosci* 15, 1735-40.

SFB 649 Discussion Paper Series 2012

For a complete list of Discussion Papers published by the SFB 649, please visit http://sfb649.wiwi.hu-berlin.de.

001 "HMM in dynamic HAC models" by Wolfgang Karl Härdle, Ostap Okhrin and Weining Wang, January 2012.

002 "Dynamic Activity Analysis Model Based Win-Win Development Forecasting Under the Environmental Regulation in China" by Shiyi Chen and Wolfgang Karl Härdle, January 2012.

003 "A Donsker Theorem for Lévy Measures" by Richard Nickl and Markus Reiß, January 2012.

004 "Computational Statistics (Journal)" by Wolfgang Karl Härdle, Yuichi Mori and Jürgen Symanzik, January 2012.

005 "Implementing quotas in university admissions: An experimental analysis" by Sebastian Braun, Nadja Dwenger, Dorothea Kübler and Alexander Westkamp, January 2012.

006 "Quantile Regression in Risk Calibration" by Shih-Kang Chao, Wolfgang Karl Härdle and Weining Wang, January 2012.

007 "Total Work and Gender: Facts and Possible Explanations" by Michael Burda, Daniel S. Hamermesh and Philippe Weil, February 2012.

008 "Does Basel II Pillar 3 Risk Exposure Data help to Identify Risky Banks?" by Ralf Sabiwalsky, February 2012.

009 "Comparability Effects of Mandatory IFRS Adoption" by Stefano Cascino and Joachim Gassen, February 2012.

010 "Fair Value Reclassifications of Financial Assets during the Financial Crisis" by Jannis Bischof, Ulf Brüggemann and Holger Daske, February 2012.

011 "Intended and unintended consequences of mandatory IFRS adoption: A review of extant evidence and suggestions for future research" by Ulf Brüggemann, Jörg-Markus Hitz and Thorsten Sellhorn, February 2012.

012 "Confidence sets in nonparametric calibration of exponential Lévy models" by Jakob Söhl, February 2012.

013 "The Polarization of Employment in German Local Labor Markets" by Charlotte Senftleben and Hanna Wielandt, February 2012.

014 "On the Dark Side of the Market: Identifying and Analyzing Hidden Order Placements" by Nikolaus Hautsch and Ruihong Huang, February 2012.

015 "Existence and Uniqueness of Perturbation Solutions to DSGE Models" by Hong Lan and Alexander Meyer-Gohde, February 2012.

016 "Nonparametric adaptive estimation of linear functionals for low frequency observed Lévy processes" by Johanna Kappus, February 2012.

017 "Option calibration of exponential Lévy models: Implementation and empirical results" by Jakob Söhl und Mathias Trabs, February 2012.

018 "Managerial Overconfidence and Corporate Risk Management" by Tim R. Adam, Chitru S. Fernando and Evgenia Golubeva, February 2012.

019 "Why Do Firms Engage in Selective Hedging?" by Tim R. Adam, Chitru S. Fernando and Jesus M. Salas, February 2012.

020 "A Slab in the Face: Building Quality and Neighborhood Effects" by Rainer Schulz and Martin Wersing, February 2012.

021 "A Strategy Perspective on the Performance Relevance of the CFO" by Andreas Venus and Andreas Engelen, February 2012.

022 "Assessing the Anchoring of Inflation Expectations" by Till Strohsal and Lars Winkelmann, February 2012.

SFB 649 Discussion Paper Series 2012

For a complete list of Discussion Papers published by the SFB 649, please visit http://sfb649.wiwi.hu-berlin.de.