Risky choices and emotion-based learning

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The paper offers a comprehensive analysis of causes and consequences of the accumulation of emotional experience, measured via skin conductance response, when taking risky choices. A large experimental data set was obtained from a psycho-physiological task conducted with 645 bank customers and financial professionals. With respect to causes, we found that the individual emotional response to gains/losses is trend-dependent and influenced by habituation, as well as by anchoring/framing due to the external layout of risky alternatives. With respect to consequences, we found evidence that the somatic reinforcement experience is able to guide asset picking, but within a long-term strategy. Consequently, selection behaviors were observed in a portfolio mean-variance framework, revealing that somatic markers lead individuals to pursue a long-term 'psycho-economic' efficiency that integrates factual information (monetary outcomes) with the implicit subjective experience.
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Introduction

A vast literature assigns a role to emotions in human decision-making, as suggested, among others, by Loewenstein (2000) and A. R. Damasio (1994). But few studies offer a comprehensive analysis, supported by a large experimental data set, of causes and consequences of the accumulation of emotional experience when taking risky choices, as in the intention of this paper.

At the individual level, any gain or loss obtained after a financial investment is 'subjectively' perceived because each person experiences a unique emotional arousal in response to returns. We propose an algorithm that models this 'money-emotions' relation, controlling for some behavioral features/biases suggested by the literature. We hypothesize that the individual emotional response can differ in the gains/losses domain, as a tribute to the prospect theory of Kahneman and Tversky (1979); emotion is trend-dependent and influenced by habituation (Thompson & Spencer, 1966); emotion is also altered by anchoring and framing (Kahneman & Tversky, 1979; Tversky & Kahneman, 1974), due to the external layout of risky choices. This model has been empirically validated thanks to a psycho-physiological task conducted with 645 bank customers and financial professionals (Caucasians, average age 44, range 18 - 82; 509 males and 136 females); they were asked to take a sequence of 100 risky choices, among four risky assets, while their emotional response to returns was measured via their Skin Conductance Response (SCR). Our experimental data allows validation of the 'money-emotions' relation within dynamic fixed-effects panel estimations.

In the second part of the paper we investigate how emotion shapes investment behaviors and we explore where the emotion-based learning leads, from both asset picking and portfolio perspectives. First, we run probit models to understand how the somatic reinforcement experience is able to induce individuals to select a specific asset, relative to the available alternatives. Evidence that asset selection is driven by a long-term strategy justifies interpreting behaviors within a portfolio framework. In order to overcome the duality of factual information (i.e., the value of money) and the implicit emotional experience marked by physiological arousal, we propose a computation of 'emotional values', intended as emotionally balanced payoffs. They are an attempt to signify the interaction of dual/multiple processes intervening in human decision-making. By applying the mean variance theory

(MVT) proposed by Markowitz (1952) to these 'emotional values', we observe the role of somatic markers in mediating risky decisions.

Decision-Making, emotions and physiological arousal

The idea of 'subjective' perception of returns is grounded in neuroeconomics (among others, Glimcher, 2010; Rustichini, 2005), according to which subjective values are assumed in a cardinal and physiological sense (i.e., numbers); they originate by jointly considering monetary outcomes and the neurophysiological substrate which is experienced when making decisions.

Since the 2000s, exploration of human decision-making has involved neuroscience, which offered support for the existence of several brain systems interacting within a network synchronization, inducing scholars to revisit standard paradigms of choice (Brocas & Carrillo, 2014). The neurophysiology of human decision-making is still under investigation and often relates to monetary rewards and risk (Levy, Snell, Nelson, Rustichini, & Glimcher, 2010).

Knowledge from neuroscience and neurobiology that sketches individuals as organizations of ('as if') cooperating/competing systems (Brocas & Carrillo, 2014) resembles a wide and variegated conceptual framework that outlines human behavior within a 'dual-processes' paradigm. Terms of duality have been differently coined by literature, over the years, according to various disciplines (economics vs. psychology), setting numerous models and/or theories (Gawronski & Creighton, 2013), and based on several criteria (Alós-Ferrer & Strack, 2014; Brocas & Carrillo, 2014): typology of thinking (controlled/reflective/rational vs. impulsive/reflexive/experiential), speed of time-response (slow vs. fast), visibility of information processing (explicit vs. implicit), degree of awareness (conscious, deliberative, effortful vs. unconscious, automatic, effortless), consideration of emotions ('cold' cognitive vs. 'hot' affective).

Within this debate, our paper roots its underpinnings in the evidence of the role of emotions while taking risky choices (among others, A. R. Damasio, 1994; Loewenstein, 2000). It stems from the so-called emotion revolution in decision-making studies (Johnson & Weber, 2009), that raised interest in indicators of affective processes, and in measures of emotional arousal, especially for large-scale experiments.

Change in electrodermal activity, and precisely the SCR, is an inexpensive, unobtrusive and reliable measure that serves as a proxy for neural and brain activation (Figner & Murphy, 2011), due to the network synchronization between central and peripheral systems, further evidence of multiplicity of processes involved in human decision-making. Varela, Lachaux, Rodriguez, and Martinerie (2001) uncover a synchronization process that solves a problem called 'large-scale integration' and describe neural mechanisms that select and coordinate this distributed brain activity to produce a flow of adapted and unified cognitive moments. Further studies integrate fMRI (Functional Magnetic Resonance Imaging) with psycho-physiological measures, in particular skin conductance (Wong, Xue, & Bechara, 2011). These authors suggest that psycho-physiological data would complement fMRI findings in providing a more comprehensive understanding of the physiological and neural mechanisms of decision-making.

Even if it is a multifaceted phenomenon, SCR is considered a valuable tool, in judgment and decision-making research, for studying psychological processes related to sympathetic arousal, and affective processes (Figner & Murphy, 2011). SCR is used in this paper to summarize the emotional experience after risky choices. It is a *neutral* measure of the intensity of activation, and it allows a valence-based interpretation (as in Lopes, 1987) only in relation to the sign of the stimulus: e.g., activations after gains should unfold positive emotions (happiness, joy), and after losses should reveal negative emotions (soreness, annoyance), or even a feeling of thrill.

Here, we consider emotions as 'immediate emotions' involved in the act of decision-making (Loewenstein & Lerner, 2003). We point out that our emotion-based learning is assumed in general terms, and it is not directly related to the Somatic Marker Hypothesis (SMH) of A. R. Damasio (1994), which would imply the consideration of anticipatory SCR, i.e. the emotional activation *before* risky choice. We disregarded anticipatory SCR, on the one hand, because it is difficult to manipulate emotion affecting judgments or decisions when observing acts before decisions. For example, as indicated by Dunn, Dalgleish, and Lawrence (2006), the physiological marker generated before the choice may not reflect attention to a single choice, but rather a shifting attentional focus across alternatives to be differently evaluated. Others (Bowman, Evans, & Turnbull, 2005) would suggest that anticipatory SCR may be proof not of emotion-based learning but rather of a concurring emotional experience of frustration, because individuals are forced to wait during the interval of SCR recovery. On the other hand, there is a debate regarding the possibility that anticipatory SCRs are related to expectations of immediate higher-magnitude monetary outcomes (Tomb, Hauser, Deldin, & Caramazza, 2002) rather than evidence of the role of somatic markers in decision-making. Last but not least, observation of activation 'before' a choice definitively requires one to pre-define the 'nature' of the risky choice to be taken (good or bad), giving rise to critiques on Damasio's distinction between 'disadvantageous' and 'advantageous' alternatives (Tomb et al., 2002).

In order to reduce all these potential biases related to the anticipatory SCR interpretation, in this paper we describe an emotion-based learning driven by the somatic past reinforcement experience.

Methods

Recruitment and sample

Experimental data are obtained within a broader research project that explored individual risk attitude in financial decision-making.[1] Cooperation with banks and investment firms was required for both recruiting and hosting the psycho-physiological task inside their offices, across the national territory (Italy). The recruitment rule consisted of asking CEOs of financial intermediaries to invite people randomly selected from the population of their customers and employees. Specifically, we assigned to banks the goal of randomly recruiting from their customers, i.e., representatives of households, and asked international asset managers and financial advisor companies to invite their employees, given our interest in observing behaviors at different levels of familiarity with decision-making under risk. In any case, the framing assigned to all the participants in the task was that they were asked to make decisions for *themselves*. Separately, we also collected socio-demographic information about participants' households, through a traditional questionnaire. Overall, we obtained a sample of 645 individuals, 509 males and 136 females, age 18 to 82 years (average age 44). The male dominance is representative of the gender gap that still characterizes finance-related issues within households, at least in Italy (ISTAT, 2011), and overall in senior-level financial professions, such as those invited to the task (i.e., not those in administrative and secretarial jobs, as in Metcalf & Rolfe, 2009).

Table 1 presents a selection of the socio-demographic information for the sample observed. It includes individuals belonging to households with an average income level higher than households living in the same geographical territory (North-Central Italy) and corresponding period (2009 and 2010) of our experiments. Our interviewees declared an average monthly income of about 4,000 Euros, while the average monthly income for the corresponding Italian households is about 3,100 Euros (ISTAT, 2011). From Table 1 we offer information about the actual investment behavior of our interviewees, both including and excluding professionals: individuals in our sample are generally confident in investing in various asset classes (e.g., bonds, stocks, and mutual funds).

INSERT TABLE 1 HERE

We checked for a potential selection bias within the sample from banks' customers: we asked CEOs of banks to collect socio-demographic and economic information of sampled individuals, extracted from the Customer Relationship Management (CRM) database, and to indicate whether they agreed or declined to take part in the task. In total, 332 individuals were invited and 222 (66.87 per cent) agreed to participate in the experiment. Comparisons between those who accepted and refused to take part to the experiment allow us to rule out a selection bias.[2] This control is omitted for samples of employees obtained from international asset managers and financial advisory companies (precisely, 84 asset managers and 150 financial advisors), because this recruitment is naturally biased by the sampling criterion itself.[3]

A team of psychologists and economists were involved in conducting the task. The use of government research funding impeded the provision of a monetary reward to participants.[4] Given this limitation, we opted for a hypothetical reward, based on the conceptual support of neurophysiology indicating that hypothetical rewards also activate the medial orbitofrontal cortex, generally relevant in the representation of rewarding goals (Bray, Shimojo, & O'Doherty, 2010). Others argue that the experience of emotion, associated with both episodic memory and imagery, is activated by a mental 'scene construction', which engages a common network of regions including the hippocampus, parahippocampal gyrus, and retrosplenial cortex, and that this happens whether through imagery, memory, or tangible reward (Bray et al., 2010; Hassabis & Maguire, 2007; O'Doherty, Deichmann, Critchley, & Dolan, 2002; Sharot, Riccardi, Raio, & Phelps, 2007). Precisely, individual feedback was offered as a personal risk profiling delivered at the end of the task in the form of a preliminary verbal discussion, followed by a written text reporting the risk attitude revealed during the experiment, plus other psychological traits, delivered via web or in sealed envelopes.[5] Participants considered this personal risk profiling as an improvement of their risk tolerance self-consciousness, valuable in their real-life investment decision process. Therefore, we associated this non-monetary reward with their mental simulation of future rewards, expected from the enhancement of understanding of their risk attitude, and exploitable with future (more adequate) investment decisions.

[1]In the early stage, the study received financial support from the Italian Government (PRIN2007-MIUR -years 2008-2010). National project entitled: 'Risk attitude in investment and debt decision-making.' Additional funding was provided by ASSORETI, the Italian Association of Financial Advisors (years 2010-2011), who requested a focus on investment decision-making.

[2]Detailed motivation for excluding selection biases is offered in the Appendix of this paper.

[3]Nevertheless, this inclusion is necessary for observing a wider range of behavior, including those of agents professionally engaged in risky decisions (even if, in the task, they were asked to take decisions for themselves).

[4]We were compelled to strictly follow public-funding regulations, which forbid any monetary assignment to persons without signing a written contract or receiving an invoice.

[5]Individual IDs and passwords were created during the experiment and personally given to each participant to allow anonymity of feedback.

The experiment

Interviewees were asked to build a portfolio by selecting from among four risky assets, namely 'A', 'B', 'C' and 'D' decks, with different risk/return combinations. Anonymous assets are preferred to real stocks or bonds, in order to avoid a framing effect due to financial knowledge or personal experience. Payoffs refer to monetary returns, in terms of game money. Before the task, participants were not given information about how many choices they would take, but were told that their goal was to conclude with a positive result. Finally, each individual was asked to take 100 choices. Namely, our psycho-physiological experiment is the computerized version of the Iowa Gambling Task (IGT) combined with the measurements of the SCR, run according to instructions by Bechara, Damasio, and Damasio (2000). Although originally intended to explain decision-making deficits in people with specific frontal lobe damage, the IGT has proved to be effective in exploring a person's physiological and emotional response whilst making risky choices. In order to perform the task, individuals were given some short verbal instructions, which appeared on the computer screen when they sat in order to run the experiment, as in Bechara, Damasio, Damasio, and Lee (1999, p. 5474-5475): *'[. . .] The goal of the game is to win as much money as possible and, if you find yourself unable to win, make sure you avoid losing money as much as possible. I won't tell you how long the game will continue. You must keep on playing until the computer stops. [. . .] It is important to know that the colors of the cards are irrelevant in this game. The computer does not make you lose money at random. However, there is no way for you to figure out when the computer will make you lose. All I can say is that you may find yourself losing money on all of the decks, but some decks will make you lose more than others. You can win if you stay away from the worst decks.'*

Detailed description of the reward (gains) and punishment (losses) schedule of the decks is offered, among others, in Tomb et al. (2002, p. 1103), Dunn et al. (2006, p. 243), and Lin, Chiu, Lee, and Hsieh (n.d.). Payoffs from the four decks appear to be a good simplification of individual decision-making in a reward-risk framework. Decks A and B are strictly dominated in terms of mean-variance criterion by decks C and D, as shown in Table 2. Moreover, B is strictly dominated by C. On the other hand, there is no trivial ordering between C and D, because the higher risk for D is counterbalanced by its higher expected payoff.

INSERT TABLE 2 HERE

The sequence of selections is singular for each individual, because it results from the precise pattern of preferences that the person exhibits during the task.

While individuals were making decisions, we measured their physiological arousal via SCR, strictly following accepted protocols (Figner & Murphy, 2011), as shown in Figure 1. We made use of the Biopac MP150 system (Biopac Systems, CA, USA).[6] From the SCR recordings, we extracted the area under the curve (mS/s) of SCR in the 6 seconds after the subject made the card selection, as shown by Figure 1.

INSERT FIGURE 1 HERE

We set an intertrial interval at six seconds, as a 'break' phase, after each choice, in order to allow the recovery of SCR to the individual's baseline. The interchoice interval varies because it may take a few additional seconds for the agent to decide which card to pick next. It is ten seconds on average. The overall task duration varies from about thirty to forty-five minutes, for each interviewee. Descriptive measurements of SCR for the 100 choices and 645 individuals are shown in Table 3.

INSERT TABLE 3 HERE

Note that the SCR values have a range for each individual that generally increases with the average SCR for the same individual, whereas for log-SCR this relation vanishes, as shown in Figure 2.[7]

INSERT FIGURE 2 HERE

Monetary payoffs and somatic experience

The 'money-emotion' algorithm

Our theory proposes an algorithm for the relation between monetary outcomes and emotions, based on, and constrained by, the somatic past reinforcement experience. In line with a general psycho-physical law (Stevens, 1957), we state an initial power-law relation between payoff values and the SCR experienced after payoffs, as:

$$E = K|X|^{\alpha}; \quad K > 0, \ \alpha > 0; \tag{1}$$

where E is the SCR, $|X|$ is the payoff value, K and α are parameters. Parameters are set to be positive to indicate a coherent relation between stimulus (money) and reaction (SCR). Then our algorithm includes hypothetical expectations concerning the emotional learning process of a sequence of N^f risky choices, where $t = 1, \ldots, N^f$, with a scaling factor K that is typical for each individual, say $K_i, \ i = 1, \ldots, M$.

[6]Recording of SCR starts at least ten minutes before the beginning of the task, and continues throughout. The computer tracks the sequence of the cards selected from the various decks. As the agent performs the task, SCR activity is recorded continuously and collected simultaneously on another personal computer, where data from the experiments are stored. The data were analyzed offline using the software AcqKnowledge 3.8. The filtering rate is set at 1 Hz. Each time the individual selects a card, this action is recorded as a 'mark' on the polygraph output of SCR activity. Each click is registered as a selection from the specific deck chosen. Thus, SCR generated in association with a specific card, from a specific deck, can be identified precisely on the polygraph output.

[7]The correlation coefficient between the individual average and the range of the SCRs is 0.8240; while using the log-SCR this correlation drops to -0.1142.

First, from the prospect theory of Kahneman and Tversky (1979) up to general principles of psychological phenomena (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001), model (1) can be differently specified in the loss and gain domains, as follows:

$$E_{it} = \begin{cases} K_i\,|X_{it}|^{\alpha_g}, & X > 0 \\ K_i\,|X_{it}|^{\alpha_l}, & X < 0 \end{cases} \qquad (2)$$

Second, we expect a trend component of the emotional experience, as suggested by Dunn et al. (2006). We consider three alternative trend features:

- E_{t-1}, the SCR obtained after the previous choice;
- ESS_{it-r}, the SCR obtained the previous time the same payoff sign occurred for a given individual (e.g., the SCR after a repeated gain, or after a repeated loss), where r may be either the choice preceding t ($r = 1$), or, more likely, an earlier choice ($r > 1$);
- ESP_{it-s}, the SCR obtained the previous time the same payoff occurred for a given individual (e.g., the SCR after a repeated gain of 200, or after a repeated loss of 50), where s may be either the choice preceding t ($s = 1$), or, more likely, an earlier choice ($s > 1$).

Third, from agreed-upon evidence of human behavior (Rankin et al., 2009; Thompson & Spencer, 1966) we expect an 'habituation effect' that should have SCR intensity decrease in response to a stimulus, when this is repeated. Therefore, we add the following variables to model (2):

- N_{it}, the progressive number of the risky choice taken by a given individual, within the whole length of the decision process (e.g., choice 18 over 100; or choice 98 over 100);
- NSP_{it}, the number accounting for how many times the same payoff is a repeated observation, for each individual (if it is the fifth time the individual gains 200, or the third time he/she loses 50).

Finally, we control for the anchoring and framing effect (Kahneman & Tversky, 1979; Tversky & Kahneman, 1974), which induces us to expect activation due to response to 'pieces' of information, such as the exterior way in which risky choices are displayed. It could be the name/label of the risky asset, or any other typology of framing, that we indicate with F_z, with $z = 1, \ldots, Z$.

Marginally, Figure 2 indicates that SCR values benefit from a log transformation; so it is applied to the model and small letters denote the log of the corresponding capital-letter variable in model (1) and (2).

Therefore, the complete model, within gain/loss domains, with trend, habituation, anchoring/framing effects, and log transformation, takes the following form:

$$e_{it} = k_i + \alpha_g x_{it}^{\text{gain}} + \alpha_l x_{it}^{\text{loss}} + \beta_1 e_{it-1} + \beta_2 eSS_{it-r} + \beta_3 eSP_{it-s} + \\ + \gamma_1 N_{it} + \gamma_2 NSP_{it} + \sum_{z=1}^{Z} \delta_z F_{zit} \qquad (3)$$

Validation of the 'money-emotion' model on experimental data

Our experiment offers data to validate model (3), where the progressive number of choices, N, goes from 1 to 100 for each individual; the sample accounts for 645 individuals, so $i = 1, \ldots, 645$. Differences between individuals require a fixed-effects panel estimation. Moreover, the general model (3) becomes dynamic due to the auto-regressive term AR(1), e_{it-1}. Note that, when the previous selection at $(t-1)$ returned the same payoff sign as the one observed at time t, r is equal to 1 and eSS_{it-r} coincides with e_{it-1}; when the previous selection at $(t-1)$ returned the same payoff as the one observed at time t, $s = r$ is equal to 1 and eSP_{it-s} coincides with e_{it-1} and eSS_{it-r}. So these variables need to be used alternatively, and they generate three model specifications:

$$e_{it} = k_i + \alpha_g x_{it}^{\text{gain}} + \alpha_l x_{it}^{\text{loss}} + \beta_1 e_{it-1} + \\ + \gamma_1 N_{it} + \gamma_2 NSP_{it} + \sum_{z=1}^{Z} \delta_z F_{zit} + \varepsilon_{it}, \qquad (4)$$

$$e_{it} = k_i + \alpha_g x_{it}^{\text{gain}} + \alpha_l x_{it}^{\text{loss}} + \beta_2 eSS_{it-r} + \\ + \gamma_1 N_{it} + \gamma_2 NSP_{it} + \sum_{z=1}^{Z} \delta_z F_{zit} + \varepsilon_{it}, \qquad (5)$$

$$e_{it} = k_i + \alpha_g x_{it}^{\text{gain}} + \alpha_l x_{it}^{\text{loss}} + \beta_3 eSP_{it-s} + \\ + \gamma_1 N_{it} + \gamma_2 NSP_{it} + \sum_{z=1}^{Z} \delta_z F_{zit} + \varepsilon_{it}. \qquad (6)$$

The layout of risky choices, F_z, is displayed as four decks with different labels, so F_z represent the dummy for deck selection (1 selected, 0 not selected) with $z = 1, \ldots, 4$, i.e., deck A, deck B, deck C and deck D. We need to point out that A and D take the external spatial position in the computerized version of the task, B and C the central spatial position. In order to exclude collinearity, and to understand the specific role of each deck, we present the parameters of estimations, including them separately. Moreover, we also test the restriction $\alpha_g = \alpha_l$.

We control the outcomes for heterogeneity, considering gender, income and age of individuals. We add to models (4), (5) and (6), alternatively, a dichotomous variable for gender (male vs. female), income (under vs. over the median income level of the sample) and age (40 years of age and under vs. over40).

INSERT TABLE 4 HERE

Table 4 presents results. Note that estimates are stable across specifications and restrictions. The gender variable is not statistically significant, and the income and age variables introduce collinearity in the regressors.[8]

There is evidence for distinguishing the exponent α between gains and losses: the exponent is larger for losses than for gains, coherent with the prospect theory. Nonetheless, the log-likelihood ratio (LR) test rejects the restriction $\alpha_g = \alpha_l$ for specification (4) but not for specifications (5) and (6).

Parameters β for the SCR trend are significant and positive, indicating that an intense emotion positively influences the following emotional activation, for all three typologies of trend (e_{t-1}, in specification (4), eSS_{it}, in specification (5) and eSP_{it}, in specification (6)).

The parameters γ_1 and γ_2 are significant and negative, offering clear proof of an habituation effect that works in contrast with the trend component, thus attenuating its effects.

An anchoring effect is proved to exist, as shown by the significance and sign of parameters δ, in favor of decks of central versus external space positioning on the screen: external decks (A and D), ceteris paribus, involve higher SCR; internal decks (B and C) involve lower SCR, even if they are economically largely different, in terms of both riskiness and frequency of gains (Lin et al., n.d.).

Overall, we can conclude that models (4), (5) and (6) deliver a good representation of the emotional decision process. Specification (6) has lower information criteria than specifications (4) and (5), in all cases.

How do emotions shape investment behavior?

Emotions and asset picking

In the second part of this paper we investigate how emotions shape investment behaviors. Here, we explore whether and where the emotion-based learning leads, in terms of asset picking. Based on our experiment, this means understanding what induces an individual to prefer a deck over the other ones available. Note that the experimental task we used has raised some discussion in the literature concerning the features of the four decks employed (among others, Tomb et al., 2002, p. 1103; Dunn et al., 2006, p. 243; Lin et al., n.d.). In the original experimental design, Bechara and Damasio (2002, p. 1677) offer a qualification of decks: A and B are defined as 'in the long run disadvantageous' and C and D as 'advantageous', because, at the end of the task, agents who prefer decks C or D gain, the others lose. Moreover, based on the pre-defined sequence of gains/losses, B and D can be considered 'high-frequency gain' decks, while A and C are 'low-frequency gain' decks (Lin et al., n.d.). Furthermore, from our estimations shown in Table 4, we also have evidence that when decks are controlled for their monetary outcomes, there is a role played by their spatial positioning on the screen. Therefore, concurring reasons might induce preference for specific decks.

Frequency of deck selection across the overall task is shown in Table 5. We confirm the 'prominent deck B' phenomenon, reported in literature (among others, Lin et al., n.d.). Even if the preference for B decreases after the first set of 20 choices, this deck is largely the favorite up to the end of the task.

INSERT TABLE 5 HERE

We build a series of probit models in order to understand how the experience accumulated during the task might influence the probability of selecting a particular deck from among the four available. This experience is alternatively described in terms of either the somatic activation registered after the recent last set of choices (model specification (7)) or the recent last set of payoffs (model specification (8)). We add the control level of the overall wealth accumulated by the individual up to the choice to be taken ($ACCw_{t-1}$), which works as the 'reference point' because 'carriers of value are changes in wealth or welfare' (Kahneman & Tversky, 1979, p. 277). We include this control in all the models because this data is always visible to participants, as a standard framing of the experimental task. Then, for a conceptual analogy, we build an additional model (model specification (9)) in which we include the overall somatic activation accumulated by the individual up to the choice to be taken ($ACCe_{t-1}$). This information is not visible to participants. These are the three specifications for probit models:

$$\begin{aligned} &\text{Prob}\left[F_z = 1 \left| \textstyle\sum_{l=1}^{L} e_{it-l}, ACCw_{t-1} \right.\right]; \\ &\text{Prob}\left[F_z = 1 \left| \textstyle\sum_{l=1}^{L} e_{it-l}, ACCw_{t-1}, d \right.\right]; \end{aligned} \tag{7}$$

$$\begin{aligned} &\text{Prob}\left[F_z = 1 \left| \textstyle\sum_{l=1}^{L} X_{it-l}, ACCw_{t-1} \right.\right]; \\ &\text{Prob}\left[F_z = 1 \left| \textstyle\sum_{l=1}^{L} X_{it-l}, ACCw_{t-1}, d \right.\right]; \end{aligned} \tag{8}$$

$$\begin{aligned} &\text{Prob}\left[F_z = 1 \left| ACCe_{t-1}, ACCw_{t-1} \right.\right]; \\ &\text{Prob}\left[F_z = 1 \left| ACCe_{t-1}, ACCw_{t-1}, d \right.\right]; \end{aligned} \tag{9}$$

where F_z represents the dummy for deck selection, that is, deck A, deck B, deck C and deck D; l stands for lags of selection, here assumed up to the third[9], $l = 1, \ldots, 3$; e_{it-l} is the log of SCR recorded after the payoff is known, in the previous $t-l$ times; X_{it-l} is the payoff received, in the previous $t-l$ times; $ACCw_{t-1}$ is the amount of money accumulated (all gains minus all losses) up to that choice $(t-1)$[10]; and $ACCe_{t-1}$ is the somatic activation accumulated (incremental sum of SCR) up to that choice $(t-1)$. In order to control for heterogeneity due to some socio-demographic features, we add a sub-specification of each model, including the dummy

[8] Results not reported, but available upon request.

[9] We considered up to the sixth lag. Nevertheless, results are consistent for model (7) and payoffs before the fourth are seldom significant for model (8).

[10] Just to improve the readability of the estimate results shown in Table 6, we rescaled X and $ACCw_{t-1}$ by dividing them by 100.

variable d, which alternatively works for gender (male vs. female; dummy *male*) and age (40 years of age and under vs. over40; dummy *under40*).[11]

Literature indicates that individuals learn which deck to prefer based on their somatic activation only in a final phase (generally, the last 60 choices). For this reason and for purposes of concision, we limit the presentation and discussion of results to this part of the task, which is typically referred to as 'choices under risk' (Brand, Recknor, Grabenhorst, & Bechara, 2007; Reimann & Bechara, 2010).

INSERT TABLE 6 HERE

Results of panel estimation indicate that the emotional experience registered after the preceding three sets of choices, e_{it-l}, is seldom able to predict a coherent selection preference. In fact, parameters of e_{it-l} are never statistically significant for B and D; they are significant for A, for the first and third lag, but with opposite signs; they are significant for C, only for the first lag, with a negative sign. Conversely, the monetary experience within the same lag order, X_{it-l}, plays a somewhat more consistent role in predicting deck selections: higher recent payoffs, that is, recent gains, reduce - significantly up to the third lag - the probability of selecting from deck A (that is, a 'disadvantageous' deck) and increase - significantly up to the second lag - the probability of selecting from decks C and D (the 'advantageous' ones). Interestingly, within the short-term past experience, emotional variables as well as monetary variables seem not to be significant in explaining the selection from deck B, even if it is the 'prominent' deck.

The value of wealth accumulated $ACCw_{t-1}$ plays a steady and reliable role, across model specifications and decks, but the third model (specification (9)) definitely shows overall the most interesting and consistent results: the experience accumulated, in terms of both stored wealth $ACCw_{t-1}$ and accumulated somatic activation $ACCe_{t-1}$, is able to significantly predict the probability of extracting from the four decks. The higher the intensity of the SCR experienced after choices and the higher the wealth obtained, the lower the probability of extracting from decks A and B and the higher the probability of extracting from decks C and D. There appears to be a selection strategy of avoiding 'disadvantageous' decks and searching for 'advantageous' ones in the original qualification of decks of Bechara and Damasio (2002).

These findings suggest that if there is some consistent experience provided by somatic markers, it should not be limited to the last three SCR activations but should be visible in the long run, within a *long-term* coherence.

Marginally, the role of the socio-demographic variable is really weak, aside from some evidence of a preference for deck A by males under 40.

Emotions and portfolio selection

The long-term coherence of choices, suggested by previous findings on asset picking preferences, is investigated within a portfolio perspective. As a theoretical basis we take a classical optimization problem, namely the MVT proposed by Markowitz (1952). The Markowitz model indicates 'the rule that the investor does (or should) consider' (Markowitz, 1952, p. 77): individuals take choices by reducing risks (variance) for any given return. Mean-variance (MV) efficient portfolios are the result of such an optimization process. In this paper, in order to explore the role of somatic markers, the MVT is applied to 'emotional values'. These values allow us to overcome the 'duality' of objective experience of monetary payoffs, on one hand, and of subjective experience of emotions, on the other hand, because both co-determine behaviors at the intra-individual level. This merging/weighting computation, described in the following section, is an effort to attest to the interaction of dual/multiple processes intervening in human decision-making.

Emotional values: functional form and parameters. We define 'emotional value' as a typology of subjective value in the neuroeconomics meaning (Glimcher, 2010), where the neurophysiological substrate here is the somatic past reinforcement experience, i.e., the SCR (E) recorded after each choice. Emotional values are intended here as emotionally balanced payoffs, EV. They are obtained from a weighting function where the monetary payoff is rescaled by (a positive power ω of) the emotion E:

$$EV = f(X) = \frac{|X|}{E^{\omega}}, \quad \omega \geq 0. \tag{10}$$

We introduce the non-negative parameter ω to embed no transformation ($\omega = 0 \Rightarrow f(X) = |X|$) and direct rescaling ($\omega = 1 \Rightarrow f(X) = \frac{|X|}{E}$) in a common general form. Note that when $\omega = 0$ it means that the 'value' is uniquely driven by money.

When including (1) in (10), we obtain:

$$f(X) = \frac{|X|}{E^{\omega}} = \frac{|X|}{K^{\omega}|X|^{\alpha\omega}} = \frac{|X|^{1-\alpha\omega}}{K^{\omega}} = \frac{|X|^{\rho}}{K^{\omega}}, \tag{11}$$

where we set $\rho = 1 - \alpha\omega$. The signs of α and ω imply that $\rho < 1$.

The absolute value $|X|$ in (10), as well as in (1), means that we assume that the emotion depends on the size of the payoff; the sign information is considered allowing for α to take different values for gains and for losses.

The function f in form (11) is increasing with respect to $|X|$, when ρ is positive. Under this condition, emotionally

[11] We also checked for income levels, with a dummy for under vs. over the median income level of the sample. This variable never yielded significant results in any model specification; therefore, it has been omitted.

balanced payoff, $f(X)$, can be interpreted as a power (concave) transformation of the payoff; that is, $f(X)$ describes individuals displaying diminishing sensitivity with respect to the payoff size. This is a generally agreed-upon phenomenon that is indicated also in Kahneman and Tversky (1979, p. 278): 'sensory and perceptual dimensions share the property that the psychological response is a concave function of the magnitude of physical change.' Thus, $\rho \in (0, 1)$ and consequently $\omega < \frac{1}{\alpha}$.

This setup implies that emotional values can be easily computed from f in form (10) under the constraints that $0 \leq \omega < \frac{1}{\alpha}$.

From validation of our 'money-emotions' algorithm we have empirical estimates of α, as shown in Table 4. Given that specification (4) shows the best information criteria and in this model α for gains is not statistically different from α for losses, we take the empirical value of $\alpha = .15417$. This implies that $0 \leq \omega < 6.48635$.

Mean-Variance Theory on emotional values. We set up a MV model on our four-risky-assessment environment. Consider:

- j: the column vector of portfolio weights;
- EV_{zi}: the column vector of emotional values provided by asset z for the agent i, obtained from function (10) under constraint $0 < \omega < \frac{1}{\alpha}$;
- $\mu_{EV_{zi}}$: the column vector containing the means of the emotional values EV_{zi} of the z asset for the agent i;
- D_{e_i}: the covariance matrix of returns EV_{zi}.

Based on the organization of the task, individuals are not able to observe the performances of four assets simultaneously: when choosing the z^{th}, the other three are neglected, so we can assume that $\text{cov}(E_{yi}, E_{zi}) = 0$, for $y \neq z$.

The optimization problem for the i^{th} individual, considering emotional values, is as follows:

$$\begin{array}{ll} \min_j & j' D_{e_i} j \\ \text{s.t.} & j' \mu_{e_i} = \mu_P \\ & j' \mathbf{1} = 1 \end{array} \tag{12}$$

where μ_P is a given level of portfolio return and $\mathbf{1}$ is a column vector of ones.

No short positions are allowed, in order to shape a theoretical contest that is coherent with the empirical validation. Therefore, we apply the restriction $0 \leq j_z \leq 1$, for $z = 1, \ldots, Z$.

Portfolio choices during the task: learning and testing periods. We set a training period (initial set of choices) that allows individuals to learn the risk/reward dynamics of assets and develop a physiological arousal. It is reminiscent of the 'first stage' of the MVT, when an individual 'starts with observation and experience, and ends with beliefs about the future performances of available securities' (Markowitz, 1952, p. 77). Then, we set a testing period (final set of choices) that corresponds to the MVT 'second stage', which 'starts with the relevant beliefs about future performances and ends with the choice of portfolio' (Markowitz, 1952, p. 77). Remember that our task comprises a sequence of 100 selections; thus, we set the first 80 choices as the learning period and the last 20 choices as the testing period.[12]

On the basis of the first 80 choices of each agent, we draw efficient frontiers resulting from the optimization solution of model (12) under four given values of ω: $\omega = 0$, lower extreme, i.e., values are exclusively driven by monetary outcomes; $\omega = 6$, close to the upper extreme;[13] $\omega = 1$, direct rescaling; and $\omega = 3$, mid-point of its bounce. Conversely, the assets combination resulting from the testing period, i.e., the last 20 choices, identifies the selected portfolio, which is exclusively based on monetary outcomes because we assume that the emotion-based learning experience from SCR has been completed.

Efficiency of choices depends on the distance of the portfolio selected by each individuals from these four different frontiers.

Relative efficiency of portfolio choices. We use the relative portfolio efficiency measure introduced by Kandel and Stambaugh (1995) to quantify distances of portfolios from efficient frontiers.[14] The ϕ of Kandel and Stambaugh (1995) is:

$$\phi_i = \frac{\mu_i - \mu_{mv}}{\mu_r - \mu_{mv}},$$

where i stands for the i^{th} agent, μ_i is the expected return of her/his testing portfolio, μ_{mv} is the expected return of the minimum variance portfolio and μ_r is the expected return of the efficient portfolio with the same risk as the testing portfolio. The value of ϕ_i lies in $(-\infty, 1]$. If $\phi_i = 1$ the individual portfolio belongs to the efficient frontier; if $\phi_i = -1$ the individual portfolio belongs to the inefficient part of the frontier, while higher negative values of the index represent 'severe' sub-efficiency.

INSERT FIGURE 3 HERE

We sort individual portfolios by increasing values of ϕ. Figure 3 shows values of ϕ, based on different values of ω, by number of corresponding individual portfolios: ϕ based on $\omega = 0$ (light blue line), ϕ based on $\omega = 1$ (red line), ϕ based on $\omega = 3$ (green line) and ϕ based on $\omega = 6$ (dark blue line). We omit representing portfolios worse than the 'severe' sub-efficiency case (ϕ lower than -1), that are less

[12] A 70-30 cut-off has been considered, as well, as a robustness check. Results are consistent and are available upon request.

[13] Note that ω cannot coincide with $1/\alpha$; otherwise, ρ would be 0.

[14] The introduction of individual emotional arousal produces large differences of scale from one model to another, and from one individual to another; this measure of relative portfolio efficiency makes the results comparable.

than 60 when $\omega = 6$, around 60 when $\omega = 3$, around 160 when $\omega = 1$ and more than 520 when $\omega = 0$.

Figure 3 reveals different progressive trends of individuals' portfolios towards 'level 1', i.e., perfect efficiency: all the ϕ distributions based on a correction with ω (different from 0) appear closer to efficiency, with respect to the light blue line, corresponding to the assumption that the 'value' is uniquely driven by money.

Note that the relative efficiency distribution is not affected by gender or age. In fact, we split our sample into two sets of sub-samples, distinguished by gender (male vs. female) and age (40 years of age and under vs. over40). We computed corresponding values for the relative efficiency distribution. We apply the K-S two-samples test for the equality in distribution. The tests do not reject the hypothesis of equality, at the 0.001 significance level, for all values of ω.[15]

Granularity of Portfolio Choices. Drawing efficient frontiers in the mean-variance space requires the assumption of infinite divisibility of assets. This is consequential to the optimization process with continuous weights $p \in \mathcal{R}^n$. When moving from theoretical to actual investing, in the real world, efficient portfolios are frequently not feasible, simply because each investment quantity is constrained by the asset denominations.

As part of the model validation, constraints on infinite divisibility of assets are set by the number of possible choices c during the learning and testing periods. For example, a testing period of 20 choices implies that the minimum share for each asset is equal to $1/20$.

The granularity of testing portfolios can reasonably affect the evaluation of their efficiency in terms of ϕ. For this reason, we introduce a condition for ϕ, in order to check, for each agent i, whether the corresponding ϕ_i is significantly different from 1. This condition allows us to distinguish, first, testing portfolios that are 'discrete' approximations of efficient ones, i.e., portfolios not significantly different from efficient ones; and second, true sub-efficient portfolios.

The condition for ϕ_i is obtained by adding an incremental component induced by the granularity of the testing choices. Specifically, given j_i the testing portfolio for the i^{th} agent, and c_{TP} the number of testing choices, j_i is not considered significantly different from an efficient portfolio if a portfolio j^* exists such that:

$$\begin{aligned} &\phi\,(j_i + j^*) = 1 \\ &\text{s.t.}\,(j^*)'\,\mathbf{1} = 0 \\ &\left|j^*_z\right| < \frac{1}{c_{TP}} \quad \text{with} \quad z = 1, \ldots, Z \end{aligned} \tag{13}$$

We verify this condition for validations obtained under different values of ω.

INSERT TABLE 7 HERE

Table 7 presents results and shows that 84.96 per cent of portfolios are not significantly different from efficient ones under the condition $\omega = 3$, and that 87.91 per cent can be considered efficient when $\omega = 6$. On the contrary, only 12.71 per cent of them can be considered efficient when $\omega = 0$; i.e., we exclude the weighting role of emotions.

Discussion

Based on a large experimental data set, we propose and validate an algorithm for the 'money-emotion' relation. We offer evidence of what mainly causes emotional arousal after risky choices, and where emotions lead, in terms of both asset selection and portfolio choices.

Surprisingly, even if we do find some evidence of a different SCR activation after gains with respect to losses, in a direction coherent with prospect theory (stronger effect on SCR from losses than from gains), this difference cannot be considered statistically relevant, in our model with the best information criteria. This supports the response (H. Damasio, Bechara, & Damasio, 2002) to Tomb et al. (2002), underlining that somatic markers can be both positive and negative. From our data, emotional intensity appears not to be basically different in the two monetary domains, supporting the presence of a complex interaction of positive-negative experiences in conditions of uncertainty.

Moreover, results on the presence of a SCR trend-dependent component should suggest cautiousness in observations of 'punctual' money-emotional reactions, because of the presence of 'waves' of emotions: an intense emotion, caused by gains or losses, of either equal or different amounts, positively influences the subsequent emotional activation. These 'waves' of excitement may indirectly explain the presence of emotionally driven stock-market trends, such as bubbles, or panic selling. Interestingly, we have evidence that such emotional waves could be mitigated by habituation (Rankin et al., 2009; Thompson & Spencer, 1966) to monetary payoffs, because we show that the higher the number of situations in which individuals experienced gains/losses (repeated stimuli) the lower their emotional reactions. This indicates that individuals become somehow habituated to monetary payoffs, the longer their involvement in taking risky choices. It would support the idea that financially experienced people are able to control their emotions while taking risky decisions, in line with findings of Lo and Repin (2002) study in which physiological responses appeared to be related to the traders' levels of experience.

Finally, an anchoring and framing role is played by the label of the deck proposed (in our task, A, B, C, D). The spatial positioning of decks generates an emotional arousal as a distinct feature, controlling for all the other information. This would imply that some heuristic biases proposed by Tversky and Kahneman (1974) originate from somatic markers.

[15] The income dummy has not been considered because it never yielded significant results in the probit models.

As far as the consequences of accumulation of emotional experience when taking risky choices, our findings support that the very short-term somatic experience is not always able to forecast the contingent selection of specific assets. Decision-making seems to be instead driven by a long-term strategy: the value of the wealth accumulated by individuals at any moment of the task works as a 'reference point' (Kahneman & Tversky, 1979) that induces a preference for / avoidance of risky assets. The same is true for accumulation of emotional experience.

These results justify interpreting the selection behaviors from a portfolio perspective. From this standpoint, based on our experimental data we have evidence that individuals do not follow a naïve diversification (Benartzi & Thaler, 2001) but instead engage in an optimization process; that is, they shape their choices with the goal of minimizing risk, at any given level of return. Interestingly, the efficiency of selected portfolios is visible only when referring to 'emotional values', and not when using monetary outcomes.

Conclusions

Overall, even if the emotion-based learning here is outside the SMH framework, we believe our findings may indirectly support it, as sometimes requested (Dunn et al., 2006). We prove that decision-making is related to emotion-based biasing signals generated by the body, i.e., somatic markers (Reimann & Bechara, 2010), both positive and negative.

Conceptually, our 'money-emotion' algorithm concerns *what* causes an emotional activation from the factual experience that is gradually enriched as the practice develops; this experience comes from both objective information (payoffs, external framing) and subjective information (emotional trend and habituation). Then, we show *how* this emotion-based learning process is able to (re-)orient choices, and whether it is able to guide one towards a given preference scheme. From a single-deck selection approach we have evidence that the recent experience (last three choices) is not sufficient to understand a steady and generalized coherence in selection schemes. On the contrary, all the variables indicating an overall accumulated experience, both objective from accumulated wealth, and subjective from accumulated SCR, manifest the presence of a coherence of preferences: it mainly results in a strategy of avoiding disadvantageous decks and preferring advantageous ones. The portfolio approach explains *why* this selection scheme is preferred: individuals do not simply follow a strategy of minimizing risks, but aim to reach a condition of personal 'psycho-economic' efficiency. This condition appears to manifest when the 'value' provided by money is mediated/weighted by the individual emotional reinforcement, supporting the importance of a very 'personal' perspective in the understanding of risk-taking behaviors.

We acknowledge limitations due to the lack of monetary rewards in our experimental framing: behaviors may differ depending on whether hypothetical or monetary incentives are provided, even if there is still no unequivocal evidence of their effects (Gneezy & A., 2000; Mørkbak, Olsen, & Campbell, 2014). In order to further investigate general or specific issues, such as the 'prominent B phenomenon', future research could address experiments, within a comparable conceptual framework and sample, in which a treatment group of individuals is given actual monetary rewards.

Appendix: Exclusion of selection bias

From data received by hosting bank CRM, we run a two-sample mean-comparison test by participation (yes/no), 5 per cent confidence interval. A slight difference emerges between participants and nonparticipants in terms of CRM class, i.e., intensity of use of banking products (p-value = .0393), and age (p-value = .0011): those customers declining to participate were less active and older than those accepting the invitation. This evidence makes sense given that the psycho-physiological task was conducted in person and required customers to make a special trip to their bank's offices, causing a drop-off of those less inclined to travel. Except for this, no socio-demographic and economic feature statistically differentiates those who accepted from those who refused: gender (p-value = .2823), marital status (p-value = .5242), or income (p-value = .5373). This supports evidence of no selection biases detrimental to the interpretation of our results.

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Table 1: Socio-demographic characteristics of the sample

Education		$N = 645$	100.00%
	Secondary School	30	4.65
	High School	283	43.88
	University Degree	261	40.47
	Master's Degree or Ph.D.	71	11.01
Profession		$N = 755$*	100.00%
	Salaried Employees	151	20
	Pensioners	72	9.54
	Managers	41	5.43
	Professionals (not Financial, e.g. Doctors, Lawyers)	115	15.23
	Entrepreneurs	58	7.68
	Financial Advisors	150	19.87
	On-Line Traders	51	6.75
	Fund Managers	84	11.13
	Unemployed	15	1.99
	Other Professions	18	2.38
Income **		$N = 645$	100.00%
	$<$ 500 Euros	2	0.31
	500 - 1000 Euros	10	1.55
	1000 - 2000 Euros	57	8.84
	2000 -3000 Euros	129	20
	3000 - 4000 Euros	124	19.22
	4000 - 5000 Euros	92	14.26
	5000 - 6000 Euros	58	8.99
	$>$ 6000 Euros	173	26.82
Marital Status		$N = 645$	100.00%
	With no family (single, divorced, widowed)	217	33.65
	With family	428	66.35
Asset allocation of real-life portfolios		Whole sample ($N = 645$)	Professionals excluded ($N = 364$)
	Cash and deposits	11.10%	12.80%
	Bonds	18.60%	20.40%
	Stocks	13.90%	11.60%
	Mutual funds	21.70%	15.60%
	Other financial investment	34.70%	39.60%

Note:
** multiple choice*
*** monthly income at the household level*

Table 2: Moments of the payoff distribution of the four decks

	A	B	C	D
Expected payoffs	-28.233	-31.933	26.447	28.449
Standard deviation of payoffs	136.613	384.083	26.864	70.168

Table 3: Statistics of SCR: whole sample

	Mean	Centile	Std. Dev.	Min	Max
mean values	0.2229	0.1653	0.2006	0.0074	1.5780
std. dev. values	0.2126	0.1649	0.1784	0.0036	1.5088
min values	0.0133	0.0061	0.0210	0.0000	0.1709
max values	1.1495	0.8698	0.9564	0.0215	5.6986

Note: This table shows the main statistics for the 100 SCR measures after choice, obtained from the 645 participants individually, during each task.

Table 4: Model estimates for the 'money-emotions' relation

parameters	spec. (4)	spec. (4) $\alpha_g = \alpha_l$	spec. (5)	spec. (5) $\alpha_g = \alpha_l$	spec. (6)	spec. (6) $\alpha_g = \alpha_l$
	loss/gain domains					
α_g	0.1025***	0.1515***	0.1395***	0.1430***	0.1337***	0.1542***
α_l	0.1261***	$= \alpha_g$	0.1411***	$= \alpha_g$	0.1432***	$= \alpha_g$
	trend					
β_1	0.1811***	0.1808***	–	–	–	–
β_2	–	–	0.1792***	0.1793***	–	–
β_3	–	–	–	–	0.0299***	0.0298***
	habituation					
γ_1	-0.0029***	-0.0021***	-0.0020***	-0.0019***	-0.0023***	-0.0020***
γ_2	-0.0010*	-0.0020***	-0.0018***	-0.0019***	-0.0026***	-0.0027***
	anchoring/framing					
δ_A	0.0599***	0.0624**	0.0381**	0.0380**	0.0507***	0.0457***
δ_B	-0.0525***	-0.0777***	-0.0805***	-0.0824***	-0.0805***	-0.0916***
δ_C	-0.0164	-0.0133	-0.0199	-0.0196	-0.0329**	-0.0325*
	goodness of fit					
R^2(adjust.)	0.6455(0.6416)	0.6461(0.6422)	0.6570(0.6531)	0.6568(0.6529)	0.6451(0.6407)	0.6455(0.6412)
F(p-val.)	166.63(0)	167.31(0)	171.45(0)	171.57(0)	149.29(0)	149.80(0)
resid skewness	-0.1645	-0.1654	-0.1733	-0.1732	-0.1804	-0.1806
resid kurtosis	3.0331	3.0303	3.0214	3.0205	2.9630	2.9624
AIC	131415.9	131481.5	128843.3	128834.2	118431.9	118408.2
BIC	137297.6	137354.3	134711.0	134692.9	124244.0	124211.4
	single deck models					
δ_A	0.0884***	–	0.0994***	–	0.0818***	–
δ_B	-0.0858***	–	-0.102***	–	-0.109***	–
δ_C	-0.0316**	–	-0.0279*	–	-0.0383***	–
δ_D	0.0057	–	0.0212*	–	0.0230*	–

Note: Asterisks indicate statistically significant parameters at 0.05 (*), 0.01 (**), 0.001 (***) confidence level. LR test rejects the restriction $\alpha_g = \alpha_l$ for specification (4) and does not for specifications (5) and (6). The bottom block shows the estimated coefficient of the models with only one deck indicator as decks's regressor (for purposes of interest and space, for each model, we report only the deck coefficient. Full results are available upon request). The parameters are estimated by LSDV method with WLS; Breush-Pagan, Koenker test does not reject homoskedasticity, in all cases; Brock, Dechert and Scheinkman test does not reject the hypotheses of residual no dependence up to lag 6, in all cases.

Table 5: Deck selection during the task

	Mean					Std. Dev.				
Sequence of choices	1-20	21-40	41-60	61-80	81-100	1-20	21-40	41-60	61-80	81-100
Deck A	0.239	0.223	0.198	0.180	0.166	0.426	0.416	0.398	0.384	0.372
Deck B	0.364	0.332	0.334	0.336	0.337	0.481	0.471	0.472	0.472	0.473
Deck C	0.196	0.210	0.220	0.232	0.245	0.397	0.408	0.414	0.422	0.430
Deck D	0.201	0.235	0.248	0.253	0.251	0.400	0.424	0.432	0.435	0.434

Note: Blocks of 20 choices; 12,900 observations for each block.

Table 6: Estimates of probit models for asset selection

	spec. (7)	spec. (7) d: male	spec. (7) d: under40
Deck A			
e_{t-1}	0.0194***	0.0193***	0.0194***
e_{t-2}	0.0004	0.0003	0.0004
e_{t-3}	-0.0134*	-0.0135*	-0.0134*
$ACCw_{t-1}$	-0.0102***	-0.0102***	-0.0101***
male		0.0736*	
under40			0.0664*
cons	-1.0094***	-1.0686***	-1.0427***
Wald $\chi2(n)$	60.95	64.10	64.85
Log lik.	-17470.2	-17468.7	-17468.4
Prob> $\chi2$	0.00	0.00	0.00
Deck B			
e_{t-1}	-0.0036	-0.0035	-0.0036
e_{t-2}	0.0017	0.0018	0.0017
e_{t-3}	0.0064	0.0065	0.0064
$ACCw_{t-1}$	-0.0158***	-0.0158***	-0.0157***
male		-0.0645	
under40			0.0541
cons	-0.5294***	-0.4779***	-0.5564***
Wald $\chi2(n)$	135.22	137.22	137.41
Log lik.	-22652.8	-22652	-22652
Prob> $\chi2$	0.00	0.00	0.00
Deck C			
e_{t-1}	-0.0149**	-0.0150**	-0.0149**
e_{t-2}	0.0015	0.0014	0.0015
e_{t-3}	0.0016	0.0015	0.0016
$ACCw_{t-1}$	0.0112***	0.0112***	0.0112***
male		0.0525	
under40			-0.0490
cons	-0.7853***	-0.8273***	-0.7608***
Wald $\chi2(n)$	67.00	68.39	68.86
Log lik.	-19681.4	-19680.8	-19680.6
Prob> $\chi2$	0.00	0.00	0.00
Deck D			
e_{t-1}	0.0022	0.00222	0.002
e_{t-2}	-0.0042	-0.0042	-0.0042
e_{t-3}	0.0016	0.0017	0.0016
$ACCw_{t-1}$	0.0148***	0.0148***	0.0147***
male		-0.0206	
under40			-0.0544
cons	-0.6929***	-0.6763***	-0.6658***
Wald $\chi2(n)$	106.90	107.09	109.11
Log lik.	-20149.2	-20149.1	-20148.2
Prob> $\chi2$	0.00	0.00	0.00

	spec. (8)	spec. (8) d: male	spec. (8) d: under40
Deck A			
X_{t-1}	-0.0295***	-0.0294***	-0.0295***
X_{t-2}	-0.0231***	-0.0231***	-0.0231***
X_{t-3}	-0.0097***	-0.0097***	-0.0097***
$ACCw_{t-1}$	-0.0045***	-0.0045***	-0.0044***
male		0.0734*	
under40			0.0682*
cons	-1.0144***	-1.0725***	-1.0484***
Wald $\chi2(n)$	185.08	187.98	188.89
Log lik.	-17413	-17411.6	-17411.2
Prob> $\chi2$	0.00	0.00	0.00
Deck B			
X_{t-1}	-0.0038	-0.0038	-0.0038
X_{t-2}	-0.0031	-0.0031	-0.0031
X_{t-3}	0.0012	0.0012	0.0012
$ACCw_{t-1}$	-0.0151***	-0.0151***	-0.0151***
male		-0.0643	
under40			0.0546
cons	-0.5391***	-0.4883***	-0.5663***
Wald $\chi2(n)$	136.77	138.73	138.97
Log lik.	-22653.9	-22653.1	-22653
Prob> $\chi2$	0.00	0.00	0.00
Deck C			
X_{t-1}	0.0149***	0.0149***	0.0149***
X_{t-2}	0.0137***	0.0137***	0.0137***
X_{t-3}	0.0035	0.0035	0.0035
$ACCw_{t-1}$	0.0084***	0.0084***	0.0084***
male		0.0522	
under40			-0.0505
cons	-0.7641***	-0.8053***	-0.7390***
Wald $\chi2(n)$	93.11	94.44	95.00
Log lik.	-19667.9	-19667.3	-19667
Prob> $\chi2$	0.00	0.00	0.00
Deck D			
X_{t-1}	0.0243***	0.0243***	0.0243***
X_{t-2}	0.0150***	0.0150***	0.0150***
X_{t-3}	0.0040	0.0040	0.0040
$ACCw_{t-1}$	0.0111***	0.0111***	0.0110***
male		-0.0196	
under40			-0.0557
cons	-0.7038***	-0.6883***	-0.6761***
Wald $\chi2(n)$	164.51	164.67	166.66
Log lik.	-20117.6	-20117.6	-20116.7
Prob> $\chi2$	0.00	0.00	0.00

	spec. (9)	spec. (9) d: male	spec. (9) d: under40
Deck A			
$ACCe_{t-1}$	-0.1037***	-0.1036***	-0.1036***
$ACCw_{t-1}$	-0.0113***	-0.0113***	-0.0112***
male		0.0755*	
under40			0.0669*
cons	-0.7930***	-0.8532***	-0.8267***
Wald $\chi2(n)$	95.20	98.34	98.80
Log lik.	-17456.2	-17454.8	-17454.5
Prob> $\chi2$	0.00	0.00	0.00
Deck B			
$ACCe_{t-1}$	-0.0332**	-0.0331**	-0.0332**
$ACCw_{t-1}$	-0.0162***	-0.0162***	-0.0161***
male		-0.0635	
under40			0.0543
cons	-0.4661***	-0.4162***	-0.4930***
Wald $\chi2(n)$	138.88	140.85	141.11
Log lik.	-22653.4	-22652.6	-22652.5
Prob> $\chi2$	0.00	0.00	0.00
Deck C			
$ACCe_{t-1}$	0.0606***	0.0604***	0.0605***
$ACCw_{t-1}$	0.0117***	0.0116***	0.0116***
male		0.0500	
under40			-0.0493
cons	-0.8937***	-0.9328***	-0.8691***
Wald $\chi2(n)$	76.85	78.09	78.69
Log lik.	-19677.5	-19676.9	-19676.6
Prob> $\chi2$	0.00	0.00	0.00
Deck D			
$ACCe_{t-1}$	0.0366**	0.0366**	0.0366**
$ACCw_{t-1}$	0.0152***	0.0152***	0.0151***
male		-0.0214	
under40			-0.0541
cons	-0.7745***	-0.7576***	-0.7476***
Wald $\chi2(n)$	112.02	112.23	114.23
Log lik.	-20147.4	-20147.3	-20146.5
Prob> $\chi2$	0.00	0.00	0.00

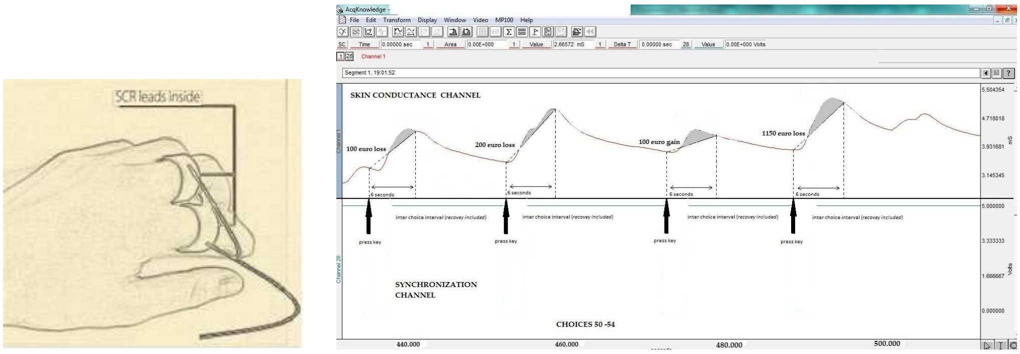
Note: This table offers results for probit estimates of model specifications (7), (8) and (9), where the dependent variable is the dummy for deck selection, i.e., deck A, deck B, deck C and deck D. Estimations refer to the last 60 choices of the experiment. We rely on 38,697 observations in model specification (7); 38,700 observations in model specification (8) and (9). In specification (7), the probability of selecting from a deck is related to e_{it-l}*, i.e., the log of SCR recorded after the payoff is known, in the previous* $t-l$ *times, up to the third lag. In specification (8), the probability to select a deck is related to* X_{it-l}*, i.e., the payoff received, in the previous* $t-l$ *times, up to the third lag. In specification (9), the probability to select a deck is related to* $ACCe_{t-1}$*, i.e., the somatic activation accumulated (incremental sum of SCR) up to that choice. The amount of money accumulated (all gains minus all losses) up to the choice considered* $ACCw_{t-1}$ *works as a control variable for all the specifications. Moreover, we add a sub-specification of each model (7), (8) and (9), including the dummy variable for gender (male vs. females, dummy* male*) and age (40 years of age and under vs. over40; dummy* under40*). Asterisks indicate statistically significant parameters at the 0.05 (*), 0.01 (**), and 0.001 (***) confidence levels.*

Table 7: Deciles of the distribution of ϕ based on different values of ω

quantile	$\omega = 6$	$\omega = 3$	$\omega = 1$	$\omega = 0$
0.1	-0.4343	-0.9080	-4.3610	-16.8418
0.2	0.6952	0.3847	-1.6002	-9.8393
0.3	0.8376	0.6726	-0.5866	-7.0888
0.4	0.8999	0.8114	-0.0917	-5.1108
0.5	0.9392	0.8627	0.3292	-3.695
0.6	0.9678	0.9159	0.6587	-2.6631
0.7	0.9852	0.9533	0.8140	-1.785
0.8	0.9961	0.9798	0.920	-1.0389
0.9	0.9995	0.9959	0.9854	0.2073
1	1	1	1	1
efficient portfolios	87.91%	84.96%	59.84%	12.71%

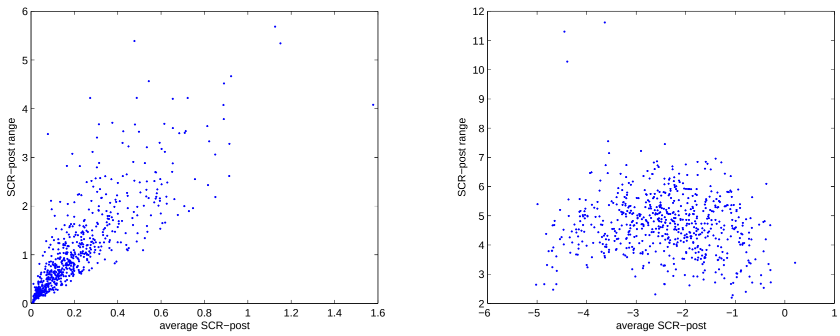
Note: Table 7 shows the empirical distribution of the relative efficiency of Kandel and Stambaugh (1995), as referred to the whole sample of 645 individuals, under different values of ω of model (8). Figures refer to the 80-20 cutoff. The last line reports the percentage of portfolios that are not statistically different from efficient ones, when granularity is considered.

Figure 1: The Skin Conductance Response measurement



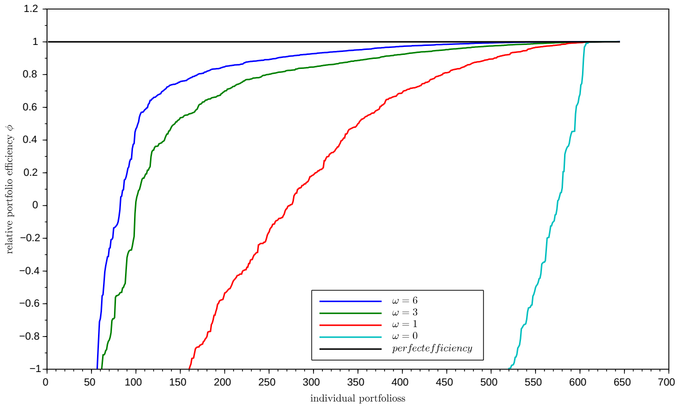
Note: The left figure shows the two electrodes placed on the skin surface of the agent running the experiment. Electrodes are attached to the palm surface of the second phalanx of the index and middle fingers of the non-dominant hand, after the agent is seated in front of the computer screen. The right chart shows the typical trend of SCR during the experiment, with upward and downward trends, due to activation and recovery towards the individual's baseline. SCR measures used in the paper correspond to the grey areas under the curve, within 6 seconds after each selection.

Figure 2: SCR after choices: relation between average and range



Note: For each individual, the relation between her/his average SCR-post (x-axis) and her/his SCR-post range (y-axis) is plotted. The left pane shows the relation between the levels of the two variables, while the right pane shows the relation between their logs. Each point represents an individual.

Figure 3: Cumulative distributions of ϕ by ω



Note: We sort individuals by increasing values of ϕ. The colored lines indicate the cumulative distributions of ϕ, by various values of ω: the best curve is the one that is leftmost.