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Types of Information Searchers: Stability in Information Search Behaviour and Its Implications

by

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Declarations

This thesis is submitted to the University of Warwick in support of my application for the degree of Doctor of Philosophy in Business and Management. It has been composed by myself and has not been submitted in any previous application for any degree.

The work presented (including data generated and data analysis) was carried out by the author except in the cases outlined below:

- The models and accompanying Matlab programmes used to generate results in Study 2 (Chapter 4) and Study 3 (Chapter 5) were written in collaboration with Professor Jerker Denrell

All external references and sources are clearly acknowledged and identified within the thesis. I am aware of the University of Warwick regulation concerning plagiarism and collusion.

Abstract

The choices individuals make are based on the information they have. Differences in search behaviours between individuals in decisions from experience experiments are therefore of importance. Studies on animal foraging provide direction for researching such differences since information search behaviours used by humans may have originally evolved for use in foraging. Such studies suggest that personality differences between individuals result in stable differences in foraging behaviours. Such differences could arise and be sustained by a changing environment where multiple stable strategies will work at least some of the time such that they are equally beneficial on average. Alternatively, the frequency dependence of some foraging behaviours may allow for the coexistence of behavioural types. Brief overviews of the literature on animal foraging behaviours, personality, decisions from experience, and frequency dependence relating to information search are provided in Chapter 2.

Chapter 3 employs decisions from experience experiments to investigate whether personality results in stable differences in information search behaviours between individuals. The results indicate that of the Big Five factors of personality Extraversion and Openness have the most consistent impact on information search behaviours. The impact is sufficient that it results in differing payoffs between individuals depending on whether search is costly or not.

Chapter 4 and Chapter 5 investigate how frequency dependence in a form of information search, social learning (learning from others), can result in heterogeneity in information search behaviours in a population. Specifically, Chapter 4 investigates how social learning may allow a population to attain greater size if it reduces per capita resource consumption, which may help explain how even nonflexible information search strategies may be beneficial and thus be more likely to coexist. Chapter 5 meanwhile investigates how the need to develop absorptive capacity (capacity to understand others) through individual learning (learning by oneself) may increase the fitness of a population but also reduce the range of types of learners.

Finally, Chapter 6 discusses the implications of the overall results while also discussing potential future research directions. I conclude that people do exhibit stable differences in their information search behaviours, these differences may be related to personality, and that they can impact how well people perform in specific circumstances (e.g. in a changing environment), which together with the frequency dependence and benefits of social learning may explain the coexistence of different types of information searchers.

Chapter 1. Introduction

Individuals make decisions based on the quality and quantity of information they have available. How much reliable information individuals possess, in turn, is largely determined by how effectively they search for information and how much time they spend on doing so. Information search behaviours are therefore highly consequential in their indirect role in shaping decision-making. Nevertheless, in experiments involving information search, such as in decisions from experience experiments, individuals tend to exhibit limited search effort (Hau, Pleskac, & Hertwig, 2010) and to differ in their search patterns when compared to other individuals (Hills & Hertwig, 2010). To help understand why and how individuals search for information in the way they do one may look to the evolutionary origins of information search. Specifically, since information search behaviours may have originally been evolved for use in foraging (Pirolli & Card, 1999), examining the foraging behaviours of animals may offer direction for research on information search behaviours.

Studies on animal foraging behaviours have identified personality as a factor contributing to stable differences in foraging behaviours between individuals (Toscano et al., 2016). Such stability in a fitness consequential behaviour as foraging may be seen as quite puzzling. After all one might expect more behaviourally flexible individuals to have a selective advantage over their more behaviourally static brethren (Wolf et al., 2007). However, a number of possible explanations for the adaptive coexistence of behavioural types have been proposed (Wolf & Weissing, 2010). One possible explanation is variation in the environment combined with flexible behaviours either not being possible or being too costly. In such a case several types of behaviour can be optimal at least some of the time such that they are equally beneficial on average allowing for multiple behavioural types to coexist.

Frequency dependent selection is another potential explanation for stable behavioural differences. In the context of foraging frequency dependence may arise in producer-scrounger games where producers find food and scroungers join the discoveries of others (Barnard & Sibly, 1981). Scroungers can thus avoid the costs of the producers will therefore grow in number but only to a point where a sufficient number of producers still remain in the population. At equilibrium both producers and scroungers will thus coexist and have equal fitness. In the context of information search, however, the frequency dependence of social learning (learning or searching for information from others) has the interesting implication that social

learning will not necessarily increase the equilibrium fitness of a population (Rogers, 1988). Since social learning seems to have been critical to human progress this result has become known as Rogers' paradox (Enquist, Eriksson, & Ghirlanda, 2007).

This thesis adopts a three-paper format to investigate why individuals may exhibit stable differences in their information search behaviours and what the consequences of such stability are. The first study uses decisions from experience experiments to investigate how the Big Five factors of personality (John, Naumann, & Soto, 2008) impact information search behaviours and whether these search behaviours will remain consistent whether optimal or not in the current search environment. Specifically, while information search is costless in the first experiment it is costly in the second experiment such that while a greater search effort may be beneficial in the first experiment it is no longer beneficial in the second. The second and third studies use modelling and simulations to examine the relationship between frequency dependence of social learning and heterogeneity of information search behaviours in a population. Specifically, the second study examines how even when subject to frequency dependence social learning may allow a population to increase in size through reducing per capita resource consumption. This factor may help explain why flexible use of social learning may not always be required and why multiple types of learners may coexist. Conversely, the third study examines how heterogeneity of information search behaviours may be reduced if individual learning (learning by oneself) is required for developing absorptive capacity (the ability to understand information from others; Cohen & Levinthal, 1990) for effective use of social learning. Thus, while the need to develop absorptive capacity may increase the equilibrium fitness of a population it also limits the range of types of information searchers.

1.1. Theoretical Framework

Information search may be researched both experimentally, as through the use of the decisions from experience paradigm, or through modelling such as when examining the effects of having different types of information searchers on a population level. These different approaches require different considerations. For example it is important to remember participants in decisions from experience experiments may be influenced by the cognitive limitations and biases of an individual and the interaction of these limitations and biases with the choice ecology (environment) to shape information search behaviour and thereby decision-making. As argued by Hau et al. (2010) a cognitive-ecological framework is therefore quite

suitable for analysing decisions from experience. Within this framework the possible impact of the Big Five factors of personality on information search behaviour may be analysed in the attempt of identifying types of information searchers. Such types of information searchers, if they exist, would be characterised by stability in information search behaviour both across time and between tasks to a sufficient degree that their behaviour could be differentiated from the information search behaviour of other types of searchers. The ability to identify types of searchers using personality rests on three crucial assumptions:

1. The Big Five factors of personality must have a relationship with information search behaviour. While direct evidence is limited, the impact of personality on animal foraging behaviour (Toscano et al., 2016) and the possible commonality between foraging and information search (Pirolli & Card, 1999) may justify this assumption. Results from the experiment performed in Chapter 3 also suggest that personality does indeed have a relationship with information search behaviours.

2. The aforementioned relationship must be substantial enough that the relationship can be easily and consistently identified. This is an important assumption since if the relationship between personality and information search behaviour is weak or unstable the relationship will have few practical implications.

3. The Big Five factors of personality must be sufficiently stable to suggest behaviour associated with them will be stable as well. Evidence from studies investigating this stability (Elkins, Kassenboehmer, & Schurer, 2017) as well as estimates of the role heritability on personality (Kandler et al., 2011) both suggest the Big Five factors of personality are sufficiently stable for this purpose. If the Big Five factors of personality are stable and have a relationship with information search behaviour it would be possible to infer that information search behaviour is stable across time as well.

A fourth assumption, although one which is not crucial for identifying types of information searchers, concerns the direction of possible causality between personality and information search behaviour. Specifically, while personality will be assumed to influence information search behaviour, it is also possible information search behaviour may itself influence personality as a consequence of influencing the information an individual is more likely to encounter in daily life. However, the relatively high heritability of personality supports the adoption of the assumption personality influences search behaviour (Jang, Livesley, & Vernon, 1996).

When using mathematical models to research the effects of stability in information search within and between individuals on a population level different

assumptions are required than when using the decisions from experience paradigm. Specifically, since no model can ever truly capture all of the complexity of real life it must be assumed that the parameters included in the model are the most crucial. In the context of using a model similar to that by Rogers (1988) choices include such things as the variability of the environment, the payoffs from successful learning (or information search), and the types of behaviours agents can engage in. Crucially, agents may be assumed to be genetically predetermined to use specific approaches to learning (or information search) as in the original model, which is certainly a vast oversimplification even if search behaviours were somewhat inherent to individuals in reality. Thus, when using such a model it must also be assumed that these simplifications do not fundamentally call the results of the model into question.

Finally, information search is a broad concept and thus it is also important to be specific about what is meant by it. In the context of decisions from experience information search refers to the choice of sample size (exclusive to the sampling paradigm) and the choice of switch rate by a participant. The interpretation of the switch rate may somewhat differ depending on whether it is exhibited in the sampling paradigm or the partial-feedback paradigm. Specifically, while in the partial-feedback paradigm more frequent switching may be indicative of exploration over exploitation, in the sampling paradigm the interpretation may be more difficult. It is possible frequent switching in the sampling paradigm is also indicative of exploration while alternatively it could be out of conscious control (Wulff, Hills, & Hertwig, 2015). If an individual exhibits frequent switching in both the sampling and partial-feedback paradigms then it may be possible to claim the behaviour is indicative of exploration in both. In the context of discussing differences in information search on a population level, such as in the model by Rogers (1988), information search may also refer to the choice between individual learning, where an individual searches for information independently, and social learning where an individual searches for information acquired by others.

1.2. Research Methods

This section describes the methodology employed during the research for this thesis.

1.2.1. Data Source and Collection Method

The research in Chapter 3 relies on primary data acquired from two decisions from experience experiments combined with Big Five personality questionnaires. The

120-item IPIP-NEO-120 personality questionnaire (Johnson, 2014) was used to measure the personality of participants in both experiments to make cross comparisons easier. The reasons the IPIP-NEO-120 was used over alternative personality questionnaires such as the IPIP-NEO-300 (Goldberg, 1999) are that it retains similar reliability and validity while being significantly shorter allowing for a faster completion time during an experimental session. Basic demographic information (age, gender, and whether they have a background in mathematics) was also requested in short questionnaires. To examine stability in information search behaviour across tasks, both experiments in Chapter 3 included four types of decisions from experience tasks, three of which had been used in previous research and had been found to have differing impacts on information search behaviours. Specifically, a sampling task (e.g. Hertwig et al., 2004), a partial-feedback task (e.g. Barron & Erev, 2003), a full-feedback task (e.g. Yechiam & Busemeyer, 2006), and a new task referred to here as a control task combining elements of the sampling paradigm and the full-feedback paradigm (see Chapter 3 for specifics), were combined in the first experiment such that participants took part in each task. The second experiment involved a variation of the first experiment where information search was costly. Both gambles in the domain of gain and gambles in the domain of losses were used in all four phases of both experiments. Participants had the chance to win money during the experiments and were provided with a show-up fee.

Both experiments were programmed using Processing (Reas & Fry, 2010) and were performed in the Warwick Business School Behavioural Science Laboratory. Participants taking part in experiments in the laboratory were recruited from the University of Warwick student population using the Warwick Research SONA sign-up system.

Neither Chapter 4 nor Chapter 5 involved experiments and were instead conducted using simulations and mathematical models.

1.2.2. Ethical Considerations

Ethical considerations are important in all experiments involving human participants (Ifcher & Zarghamee, 2016). Specifically, the informed consent of participants, the use of monetary compensation, and ensuring confidentiality and anonymity, have to be considered. These considerations were relevant for the experiments in Chapter 3. The informed consent of participants was acquired using Participant Information forms and Informed Consent forms. Participants were also provided the explicit right to withdraw their consent at any time during the experiments without any negative

repercussions and this right was explicitly stated in the Informed Consent form. In addition, while the specific hypotheses tested during the research were not stated due to practical concerns, deception was not employed during the experiments thus further ensuring the informed consent of participants.

The use of monetary compensation during experiments also related to the issue of informed consent since participants could potentially have felt coerced to participate in the experiments. Explicitly stating participants would be able to keep their show-up fee even if they decided not to complete the experiment mitigated such potential issues. All participants chose to complete the experiments. Furthermore, both the show-up fee of £2 and the potential additional rewards of up to £20 in Experiment 1 and £23.85 in Experiment 2 in Chapter 3 were relatively modest, reducing the extent to which participant could feel coerced to participate in the experiments.

Ensuring the confidentiality and anonymity of participants were also important considerations. Each participant was assigned a reference number at the beginning of the experiment and this reference number was recorded in the data instead of participant names such that participants could not be directly identified. The data obtained from participants (search and choice behaviour during the experiment, age, gender, whether the participant had a background in mathematics, and their personality measures) were also not sufficiently specific for participants to be easily identified. Finally, experimental data was stored on password-protected computers, and Informed Consent forms were stored in locked lockers, both at the University of Warwick.

Since the research conducted for Chapter 4 and Chapter 5 did not involve experiments, but rather mathematical models and simulations, the above ethical concerns did not apply to them.

1.3. Plan of Thesis

A brief literature review of foraging behaviour research relating to animal personality, decisions from experience, and frequency dependence is provided in Chapter 2. Chapter 3 then uses decisions from experience experiments to investigate whether stable differences in information search behaviours between individuals exist, whether these differences correlate with personality measures, and whether this influences decision-making. Chapter 4 then develops a model demonstrating how social learning may be beneficial to a population through reducing per capita resource consumption, which can help explain how it can be sustained on a population level. Chapter 5 then develops a model demonstrating

how requiring individual learning for develop absorptive capacity for effective use of social learning may increase the fitness of a population but reduce the heterogeneity of behaviours present in a population. Finally, Chapter 6 summarizes results from Chapter 3 to 5 and discusses some implications of the studies and some possible future directions.

Chapter 2. Literature Review

The literature reviewed here is divided into three sections. The first provides a brief review of the literature on animal foraging behaviour and how it relates to personality. The second section provides a brief review of the literature on decisions from experience. Finally, the third section provides a brief review of models of foraging behaviour and learning behaviour where some of these information search behaviours are subject to frequency dependence. The first two sections provide a foundation for the research conducted in Chapter 3 while the third section provides a foundation for the research conducted in Chapters 4 and 5.

2.1. Foraging Behaviour, Information Search, and Personality

The processes and traits humans make use of during information search may be exaptations originally evolved for use in foraging. Using such an assumption Pirolli and Card (1999) developed information foraging theory based on optimal foraging theory (MacArthur & Pianka, 1966; Werner & Hall, 1974), to describe how people search for information. A central assumption of their theory, taken from optimal foraging theory, is that people are able to near optimally adjust their information search strategies based on their current environment to maximise their rate of information acquisition. However, such an assumption is called into question given evidence of consistent differences in foraging behaviour between individuals within the same animal species. For example stable individual differences in foraging behaviour have been observed in the great tit (Aplin et al., 2014), black browed albatross (Patrick & Weimerskirch, 2014), barnacle geese (Kurvers et al., 2010), the old field jumping spider (Sweeney et al., 2013), and chacma baboons (Carter et al., 2013). Since these stable individual differences in foraging behaviour may be explained by animal personality (Toscano et al., 2016) it is possible similar stable individual differences in information search may exist between people and that these differences may be explained by differences in personality. Thus, while variation in information search behaviour within individuals may be limited, such variation may nonetheless be substantial between individuals.

If the goal is to capture stability in information search behaviour between individuals, it is important the measure of personality used to do so is itself stable. In addition, since information search may involve numerous behaviours with distinct motivators the model of personality used to explain them should also be sufficiently broad to be able to do so. The most commonly used measure of human personality

traits, the Five-Factor Model of personality (for a review see John et al., 2008), may therefore be suitable for this purpose. The measures of personality described by the

Table 2.1: The Big Five personality factors and their facets as measured using the IPIP-NEO-120

Personality factor	Personality facets	Examples of items used in the questionnaire
Openness to Experience	Imagination	Have a vivid imagination
	Artistic interests	Believe in the importance of art
	Emotionality	Experience my emotions intensely
	Adventurousness	Prefer variety to routine
	Intellect	Love to read challenging material
	Liberalism	Tend to vote for liberal political candidates
Conscientiousness	Self-efficacy	Complete tasks successfully
	Orderliness	Like to tidy up
	Dutifulness	Keep my promises
	Achievement-striving	Work hard
	Self-discipline	Am always prepared
	Cautiousness	Make rash decisions (reverse scored)
Extraversion	Friendliness	Make friends easily
	Gregariousness	Love large parties
	Assertiveness	Take charge
	Activity level	Am always busy
	Excitement seeking	Love excitement
	Cheerfulness	Radiate joy
Agreeableness	Trust	Trust others
	Morality	Use others for my own ends (reverse
	Altruism	scored)
	Cooperation	Love to help others
	Modesty	Love a good fight (reverse scored)
	Sympathy	Think highly of myself (reverse scored)
		Sympathise with the homeless
Neuroticism	Anxiety	Worry about things
	Anger	Get angry easily
	Depression	Often feel blue
	Self-consciousness	Find it difficult to approach others
	Immoderation	Go on binges
	Vulnerability	Panic easily

Note. Based on table in Johnson (2014). Items are scored on a 5-point scale where 1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, and 5=Strongly Agree. Some items are reverse scored.

model have been found to be quite stable particularly once a person has reached adulthood (Cobb-Clark & Schurer, 2012; Rantanen et al., 2007; Elkins et al., 2017) and heritability explains 40 to 60 per cent of the variance (Jang et al., 1996; Ono et al., 2000; Vernon et al., 2008; Kandler et al., 2011). The factors of personality described in the model include Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Termed the "Big Five" factors of personality by Goldberg (1981) due their broad descriptive natures, each can be further divided into more specific personality facets. Measuring the personality facets can only be done using sufficiently long questionnaires such as the 300-item IPIP-NEO-300 (Goldberg, 1999) and the 120-item IPIP-NEO-120 (Johnson, 2014) since shorter questionnaires such as the 60-item NEO Five-Factor Inventory (NEO-FFI; Costa & McCrae, 1992) can only be used to measure the broader personality factors. Table 2.1 provides the personality facets of each personality factor as well as examples of items used to measure them in the IPIP-NEO-120 questionnaire.

In contrast to the questionnaires used to measure the Big Five factors of personality, animal personality traits (see Table 2.2) are instead measured using various behavioural tests (Réale et al., 2007). On the surface, animal personality and human personality may therefore seem quite distinct from each other. However, in a cross-species review of personality research on animals Gosling and John (1999) found that several of the personality factors from the Five-Factor Model of personality were generalizable across numerous species, which was determined through comparison of the item definitions for animal personality factors and item definitions for the personality factors in the Five-Factor Model of personality. Specifically, the authors found Extraversion, Agreeableness, and Neuroticism to be

Table 2.2: Major animal personality axes

Personality axes	Examples of tests	Examples of definitions
Boldness	Predator presentation test	Avoidance or inspection of the predator
Exploration	Novel environment test	Distance covered / defecation and urination / time spent rearing/per cent of time spent with the head in the holes
Activity level	Open-field test/cage activity test	Distance covered
Sociability	Separation test	Reaction to separation from the group / latency to join the group when isolated
Aggressiveness	Mirror image stimulus	Aggressive display or contact

Note. Based on table in Réale et al. (2007).

the most generalizable personality factors followed closely by Openness to Experience. Conscientiousness, however, in addition to being measurable in humans was only found as a separable personality trait in chimpanzees. The use of specifically the Five-Factor Model of personality to seek to categorise and explain human information search behaviour may therefore be justified.

Despite the animal foraging literature providing a foundation for expecting personality to influence human information search behaviour, investigating the specifics of this relationship requires a research paradigm suitable for studying humans. One research paradigm used with humans, which is closely aligned with foraging, is the so-called "decisions from experience" paradigm, used to investigate the effect of experience on the decision-making of human participants (Hertwig et al., 2004). Decisions from experience may thus be an appropriate paradigm to adopt, particularly due to its close methodological similarities to risky foraging tasks used to investigate animal foraging behaviour (Weber, Shafir, & Blais, 2004). The following section will therefore provide an overview of the current findings in the decisions from experience literature.

2.2. Information Search in Decisions From Experience

Everyday decisions whether big or small can broadly be characterized as choices between gambles, which include two primary elements: payoffs and probabilities associated with those payoffs. The choice of restaurant for a dinner reservation, for example, may be viewed as such a choice even if it may prove difficult to provide numerically precise descriptions of the gambles. Experimentally matters are simplified as participants may be asked to choose between a gamble A with a 20 per cent probability of a payoff of 4 and a 80 per cent probability of a payoff of 0, and a gamble B with a 25 per cent probability of a payoff of 3 and a 75 per cent probability of a payoff of 0 (Barron & Erev, 2003). Furthermore, the probabilities can be in the form of either a priori or statistical probabilities depending on whether they have been made available to the decision-maker through description or through experience respectively (Hau et al., 2010). In decisions from experience participants can either be allowed to learn about the presented gambles through costless search as in the sampling paradigm (Hertwig et al., 2004), through a repeated number of payoff-consequential decisions providing information on received as well as forgone payoffs as in the full-feedback paradigm (Yechiam & Busemeyer, 2006), or through repeated payoff-consequential decisions providing information only on received payoffs as in the partial-feedback paradigm (Barron & Erev, 2003). Of these the sampling paradigm and partial-feedback paradigm allow for the investigation of

information search behaviour (exploration) rather than simply choice behaviour (exploitation).

Substantial differences in the choices made by participants in decisions from experience when compared to decisions from description have emerged prompting interest in examining the role of experience in decision-making under risk. Specifically, while small probabilities are seemingly overweighted in decisions from description according to estimates of the probability weighting function in cumulative prospect theory (CPT; Tversky & Kahneman, 1992), the predominant descriptive theory of decisions under risk, they are instead seemingly underweighted in decisions from experience (Hertwig et al., 2004). In practice this means that when presented with a risky option (e.g. payoff of 30 with a probability of 10 per cent or a payoff of 0 otherwise) participants are more likely to choose it when the gamble is described rather learned through experience. This difference in choice behaviour in decisions from description and decisions from experience has become known as the description-experience gap. Research on the nature of this gap has largely focused on the extent to which it results from external sampling biases (observed samples) arising from limited sampling, and internal sampling biases (samples taken into account during decision-making) such as recency effects (Hertwig & Erev, 2009).

Evidence seems to suggest the description-experience gap is mostly or entirely caused by external sampling bias and internal sampling bias (Camilleri & Newell, 2011; Glöckner et al., 2016). Investigating the sources of these biases is therefore warranted. One such source may be the choice of experimental paradigm used to investigate decisions from experience. Specifically, while internal sampling biases seem largely unaffected, the choice of experimental paradigm used to study decisions from experience may have a substantial impact on the source of external sampling bias. For example, memory limitations (Ashby & Rakow, 2014), which are independent of the choice of experimental paradigm, may explain why recency has been observed in both the sampling paradigm and the partial-feedback paradigm (Hertwig et al., 2006), at least when the number of samples participants experienced were not predetermined as in some studies (Rakow, Demes, & Newell, 2008; Ungemach, Chater, & Stewart, 2009; Hau et al., 2010), possibly highlighting the importance of allowing participants to choose their own sample sizes through self-directed information search (Gureckis & Markant, 2012). The presence of an exploration-exploitation dilemma (choosing from a more well known gamble or searching for potentially higher payoffs in a less known gamble) in the partial-feedback paradigm and the lack thereof in the sampling paradigm, however, may

have an impact on the source of external sampling bias through its effects on information search. Specifically, while participants in the partial-feedback paradigm may underweight rare events due to choosing risky options less often (Yechiam & Busemeyer, 2006), possibly due to the hot-stove effect where participants may choose to avoid initially less appealing options (Denrell & March, 2001), participants in the sampling paradigm seem to exhibit such behaviour due to insufficient search effort resulting in rare events not being observed according to their objective probabilities (Hertwig et al., 2004).

Beyond the choice of experimental paradigm, more specific sources of external sampling bias have also been observed. Within typical experiments in the sampling paradigm (when participants are presented with two options and given one payoff after their choice), search effort (sample size) has been found to increase in response to higher experienced payoffs (Hau et al., 2008), increase in response to options in the domain of losses rather than gains, and possibly increase in response to an increase in experienced variance in payoffs (Lejarraga, Hertwig, & Gonzalez, 2012) although this may in fact be due to an increase in sampling resulting in a higher probability of experiencing increased variance (Mehlhorn et al., 2014). Modified sampling paradigm experiments such as those used to simulate long-term payoffs through drawing multiple payoffs from the chosen option have been found to result in increased sampling effort (Wulff et al., 2015) while increasing the number of options results in decreased sampling per option thus attenuating external sampling bias (Hills, Noguchi, & Gibbert, 2013; Noguchi & Hills, 2016).

In addition to sampling effort, the rate of switching between options during sampling has also been found to be of consequence in subsequent decision-making (Hills & Hertwig, 2010). Specifically, those switching frequently (piecewise sampling) have been found to make decisions as if comparing samples each round and choosing the option winning more often (round-wise decision strategy), while those switching infrequently (comprehensive sampling) have been found to make decisions as if choosing based on higher sample means (summary decision strategy). Interestingly, this switching behaviour may in fact imply commonality between behaviour in the sampling paradigm and the partial-feedback paradigm particularly in the possibility of exploration-exploitation dilemma during sampling as switching seems to reduce prior to choice (Gonzalez & Dutt, 2011; 2012; 2016) although such a view has been challenged (Hills & Hertwig, 2012). Overall, fewer factors influencing switch rate than sample size have been identified thus far, the behaviour as an example seemingly not being influenced by memory capacity

(Wulff et al., 2015), although switching does for example seem to be reduced by a state of fear (Frey, Hertwig, & Rieskamp, 2014).

The various results from decisions from experience experiments imply the presence of motivational factors in information search. Studies outside the decisions from experience literature also suggest these motivational concerns and the arising search behaviours are at least partially a result of stable individual differences. For instance differences in exploration and exploitation behaviour may be predicted through genetics (Frank et al., 2009) and reward-seeking behaviour may be related to an individual's level of Extraversion (Depue & Collins, 1999). Impulsivity measured using the Barrat Impulsivity Scale (BIS-11; Patton, Stanford, & Barratt, 1995) has also been found to predict switching behaviour in participants in experiments with a similar structure to partial-feedback experiments (Sali, Anderson, & Yantis, 2013) and this measure of impulsivity correlates with both Extraversion and Neuroticism (Whiteside & Lynam, 2001; Lange et al., 2017). The multidimensional nature of the Five-Factor Model of personality may thus prove advantageous in simultaneously explaining numerous forms of information search behaviour.

2.3. Frequency Dependence and Heterogeneity in Information Search Behaviours

Producer-scrounger games, a form of model used to study animal foraging behaviours (Barnard & Sibly, 1981; Giraldeau, Soos, & Beauchamp, 1994), demonstrate how some forms of information search may be subject to frequency dependence. In these models producers search for locations with food and scroungers avoid the costs of search by exploiting the finds of producers. While the fitness (a measure of biological success defined as the ability of an individual to survive and reproduce) of producers is independent of their frequency in the population, the fitness of scroungers is subject to frequency dependence. When proportionately low in number, scroungers have many producers that they can follow, increasing the probability the scroungers will find food, which allows them to have high fitness and to grow in number. Conversely, when proportionately high in number, scroungers have few producers that they can follow, decreasing the probability the scroungers will find food, which leads them to have low fitness and to decrease in number. Thus, at equilibrium both producers and scroungers will be present in the population. However, in models of social learning, a similar class of models to producer-scrounger games (Laland, 2004), this same result has proved controversial.

Social learning, acquiring information from others, is considered to have had a central role in the success of humans as a species through allowing the development and spread of culture, which may be defined as the accumulation of knowledge, attitudes, and behaviours (Boyd, Richerson, & Henrich, 2011; Laland, 2017). It was commonly believed the presence of social learning would therefore necessarily increase the fitness of a population. However, using a simple model of simultaneous cultural and genetic evolution, Rogers (1988) demonstrated how social learning does not necessarily increase the equilibrium fitness of a population if social learning is subject to negative frequency dependence. This result has since become known as Rogers' paradox (Enquist et al., 2007).

2.3.1. Rogers' Paradox

In his model Rogers assumed a species living in a temporally varying environment, which can be in either state 0 or state 1, where every generation the state of the environment changes with probability u. Individuals could adopt a behaviour 0 or a behaviour 1 (representing alternative hunting strategies for example), where if their behaviour and the state of the environment matched then their base fitness ω would be increased by b while if their behaviour and the state of the environment did not match then their base fitness would be reduced by b (see Figure 2.1).

		Environmental State	
		0	1
Behaviour	0	$\omega + b$	$\omega - b$
	1	$\omega - b$	$\omega + b$

Figure 2.1. Fitness acquired depending on behaviour and environmental state. Recreation of figure in Rogers (1988).

If individuals are unaware of the state of the environment and were to randomly choose their behaviour then their fitness would be $\omega + 0.5b - 0.5b = \omega$. However, individuals may increase their fitness if they are able to learn accurate information about the state of the environment. The population consists of two types of learners with genetically determined learning strategies: individual learners and social learners. Individual learners learn about the environment directly, providing them accurate information (such that they always perform the appropriate behaviour) but at a cost bc_i (reflecting the expenditure of time or energy or an increased risk of predation). The fitness of individual learners is therefore given by

$$\omega_i = \omega + b(1 - c_i). \tag{2.1}$$

Social learners learn about the environment indirectly through randomly selecting an individual from the previous generation to learn from. The information the social learner acquires will originally have been learned by an individual learner, which occurred τ generations ago with probability $p_s^{\tau-1}(1 - p_s)$, where p_s is the proportion of the population that are social learners. Since cultural evolution is assumed to be much faster than genetic evolution p_s may be considered a constant for the purposes of finding the cultural equilibrium $\widetilde{\omega}_s$, which is the equilibrium value of ω_s from cultural evolution only. The benefit of the information is assumed to be zero if the environment has changed since the information was originally learned by an individual learner, while providing a benefit of b if the environment has not changed since then. The probability the environment has changed since the information was originally learned by an individual learner is $(1 - u)^\tau$. The fitness of social learners is therefore given by

$$\begin{aligned}\widetilde{\omega}_s &= \omega + b\sum_{r=1}^{\infty} p_s^{\tau-1}\,(1 - p_s)(1 - u)^\tau \\ &= \omega + b(1 - p_s)(1 - u)\textstyle\sum_{r=1}^{\infty} p_s^{\tau-1}\,(1 - u)^{\tau-1} \\ &= \omega + \tfrac{b(1-p_s)(1-u)}{1-p_s(1-u)}.\end{aligned} \tag{2.2}$$

The fitness of social learners therefore decreases in relation to the proportion of social learners in the population such that at some point it is equal to the fitness of individual learners. Equation 2.2 then implies that $\omega_i = \widetilde{\omega}_s$ at the equilibrium value of p_s given by

$$p_s^* = 1 - \tfrac{(1-c_i)u}{(1-u)c_i}. \tag{2.3}$$

At any $p_s < p_s^*$ the fitness of social learners would be greater than the fitness of individual learners. Thus, the proportion of social learners in the population would increase until $\omega_i = \widetilde{\omega}_s$. Conversely, at any $p_s > p_s^*$ the fitness of social learners would be less than the fitness of individual learners and thus the proportion of social learners in the population would decrease until $\omega_i = \widetilde{\omega}_s$. This result can be seen in Figure 2.2.

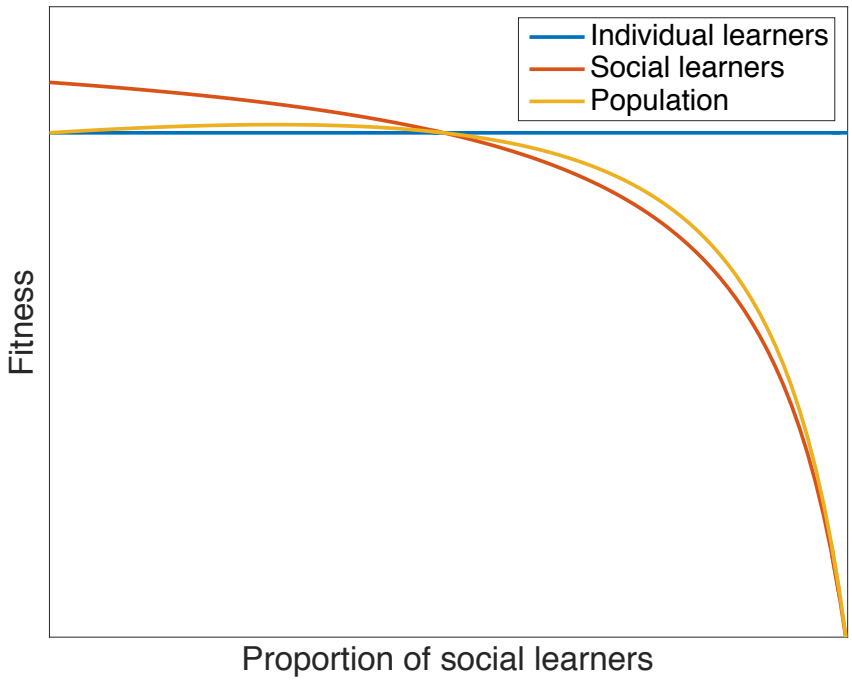

Figure 2.2. Rogers' paradox where the frequency dependence of social learning results in no increase to the fitness of the population at equilibrium. Recreation of figure in Rogers (1988).

2.3.2. Past Solutions to Rogers' Paradox

The fundamental reason for Rogers' paradox is the negative frequency dependence of social learning. Furthermore, this result will remain as long as the only benefit of social learning is that it allows for the costs of individual learning to be avoided (Boyd & Richerson, 1995). The key to solving the paradox thus seems to be to remove or reduce the negative frequency dependence of social learning. Numerous ways to achieve this have been proposed.

Flexible Learning

Rogers' model assumed the existence of distinct types of learners with stable preferences in how they searched for (learned) information. However, individuals could instead be flexible in their learning strategies such that they engage in individual learning when it is cheap and accurate, and engage in social learning when individual learning is costly or inaccurate (Boyd & Richerson, 1995). For example the cost of individual learning can determine the proportion of individuals engaging in individual learning in both simulations as well as in experiments, although participants were found to exhibit stability in their preferences (Kameda &

Nakanishi, 2002). Both simulations and experiments with participants also show that if individuals can switch between individual learning and social learning selectively then social learning can increase equilibrium population fitness (Kameda & Nakanishi, 2003).

The more adaptively individuals can switch between individual learning and social learning the higher their fitness will be. For example both conditional social learners, that initially engage in individual learning and switch to social learning if individual learning is not sufficiently beneficial, and critical social learners, that initially engage in social learning and switch to individual learning if social learning is not sufficiently beneficial, can substantially increase the fitness of a population beyond fitness acquired through individual learning alone (Enquist et al., 2007). Of these critical social learners have higher fitness and their fitness increases as the proportion of critical social learners in the population increases until only critical social learners remain. The importance of social learning over individual learning was echoed in the results from a social learning strategies tournament where multiple learning strategies were tested against each other simultaneously, as the winning strategy relied mostly on social learning (Rendell, Boyd, Cownden, et al., 2010).

Specialised Hybrid Learners

Flexibility in the use of individual learning and social learning may not be necessary for social learning to increase equilibrium fitness. Specifically, hybrid learners that specialise in using individual learning to learn in some contexts while using social learning in other contexts may have higher fitness than pure individual learners (Kharratzadeh et al., 2017). Rogers' model assumed a single dimension of the environment about which individuals had to learn. However, if individuals have to learn about two or more dimensions simultaneously then they would have to divide their attention between them. In such a case, regardless of how pure individual learners divide their attention between the two environmental dimensions their fitness would be the same as if only tracking a single dimension. Pure social learners would now, however, have an increases probability of learning incorrect information, as individual learners may not be giving their full attention to learning from a given dimension. In contrast, a population with different types of hybrid learners that use their full attention in individual learning to learn from one dimension and use social learning to learn from another dimension (social learning is assumed to not require much attention) can have higher fitness than either

individual learners or social learners since they can learn effectively about both dimensions.

Cumulative Improvements to Culture Across Generations

If socially learned information is improved upon every generation, then social learning can allow a population to achieve higher equilibrium fitness than individual learning. For example if individuals use social learning to randomly learn from an individual from the previous generation, as social learners do in Rogers' model, but then do some level of individual learning (less than individual learners would) to improve on the information, then at equilibrium all learners will adopt this strategy and their fitness will be higher than the fitness of individual learners would be (Boyd & Richerson, 1995). Crucially, however, for cumulative culture to provide a solution to Rogers' paradox the population cannot consist of pure individual learners and pure social learners. In addition, learning strategies that are useful in a non-cumulative culture setting, such as critical social learning, may not evolve in a cumulative culture setting (Ehn & Laland, 2012).

Cumulative culture faces a challenge in its long-term usefulness in that inaccurate information may accumulate in addition to accurate information. If a sufficient amount of inaccurate information accumulates then culture may no longer provide a benefit beyond acquiring information through individual learning and may even prove detrimental (Lehmann & Feldman, 2009). For cumulative culture to remain useful in such cases thus requires individuals to be able to adaptively filter information while using social learning such that they somewhat or fully ignore inaccurate information (Enquist & Ghirlanda, 2007).

Spatial Structure

Adding spatial structure to evolutionary model can greatly affect results. Rogers' model did not include spatial structure and thus the effect if may have on populations has been investigated. Models of social learning including spatial structure show that it does indeed have a substantial impact on how a population may evolve. For example in populations with pure individual learners and pure social learners, the fitness of the population at equilibrium may be below that of a population with only individual learners (Rendell, Fogarty, & Laland, 2010). This result can occur if social learners can only learn from individuals close to them (instead of the entire population as in Rogers' model) and population dispersal is local (such that the new generation will stay close to where their parents were). However, this issue does not occur in populations of critical social learners or

conditional social learners. Spatial structure has also been found to interact with previous solutions to Rogers' paradox in other ways. For example cumulative culture may prove more beneficial to a population when spatial structure is introduced at least when the population is living on a very small island (Ohtsuki, Wakano, & Kobayashi, 2017).

Chapter 3. Stable Differences in Search Behaviours Between Individuals Explained by Personality

3.1. Introduction

Traits and even behaviours originally evolved for specific purposes often end up being used successfully for entirely different purposes. Such exaptations may explain how early birds gained flight as well as how the human brain is capable of much more than seemingly necessary in the wilderness (Gould & Vrba, 1982). Finding the original role of exaptations may prove enlightening as to their functions and limitations even in their current roles. Applying such an approach, Pirolli and Card (1999) argued that information search behaviour people use in web searches might be an exaptation of the plasticity humans evolved for use in foraging. If the relationship proposed by the authors is correct, findings from the foraging literature may also have applications in helping understand information search in the context of decisions under risk, wherein people are presented with and asked to choose between monetary gambles. Search behaviours in this context may be investigated by allowing participants to learn about the gambles through experience, such that they make *decisions from experience* (Hertwig et al., 2004). The similarities between the foraging behaviour of non-human animals in risky foraging tasks, and the information search behaviour of humans in decisions from experience, may suggest comparisons between the animal foraging literature and decisions from experience literature are quite meaningful (Weber et al., 2004).

The manner in which a person searches for information in decisions from experience experiments seems to have a substantial impact on their decision-making. For example, on average people exhibit quite limited search (taking few samples), which results in rare payoffs being seen less often than according to their objective probabilities and thus detrimentally influencing decision-making (Hau et al., 2010). Investigations as to the factors influencing the amount of search people engage in have found for instance the size of payoffs (Hau et al., 2008) and variance in payoffs (Lejarraga et al., 2012) to be relevant. In addition to sample size the pattern of search people exhibit, specifically how often they switch between options when searching, has also been shown to be related to subsequent decisions (Hills & Hertwig, 2010). Some new directions for the research on decisions from experience may be obtained from relatively recent findings in animal foraging studies. Specifically, a surprising amount of stability in foraging behaviour within individuals and heterogeneity between individuals of the same species has

been observed. Further, such stability in behaviour seems to arise as a consequence of animal personality (Toscano et al., 2016). Due to the aforementioned similarities between foraging behaviour in animals and information search behaviour in humans, investigating whether similar stability occurs in human information search in decisions from experience as a consequence of human personality traits, is worthwhile. Such stability in information search could for example prove quite consequential if it reduces the extent to which people are able to adapt their information search behaviour when it would be optimal for them to do so. Possible evolutionary reasons for and possible advantages of such stability would also be worthy of investigation.

The Five-Factor Model of personality (John et al., 2008) is the most commonly used measure of human personality traits and may thus prove suitable for identifying possible stability in information search within decisions from experience. The "Big Five" factors of personality of Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism will thus be used to seek to explain stability in specific aspects of information search. If these personality factors prove to reliably influence information search behaviour, they may be used to identify and differentiate between different types of information searchers.

Two experiments were performed to investigate the extent to which individuals exhibit stability and differences from others in their search behaviours. Both experiments involved four sets of gamble choice tasks in which participants had to learn about the gambles to make informed choices. Each task differed in how participants could learn about the options available to them and how much information they were provided while searching. Furthermore, the two experiments differed in that while in the first experiment searching did not involve an explicit cost it did in the second experiment. By comparing search behaviours between tasks the stability in search behaviours could be established even when such stability would be detrimental. In addition, by investigating the relationship between personality and the choice behaviours some indications as to the possible innate nature of these search behaviours could be established.

The results from both experiments suggest that Extraversion has a positive relationship with sample size while Openness to Experience has a negative relationship with switching. Given participants taking more samples had higher expected payoffs in the first experiment (without search costs) but lower expected payoffs in the second experiment (with search costs), participants with higher Extraversion did better in the first experiment and worse in the second experiment.

Given higher amounts of switching resulted in lower expected payoffs in the second experiment, participants with higher Openness to Experience did better in the second experiment than in the first experiment. Thus, stable differences in search behaviours between individuals were found and these behaviours seemed to be related to personality traits allowing for different types of searchers to be identified: extensive searchers (high Extraversion) and low switchers (high Openness to Experience). In addition, the behaviours of these types of searchers remained sufficiently different from others to impact their performance depending on whether search was costly or not.

3.2. Experiment 1: Search Tasks

One hundred and eight participants from the University of Warwick were recruited using the university SONA system to take part in one of four experimental sessions taking place in the Warwick Business School Behavioural Science Laboratory. The participants took part in four decisions from experience tasks involving learning about and making choices between gambles in the six decision problems used by Hertwig et al. (2004), which are presented in Table 3.1. The four tasks included a sampling task, a partial-feedback task, a full-feedback task, and a task that will henceforth be referred to as the control task. Participants were also asked to complete the IPIP-NEO-120 personality questionnaire (Johnson, 2014) and a short demographics questionnaire asking about their age, gender, education, and whether they had studied mathematics related subjects at university level. Participants were paid a show-up fee of £2 and had the opportunity to win up to £20 more depending on the number of combined points they won from all four experimental tasks. Total points were converted to GBP at a rate of £1 per 20 points. Winnings were capped at £20 and were rounded to the nearest £0.10.

Table 3.1: Choice problems and order of presentation between tasks and sessions

	Option Description		Expected value of options		Order of presentation in different tasks			
Decision problem	A	B	A	B	Sampling task	Partial-feedback task	Control task	Full-feedback task
1	4, 0.8 0, 0.2	3, 1.0	3.2	3	1	6	4	2
2	4, 0.2 0, 0.8	3, 0.25 0, 0.75	0.8	0.75	4	3	1	5
3	-3, 1.0	-32, 0.1 0, 0.9	-3	-3.2	3	2	6	4
4	-4, 0.8 0, 0.2	-3, 1.0	-3.2	-3	5	4	2	6
5	3, 1.0	32, 0.1 0, 0.9	3	3.2	6	5	3	1
6	3, 0.25 0, 0.75	32, 0.025 0, 0.975	0.75	0.8	2	1	5	3

Note. Values for the gambles are presented as in Hertwig et al. (2004) while the values shown to participants in the experimental tasks were altered slightly. Specifically, in the sampling task and the control task the payoff values of gambles were multiplied by 10 (e.g. payoff of 4 was 40) while in the partial-feedback task and the full-feedback task the values were divided by 5 (e.g. payoff of 4 was 0.8) to equalise the expected payoffs between tasks since 50 repeated payoff consequential choices were made in the partial-feedback task and full-feedback task for every 1 payoff consequential choice made in the sampling task and the control task. The order in which the decision problems were presented was also changed between experimental tasks such that participants would be less likely to notice they were presented with the same gambles they had been presented with in previous tasks. The numbers 1 to 6 represent the orderings for the decision problems in the different tasks. Finally, the gambles associated with Options A (presented to participants on the left side of the screen) and Options B (presented to participants on the right side of the screen) for decision problems 4, 5, and 6 were reversed in comparison to Hertwig et al. (2004) but otherwise remain unchanged. Reversing these gambles was done to equalise the overall expected value of Options A and Options B and to thus reduce the possibility of participants starting to prefer options presented on one side of the screen to the other.

The four decisions from experience tasks used in the experiment shared several features. In all the tasks participants were presented with a pair of gambles at a time and tasked with learning about and making payoff-consequential choices between them for the purpose of winning points. The same gambles were used in

all four tasks for the purposes of making direct comparisons in search and choice decisions between tasks easier. Two primary measures were taken to reduce the chance of participants realising they were presented with the same decision problems repeatedly. First, the order in which decision problems were presented to participants was changed between tasks such that the same decision problem would not be presented twice in a row (see Table 3.1). Second, the number of points participants could win in the tasks was modified such that they were lesser per choice in the partial-feedback task and full-feedback task when compared to the sampling task and control task while nonetheless resulting in equal overall payoffs

		Exploitation	
		Exploitation while learning	No exploitation while learning
Exploration	Partial feedback	Partial-feedback task (explore-exploit trade-off)	Sampling task (separated exploration and exploitation)
	Full feedback	Full-feedback task (exploit only)	Control task (separated exploration and exploitation)

Figure 3.1: The exploration and exploitation dimensions of the experimental tasks used in Chapter 3. Exploration refers to participants drawing samples from the gambles they are presented with for the purpose of learning about the gambles. Partial-feedback only provides information about the selected gamble while full-feedback provides information about both gambles. Exploitation refers to choices participants make that may lead to them receiving rewards dependent on the chosen gamble. Exploitation while learning simultaneously provides information about the gambles and the opportunity to receive rewards, as participants draw samples while no exploitation while learning only provides information about the gambles. The four tasks including the sampling task, the partial-feedback task, the full-feedback task, and the control task combine different dimensions of exploration and exploitation.

between tasks. While the tasks were similar they also differed in some fundamental aspect. Specifically, the tasks varied between each other on two dimensions: exploration and exploitation. Exploration, defined as the process of searching for information about the presented gambles, was influenced by whether the experimental task allowed for full feedback (samples from both gambles) or only partial feedback (samples from the chosen gamble) when participants chose a gamble. Exploitation, defined as the process of making choices for the purpose of receiving a reward, was influenced by whether the experimental task allowed for exploitation simultaneously with exploration or whether exploitation and exploration were inherently separate activities. Thus, the decisions from experience tasks used in the experiment may be identified along these two dimensions as shown in Figure 3.1.

The sampling task followed the same design used by Hertwig et al. (2004). The task involved two stages: a sampling stage during which participants would have a chance to learn about the gambles they were presented with and a choice stage in which they would choose one of the gambles to receive rewards from. In the sampling stage participants were presented with a screen showing two squares titled Option A and Option B (see Table A.1), which were associated with different gambles. For example, in decision problem 1 Option A would be associated with a gamble providing 40 points with a probability of 0.8 while Option B would be associated with a gamble providing 30 points with certainty (see Table 3.1). Note that points provided by the gambles in the sampling task were multiplied by 10 when compared to the values shown in Table 3.1. Clicking on the squares would show participants a sample from the associated gamble for a duration of 0.5 seconds (e.g. 40 when clicking on the square for Option A in the example). Participants would be encouraged to take as many samples as they felt necessary to be confident about making their payoff-consequential choice. Once ready to make a choice between the gambles, participants would be presented with a new screen presenting them with the same gambles and they would be asked to click on the gamble of their choosing. After making their choice, the next pair of gambles would be presented to the participants and the process would continue until they had made choices in all six decision problems.

The partial-feedback task followed a similar design to the one used by Barron and Erev (2003). The task involved making 50 repeated payoff-consequential decisions in each of the six decision problems. Participants were presented with a screen with two squares titled Option A and Option B, each associated with a gamble, and were asked to click on the squares to make a number of repeated

choices between the same gambles. Participants were not informed of how many choices they were allowed to make prior to being presented with the next decision problem. After each choice participants were shown how many points they had won from their choice of gamble for a duration of 0.5 seconds. Note that points provided by each choice were divided by 5 when compared to the values shown in Table 3.1. For example, in decision problem 1 participants could win 0.8 points or 0 points when choosing Option A or 0.6 points when choosing Option B. Participants were awarded fewer points per choice in the partial-feedback task when compared to the sampling task for two reasons. First, since 50 payoff-consequential choices were made in the partial-feedback task for every 1 payoff-consequential choice in the sampling task, the number of points awarded per choice in the partial-feedback task had to be one fiftieth of that awarded in the sampling task to equalise the expected number of points participants could win in the two tasks (e.g. 0.8 points multiplied by 50 is 40 points). Second, by providing seemingly very different rewards in the partial-feedback task when compared to the sampling task and by not revealing the number of choices they were allowed to make in the partial-feedback task, participants could be shown the same gambles in the two tasks with a lesser chance of participants realising it.

The full-feedback task followed a similar design to the one used by Yechiam and Busemeyer (2006). Similarly to the partial-feedback task, the full-feedback task involved making 50 repeated payoff-consequential choices in each of the six decision problems. As in the partial-feedback task, the participants were not informed of how many choices they could make in each of the decision problems. The problems were again presented on the screen with two squares titled Option A and Option B, as in the previous tasks. Clicking on one of the squares would show participants samples from both the selected gamble and the other gamble for a duration of 0.5 seconds. However, participants would only receive the points from the option they chose. For example, in decision problem 1 a participant selecting Option A could be shown a sample of 0.8 from Option A and a sample of 0.6 from Option B but would only receive 0.8 points from their choice. Note that participants received the same number of points per choice as they did in the partial-feedback task to equalise the total number of points received between tasks and to reduce the chance participants would realise they were facing the same gambles in each task.

The control task combined features of both the sampling task and the full-feedback task. As in the sampling task, the task involved two stages: a sampling stage and a choice stage. In the sampling stage participants were presented with

the two squares for Option A and Option B and were asked to sample for as long as they wished prior to making a payoff-consequential choice between the two options. Similarly to the full-feedback task, clicking on the square for either option during the sampling phase would result in samples from both options being shown on the screen for a duration of 0.5 seconds. Once ready to make a choice between the gambles, participants would be presented with a new screen allowing them to make a payoff-consequential choice between the gambles.

The experiments were performed during four sessions. Each session was started with providing instructions to participants about the experiment. Participants were asked to read written instructions and to sign consent forms provided to them after which they were allowed to start the experiment at their own pace. The experiment started with the four decisions from experience tasks after which participants were asked to complete the IPIP-NEO-120 personality questionnaire and a short demographics questionnaire. The order in which the decisions from experience tasks were performed differed depending on the session (see Table 3.2). Doing so allowed for the possible order effect of performing the different tasks to be controlled for. However, the relative order of the tasks was kept constant such that, unless performed last, the sampling task was always followed by the partial-feedback task, which was always followed by the control task, which was always followed by the full-feedback task. This relative order was kept constant since separating tasks with the same magnitude of payoffs per choice made it less likely for participants to realise the same decision problems were used in each task.

Table 3.2: Order of the decisions from experience tasks by session

	Session			
Tasks	1	2	3	4
Sampling task	1	4	3	2
Partial-feedback task	2	1	4	3
Control task	3	2	1	4
Full-feedback task	4	3	2	1

Note. The numbers refer to the order in which a task was performed during a given experimental session. The relative order of the tasks was kept constant between sessions such that the sampling type tasks, namely the sampling task and the control task, were always followed by a feedback type task, namely the partial-feedback task and the full-feedback task respectively unless the sampling type tasks were performed last.

3.2.1. Hypotheses

Each hypothesis is concerned with the influence of the Big Five factors of personality on either sample size or switch rate in response to an aspect of the choice ecology. Extraversion is a personality factor composed of the more specific facets of Friendliness, Gregariousness, Assertiveness, Activity Level, Excitement Seeking, and Cheerfulness (Costa & McCrae, 1992). In relation to preferences and behaviours relevant to information search, Extraversion has been associated with both reward sensitivity (Depue & Collins, 1999; Lucas et al., 2000) as well as impulsivity (Lange et al., 2017). Greater reward sensitivity implies the willingness to apply more effort to receive rewards lending itself to the following hypothesis:

Hypothesis 1: Extraversion will have a positive relationship with sample size in the sampling task and the control task.

Since impulsivity has been linked with increased switching between options during information search in previous research (Sali et al., 2013) it follows that Extraversion may lead to similar behaviour. Furthermore, this tendency implies the presence limited forethought, which may lead to similar behaviour across contexts leading to the following hypothesis:

Hypothesis 2: Extraversion will have a positive relationship with the switch ratio in all four experimental tasks.

Neuroticism is a personality factor composed of the more specific facets of Anxiety, Anger, Depression, Self-Consciousness, Immoderation, and Vulnerability (Costa & McCrae, 1992). Neuroticism has been found to have a positive relationship with risk aversion (Becker et al., 2012), and thus higher Neuroticism may lead to an increased willingness to apply more effort in an attempt to minimize risk, leading to the following hypothesis:

Hypothesis 3: Neuroticism will have a positive relationship with sample size in the sampling task.

Openness to Experience is a personality factor composed of the more specific facets of Imagination, Artistic Interests, Emotionality, Adventurousness, Intellect, and Liberalism (Costa & McCrae, 1992). Openness to Experience describes the extent to which a person desires novel experiences (McCrae & Sutin, 2009), which may be reflected in information search as a general tendency for increased exploration, leading to the following hypothesis:

Hypothesis 4: Openness to Experience will have a positive relationship with the switch ratio in all four experimental tasks.

Conscientiousness is a personality factor composed of the more specific

facets of Self-efficacy, Orderliness, Dutifulness, Achievement-striving, Self-discipline, and Cautiousness (Costa & McCrae, 1992). Conscientiousness has been shown to be a strong predictor of job performance due to its association with effort levels (Barrick, Mount, & Judge, 2001), which may be reflected as a greater willingness to apply more effort during information search. Conscientiousness has also been shown to have a positive relationship with loss aversion (Boyce, Wood, & Ferguson, 2016), which may be reflected as a greater willingness to apply more effort during information search when seeking to avoid losses. The following hypothesis concerning the relationship between Conscientiousness and information search may therefore be formed:

Hypothesis 5: Conscientiousness will have a positive relationship with sample size in the sampling task and the control task.

Finally, Agreeableness is a personality factor composed of the more specific facets of Anxiety, Anger, Depression, Self-Consciousness, Immoderation, and Vulnerability (Costa & McCrae, 1992). Agreeableness has been shown to be predictive of cooperative behaviour and trust towards others (Kagel & McGee, 2014) and may thus be expected to influence information search in a social setting. However, since the experimental tasks do not involve interaction with other participants Agreeableness is not expected to influence search.

3.2.2. Results

The main results of interest in the experiment concerned stability of search behaviour across tasks within individuals and whether this stability correlated with the Big Five factors of personality. Search behaviour was measured in two primary ways: in the number of samples a participant took prior to making a payoff-consequential choice (in the sampling task and the control task) and a measure of switching behaviour between options participants exhibited during each decision problem in the sampling task and the partial-feedback task. Switching behaviour in the control task is used as a control for unexplained switching behaviour, as switching between options in the task provides no additional information to participants. Switching behaviour was calculated in the same manner as done by Hills and Hertwig (2010) by taking the ratio between the number of switches a participant made and the maximum number of switches the participant could have made ($n - 1$, where n is the total number of samples acquired during a decision problem). Analysing the number of samples participants took was only relevant in the sampling task and the control task since the number of samples taken were predetermined in the partial-feedback task and the full-feedback task (i.e. 50 in each

decision problem in both tasks). Switching behaviour, however, could be compared across all four tasks since this was not predetermined in any of the tasks.

Regressions were performed separately with both personality factors and personality facets, as the latter are more specific and may thus better explain behaviours (Paunonen & Ashton, 2001). Quantile regressions were performed in addition to ordinary least squares regressions to reduce the effect of outliers in the data as well as test the effects of personality on search behaviours at different quantiles (0.1, 0.25, 0.50, 0.75, 0.9). To correct for multiplicity in the quantile regressions Bonferroni corrections were used. Specifically, only results that remained significant after their p-values were multiplied by 5 (the number of quantiles tested) were analysed.

Descriptive Statistics

The variables used in the regression analysis are listed in Table 3.3. The variables included the age of the participants in years, whether they were female, their current education status (undergraduate, postgraduate, or PhD student), whether they had taken any university courses or modules involving mathematics, scores for the Big Five factors of personality (Neuroticism, Extraversion, Agreeableness, Openness to Experience, and Conscientiousness), risk aversion (estimated from the combined number of times the risky gamble was chosen from the last 10 choices in each of the decision problems in the full-feedback task), the number of samples taken in the six decision problems (in the sampling task and the control task), the switch ratio exhibited in the six decision problems (in the sampling task, the control task, the partial-feedback task, and the full-feedback task), the number of points the participants won and the number of points they would be expected to win on average given their choices (based on the expected value of the gambles chosen). It should be noted that in cases where the number of samples taken was only 1, resulting in the switch ratio not being possible to calculate due to a dividing by zero error, the switch ratio was set to 0.

Apparent outliers for the number of samples taken in both the sampling task and control task were found. Specifically, the maximum values of 435 samples and 182 samples for the sampling task and the control task respectively were considered outliers possibly caused by confusion about the tasks. The participant in the sampling task who took 435 samples did so only in the first decision problem faced in the sampling task and took fewer than 10 samples in the remaining five decision problems. The participant in the control task who took 182 samples did so only in the first decision problem faced in the control task and while taking 94

samples in the second decision problem, took 21 or fewer samples in the remaining four decision problems in the control task. Others may have made similar errors causing outliers in the data. However, due to uncertainty about which data were truly caused by such errors the outliers were not removed from the analysis. Instead, in addition to ordinary least square regressions, quantile regressions were performed to reduce the effect of the outliers.

Table 3.3: Descriptive statistics of the variables used in the regression analysis

Variable	N	Mean	Std. Dev.	Minimum	Maximum
Age	108	20.759	2.148	18	31
Female	108	0.528	0.502	0	1
Education	108	1.167	0.421	1	3
Quantitative background	108	0.806	0.398	0	1
Neuroticism	108	2.933	0.570	1.208	4.333
Extraversion	108	3.321	0.551	1.958	4.667
Agreeableness	108	3.546	0.492	2.375	4.625
Openness to Experience	108	3.369	0.499	2.083	4.750
Conscientiousness	108	3.538	0.528	2.375	4.750
Risk preference	108	29.139	8.178	7	48
Samples (sampling task)	648	27.049	34.550	1	435
Samples (control task)	648	20.148	19.336	1	182
Switch ratio (sampling task)	648	0.353	0.383	0	1
Switch ratio (control task)	648	0.072	0.195	0	1
Switch ratio (partial-feedback task)	648	0.262	0.200	0	1
Switch ratio (full-feedback task)	648	0.192	0.152	0	0.776
Total payoffs (sampling task)	648	11.574	110.406	-330	360
Total expected payoffs (sampling task)	648	15.162	1.807	11	19.5
Total payoffs (control task)	648	13.704	115.090	-320	370
Total expected payoffs (control task)	648	15.287	1.914	11	20
Total payoffs (partial-feedback task)	648	15.859	13.605	-20	54.200
Total expected payoffs (partial-feedback task)	648	15.404	0.978	12.730	18.370
Total payoffs (full-feedback task)	648	16.813	14.335	-23.200	50.000
Total expected payoffs (full-feedback task)	648	15.776	0.984	13.320	18.830

Note. Current education status was recorded on a scale from 1 to 4 where 1 = Undergraduate, 2 = Postgraduate, 3 = PhD student, and 4 = Prefer not to answer. Whether a participant had taken any university courses or modules that involved mathematics was recorded as 1 = Yes, and 2 = No. The personality factors of Neuroticism, Extraversion, Agreeableness, Openness to Experience, and Conscientiousness were calculated and recorded on a scale from 1 to 5. Risk aversion was estimated from the combined number of risky choices from each of the last 10 choices in the 6 problem sets presented during the full-feedback task. Switch ratios were calculated by taking the ratio between the number of switches and the maximum number of possible switches (n – 1, where n is the total number of samples taken). For participants that only took one sample the switch ratio was considered 0. Total payoffs in the experimental tasks are the actual point totals received by participants while total expected payoffs are calculated from the expected values of the gambles chosen by participants.

Do the Search Behaviours Correlate Across the Tasks?

Due to the outliers in the data Spearman correlations were performed to test the correlations between the search behaviours in the four experimental tasks. The results in Table 3.4 show that the search behaviours correlate across the tasks. Specifically, sample size in the sampling task has a positive correlation with the sample size in the control task. The sample size in the sampling task also has a strong negative correlation with the switch ratio in the sampling task, which supports the findings of Hills and Hertwig (2010). The switch ratio in the sampling task also correlates positively with the switch ratio in the partial-feedback task.

Table 3.4: Spearman correlations between search behaviours in the experimental tasks

	Sampling task samples	Control task samples	Sampling task switch ratio	Control task switch ratio	Partial-feedback switch ratio	Full-feedback switch ratio
Sampling task samples	1					
Control task samples	0.152***	1				
Sampling task switch ratio	-0.526***	-0.426***	1			
Control task switch ratio	-0.018*	0.072***	0.032***	1		
Partial-feedback switch ratio	-0.067***	-0.034***	0.200***	-0.025***	1	
Full-feedback switch ratio	-0.047***	-0.216***	0.294***	0.147***	0.182***	1

Note. ***p<0.001, **p<0.01, *p<0.05.

Does Personality Relate to Sample Size and the Switch Ratio?

Participants could only decide on the number of samples in the sampling task and the control task and thus only these tasks were analysed. The regressions for sample size in the sampling task with personality factors and personality facets as regressors are shown in Appendix A in Table A2 and Table A3 respectively. The regressions for sample size in the control task with personality factors and personality facets as regressors are shown in Table A4 and Table A5 respectively. The hypotheses and the results are summarized in Table 3.5.

Table 3.5. Summary of hypotheses and results for experiment 1

Hypotheses	Results
Extraversion and • Sample size will have a positive relationship in the sampling task and the control task • The switch ratio will have a positive relationship in all four tasks	Extraversion and • Sample size had a positive relationship in the sampling task and the control task • The switch ratio had a positive relationship in the full-feedback task only
Neuroticism and • Sample size will have a positive relationship in the sampling task	Neuroticism and • Sample size did not have any relationship in any task
Openness to Experience and • The switch ratio will have a positive relationship in all four tasks	Openness to Experience and • The switch ratio had a negative relationship in the control task and the full-feedback task • Sample size had a negative relationship in the sampling task and a positive relationship in the control task
Conscientiousness and • Sample size will have a positive relationship in the sampling task and the control task	Conscientiousness and • Sample size had a positive relationship in the sampling task • The switch ratio had a negative relationship in the control task and the full-feedback task
Agreeableness • Will not have any relationship with sample size or the switch ratio in any task	Agreeableness and • Sample size had a positive relationship in the sampling task

In the sampling task Extraversion, Agreeableness, and Conscientiousness had a positive relationship with sample size while Openness to Experience had a negative relationship. In the control task Extraversion and Openness to Experience had a positive relationship with sample size. Note that while Agreeableness had a negative relationship at the 0.1 and 0.25 quantiles these are not significant after correcting for multiplicity. Thus, Extraversion and Openness to Experience had a

relationship with sample size in both the sampling task and control task. The reversal in the direction of the relationship between sample size and Openness to Experience between the two tasks is explained by the differing effect sizes at the facet level between the two tasks. Specifically, while Imagination (O1) and Adventurousness O4 had a positive relationship and Artistic Interests O2, Emotionality O3, and Liberalism O6 had a negative relationship with sample size in both the sampling task and control task their differing effect sizes result in a reversal in the relationship on the factor level.

Since participants were in control of their switching behaviour in all four of the decisions from experience tasks, the switch ratios in all four were analysed. The regressions for the switch ratio in the control task with personality factors and personality facets as regressors are shown in Appendix A in Table A6 and Table A7 respectively. The regressions for the switch ratio in the sampling task with personality factors and personality facets as regressors are shown in Table A8 and Table A9 respectively. The regressions for the switch ratio in the partial-feedback task with personality factors and personality facets as regressors are shown in Table A10 and Table A11 respectively. The regressions for the switch ratio in the full-feedback task with personality factors and personality facets as regressors are shown in Table A12 and Table A13 respectively. The regressions for the switch ratio in the sampling task, the partial-feedback task, and the full-feedback included the switch ratio in the control task as a control variable.

In the control task both Openness to Experience and Conscientiousness had a negative relationship with the switch ratio, which may indicate that these personality factors reduce the tendency to switch between the options erratically. In the sampling task Extraversion has a negative relationship with the switch ratio although the result is not significant when correcting for multiplicity. In the partial-feedback task Extraversion and Openness to Experience have a negative relationship with the switch ratio although the results aren't significant when correcting for multiplicity. In the full-feedback task Extraversion had a positive relationship with the switch ratio while Openness to Experience and Conscientiousness had a negative relationship although these only indicate the effect these personality factors have on exploitation rather than exploration as the full-feedback task does involve exploration.

Search Behaviours and Payoffs

The regressions for the relationship between sample size and expected payoffs given the choices of the participants in the sampling task and control task are

shown in Appendix A in Table A14. The regressions for the relationship between the switch ratio and the expected payoffs given the choices of the participants in the sampling task, the control task, the partial-feedback task, and the full-feedback task are shown in Table A15. The results show that only the number of samples in the sampling task had a positive relationship with the expected payoffs while the other results were not significant.

3.3. Experiment 2: Costly Search Tasks

The design of second experiment followed the first experiment closely with some key differences. One hundred and sixty participants from the University of Warwick were recruited using the university SONA system to take part in one of four experimental sessions taking place in the Warwick Business School Behavioural Science Laboratory. The participants took part in four decisions from experience tasks involving learning about and making choices between gambles in the six decision problems used by Hertwig et al. (2004), which are presented in Table 3.1. The four tasks included a sampling task, a partial-feedback task, a full-feedback task, and a task that will henceforth be referred to as the control task. However, unlike in the first experiment search was made costly. Specifically, each sample in the sampling task and control task had a cost of 0.4 points and each switch in all four tasks had a cost of 0.4 points. The search cost accumulated while searching between a pair of presented gambles was shown on the screen. Participants were

Table 3.6: Lottery choices with probabilities and payoffs in the lottery choice task

Lottery A	Lottery B	Expected Value of Lottery A	Expected Value of Lottery B
1/10 of £2.00, 9/10 of £1.60	1/10 of £3.85, 9/10 of £0.10	£1.64	£0.48
2/10 of £2.00, 8/10 of £1.60	2/10 of £3.85, 8/10 of £0.10	£1.68	£0.85
3/10 of £2.00, 7/10 of £1.60	3/10 of £3.85, 7/10 of £0.10	£1.72	£1.23
4/10 of £2.00, 6/10 of £1.60	4/10 of £3.85, 6/10 of £0.10	£1.76	£1.60
5/10 of £2.00, 5/10 of £1.60	5/10 of £3.85, 5/10 of £0.10	£1.80	£1.98
6/10 of £2.00, 4/10 of £1.60	6/10 of £3.85, 4/10 of £0.10	£1.84	£2.35
7/10 of £2.00, 3/10 of £1.60	7/10 of £3.85, 3/10 of £0.10	£1.88	£2.73
8/10 of £2.00, 2/10 of £1.60	8/10 of £3.85, 2/10 of £0.10	£1.92	£3.10
9/10 of £2.00, 1/10 of £1.60	9/10 of £3.85, 1/10 of £0.10	£1.96	£3.48
10/10 of £2.00, 0/10 of £1.60	10/10 of £3.85, 0/10 of £0.10	£2.00	£3.85

Note. Based on Holt and Laury (2002)

also asked to complete the IPIP-NEO-120 personality questionnaire (Johnson, 2014) and a short demographics questionnaire asking about their age, gender, education, and whether they had studied mathematics related subjects at university level. In addition a lottery choice task (Holt & Laury, 2002) was used to measure risk preference. The options presented to participants in the lottery choice task are shown in Table 3.6. Participants were paid a show-up fee of £2 and had the opportunity to win up to £20 more depending on the number of combined points they won from all four experimental tasks (taking search costs into account) as well as up to an additional £3.85 from the lottery choice task. Total points were converted to GBP at a rate of £1 per 20 points. Winnings were capped at £23.85 and were rounded to the nearest £0.10.

3.3.1. Hypotheses

The main purpose of the second experiment was to see whether the relationships between personality and search behaviours would be replicated when search was costly. If the same relationships remained it would be additional evidence of stability in information search behaviours within individuals and would show that such stability can be detrimental. The costs associated with search would also make searching less more advantageous in these tasks, which could help explain why some individuals have the tendency to search less than others as search often involves costs in the real world.

The positive relationship between Extraversion and sample size in both the sampling task and the control task in Experiment 1 results in the following hypothesis:

> Hypothesis 6: Extraversion will have a positive relationship with sample size in both the costly sampling task and the costly control task.

The positive relationship between Conscientiousness and sample size in the sampling task in Experiment 1 results in the following hypothesis:

> Hypothesis 7: Conscientiousness will have a positive relationship with sample size in both the costly sampling task and the costly control task.

Openness to Experience had an inconsistent relationship with sample size in Experiment 1. Specifically, Openness to Experience had a negative relationship with sample size in the sampling task but a positive relationship with sample size in the control task. Despite the inconsistency it can be hypothesised that:

> Hypothesis 8: Openness to Experience will have a negative relationship with sample size in the costly sampling task and a positive relationship with sample size in the costly control task.

Extraversion had a positive relationship with the switch ratio in the full-feedback task. Extraversion may also have a negative relationship with the switch ratio in the sampling task and partial-feedback despite the nonsignificant results when corrected for multiplicity. Thus, it may be hypothesised that:

> Hypothesis 9: Extraversion will have a negative relationship with the switch ratio in the costly sampling task and the costly partial-feedback task and a positive relationship with the switch ratio in the costly full-feedback task.

Openness to Experience had a negative relationship with the switch ratio in the control task in Experiment 1. Openness to Experience may also have a negative relationship with the switch ratio in the partial-feedback task and the full-feedback task despite the nonsignificant results when corrected for multiplicity. Thus, it may be hypothesised that:

> Hypothesis 10: Openness to Experience will have a negative relationship with the switch ratio in the costly control task, the costly partial-feedback task, and the costly full-feedback task.

Conscientiousness had a negative relationship with the switch ratio in both the control task and the full-feedback task in Experiment 1 leading to the following hypothesis:

> Hypothesis 11: Conscientiousness will have a negative relationship with the switch ratio in the costly control task and the costly full-feedback task.

3.3.2. Results

As in Experiment 1 the main results of interest in the experiment concerned stability of search behaviour across tasks within individuals and whether this stability correlated with the Big Five factors of personality. Regressions were again performed separately with both personality factors and personality facets. Quantile regressions were performed in addition to ordinary least squares regressions to reduce the effect of outliers in the data as well as test the effects of personality on search behaviours at different quantiles (0.1, 0.25, 0.50, 0.75, 0.9). To correct for multiplicity in the quantile regressions only results that remain significant after being multiplied by 5 (the number of quantiles tested) were analysed.

Descriptive Statistics

The variables used in the regression analysis are listed in Table 3.7. The variables included the age of the participants in years, whether they were female, their current education status (undergraduate, postgraduate, or PhD student), whether they had

taken any university courses or modules involving mathematics, their scores for the

Table 3.7: Descriptive statistics of the variables used in the regression analysis

Variable	N	Mean	Std. Dev.	Minimum	Maximum
Age	160	21.844	3.532	18	43
Female	160	0.556	0.498	0	1
Education	160	1.350	0.596	1	3
Quantitative background	160	0.706	0.457	0	1
Neuroticism	160	2.987	0.549	1.5	4.542
Extraversion	160	3.291	0.493	2.083	4.333
Agreeableness	160	3.608	0.498	2.292	4.833
Openness to Experience	160	3.393	0.419	2.500	4.667
Conscientiousness	160	3.532	0.492	2.208	4.500
Risk preference	160	4.413	1.901	0	10
Samples (costly sampling task)	960	7.919	37.311	1	930
Samples (costly control task)	960	4.223	13.240	1	290
Switch ratio (costly sampling task)	960	0.552	0.440	0	1
Switch ratio (costly control task)	960	0.088	0.246	0	1
Switch ratio (costly partial-feedback task)	960	0.118	0.178	0	1
Switch ratio (costly full-feedback task)	960	0.090	0.145	0	1
Total payoffs (costly sampling task)	960	-8.540	119.444	-569.196	347.600
Total expected payoffs (costly sampling task)	960	-8.146	54.556	-561.700	15.600
Total payoffs (costly control task)	960	8.292	97.756	-411.200	357.600
Total expected payoffs (costly control task)	960	4.077	18.199	-123.700	17.600
Total payoffs (costly partial-feedback task)	960	-0.386	23.320	-110.600	53.600
Total expected payoffs (partial-feedback task)	960	1.773	18.518	-100.550	16.120
Total payoffs (full-feedback task)	960	5.090	19.504	-86.000	60.000
Total expected payoffs (full-feedback task)	960	5.050	13.939	-93.510	17.500

Note. Current education status was recorded on a scale from 1 to 4 where 1 = Undergraduate, 2 = Postgraduate, 3 = PhD student, and 4 = Prefer not to answer. Whether a participant had taken any university courses or modules that involved mathematics was recorded as 1 = Yes, and 2 = No. The personality factors of Neuroticism, Extraversion, Agreeableness, Openness to Experience, and Conscientiousness were calculated and recorded on a scale from 1 to 5. Risk preference is based on the number of risky choices made in the lottery choice task (Holt & Laury, 2002). Switch ratios were calculated by taking the ratio between the number of switches and the maximum number of possible switches (n – 1, where n is the total number of samples taken). For participants that only took one sample the switch ratio was considered 0. Total payoffs in the experimental tasks are the actual point totals received by participants while total expected payoffs are calculated from the expected values of the gambles chosen by participants minus their search costs.

Big Five factors of personality (Neuroticism, Extraversion, Agreeableness, Openness to Experience, and Conscientiousness), risk aversion (estimated from the combined number of times the risky gamble was chosen in the lottery choice task), the number of samples taken in the six decision problems (in the costly sampling task and the costly control task), the switch ratio exhibited in the six decision problems (in the costly sampling task, the costly control task, the costly partial-feedback task, and the costly full-feedback task), the number of points the participants won and the number of points they would be expected to win on average given their choices (based on the expected value of the gambles chosen). Note that in cases where the number of samples taken was only 1, resulting in the switch ratio not being possible to calculate due to a dividing by zero error, the switch ratio was set to 0.

When compared with Experiment 1 the differences in the mean search behaviours are substantial. In Experiment 1 the mean sample sizes in the sampling task and control task were 27.049 and 20.148 respectively while in Experiment 2 they are 7.919 and 4.223 in the costly sampling task and the costly control task respectively. In Experiment 1 the mean switch ratios in the sampling task, the control task, the partial-feedback task, and the full-feedback task were 0.353, 0.072, 0.262, and 0.192 respectively while in Experiment 2 they are 0.552, 0.088, 0.118, and 0.090 in the costly sampling task, the costly control task, the costly partial-feedback task, and the costly full-feedback task respectively. Thus, substantially fewer samples were taken in Experiment 2 and the switch ratios were substantially lesser in the costly partial-feedback task and the costly full-feedback task.

Do the Search Behaviours Correlate Across Tasks?

Spearman correlations were performed to investigate relationships between search behaviours in the experimental tasks (see Table 3.8). Unlike in Experiment 1 the correlation between the sample size in the costly sampling task and the sample size in the costly control task is negative. The correlation between the switch ratio in the costly sampling task and the switch ratio in the costly partial-feedback task is also negative. However, the correlation between the sample size and the switch ratio in the costly sampling task is negative as before.

Table 3.8: Spearman correlations between search behaviours in the experimental tasks

	Costly Sampling task samples	Costly Control task samples	Costly Sampling task switch ratio	Costly Control task switch ratio	Costly Partial-feedback switch ratio	Costly Full-feedback switch ratio
Costly Sampling task samples	1					
Costly Control task samples	-0.191***	1				
Costly Sampling task switch ratio	-0.610***	0.249***	1			
Costly Control task switch ratio	-0.096***	0.462***	0.228***	1		
Costly Partial-feedback switch ratio	0.313***	-0.244***	-0.050***	-0.012	1	
Costly Full-feedback switch ratio	0.517***	-0.406***	-0.332***	-0.008	0.546***	1

Note. ***p<0.001, **p<0.01, *p<0.05.

Does Personality Relate to Sample Size and the Switch Ratio?

The regressions for sample size in the costly sampling task with personality factors and personality facets as regressors are shown in Appendix A in Table A17 and Table A18 respectively. The regressions for sample size in the costly control task with personality factors and personality facets as regressors are shown in Table A19 and Table A20 respectively. The regressions for the switch ratio in the costly control task with personality factors and personality facets as regressors are shown in Appendix A in Table A21 and Table A22 respectively. The regressions for the switch ratio in the costly sampling task with personality factors and personality facets as regressors are shown in Table A23 and Table A24 respectively. The regressions for the switch ratio in the costly partial-feedback task with personality factors and personality facets as regressors are shown in Table A25 and Table A26 respectively. The regressions for the switch ratio in the costly full-feedback task with personality factors and personality facets as regressors are shown in Table A27 and Table A28 respectively. The regressions for the switch ratio in the costly sampling task, the costly partial-feedback task, and the costly full-feedback included the switch ratio in the control task as a control variable. The hypotheses and the results for experiment 2 are summarized in Table 3.9.

Table 3.9. Summary of hypotheses and results for experiment 2

Hypotheses	Results
Extraversion and • Sample size will have a positive relationship in the costly sampling task and the costly control task • The switch ratio will have a negative relationship in the costly sampling task and the costly partial-feedback task and a positive relationship in the costly full-feedback task	Extraversion and • Sample size had a positive relationship in the costly sampling task and the costly control task • The switch ratio had a positive relationship in the costly partial-feedback task
Neuroticism and • Will not have any relationship with sample size or the switch ratio in any task	Neuroticism and • The switch ratio had a positive relationship in the costly partial-feedback task
Openness to Experience and • Sample size will have a negative relationship in the costly sampling task and a positive relationship in the costly control task • The switch ratio will have a negative relationship in the costly control task, the costly partial-feedback task, and the costly full-feedback task	Openness to Experience and • The switch ratio had a negative relationship in the costly sampling task, the costly control task, and the costly partial-feedback task
Conscientiousness and • Sample size will have a positive relationship in the costly sampling task and the costly control task • The switch ratio will have a negative relationship in the costly control task and the costly full-feedback task	Conscientiousness and • The switch ratio had a negative relationship in the costly full-feedback task
Agreeableness • Will not have any relationship with sample size or the switch ratio in any task	Agreeableness and • The switch ratio had a negative relationship in the costly full-feedback task

The results show that Extraversion had a positive relationship with sample size in both the costly sampling task and the costly control task. In the costly control task Openness to Experience had a negative correlation with the switch ratio. In the

costly sampling task Openness to Experience had a negative correlation with the switch ratio. In the costly partial-feedback task Neuroticism and Extraversion had a positive relationship with the switch ratio while Openness to Experience had a negative relationship. In the costly full-feedback task Agreeableness and Conscientiousness had a negative relationship with the switch ratio. Thus, Openness to Experience had a consistent negative relationship with the switch ratio.

Search Behaviours and Payoffs

The regressions for the relationship between sample size and expected payoffs given the choices and search costs of the participants in the costly sampling task and costly control task are shown in Appendix A in Table A29. The regressions for the relationship between the switch ratio and the expected payoffs given the choices and search costs of the participants in the costly sampling task, the costly control task, the costly partial-feedback task, and the costly full-feedback task are shown in Table A30. The results show that the sample size in both the costly sampling task and costly control task have a negative relationship with expected payoffs. The switch ratio also has a negative relationship with expected payoffs in the costly control task, the costly partial-feedback, and the costly full-feedback task.

Comparing Results from Experiment 1 and Experiment 2

One of the main purposes of Experiment 2 was to see whether the personality of participants would influence their search behaviours in similar ways when search was costly. Specifically, would personality factors that correlated with higher amounts of search (higher sample size and higher switch ratios) in Experiment 1 still correlate with higher amounts of search in Experiment 2? Overall, the results are mixed although they do suggest that some personality factors may result in some consistency in search behaviours (see Table 3.10).

Extraversion had the most consistent relationship with search behaviours between the two experiments. Specifically, it had a positive relationship with sample size in costly and non-costly versions of the sampling tasks and the control task. It also had a positive relationship with the switch ratio in the non-costly full-feedback task and the costly partial-feedback task, which may show some level of relationship between Extraversion and an increased switch ratio (note that Extraversion was also hypothesised to have a positive relationship with the switch ratio in all four tasks in Experiment 1).

Table 3.10. Summary of results for experiment 1 and experiment 2

Hypotheses for Experiment 2	Results for Experiment 2
Extraversion and • Sample size had a positive relationship in the sampling task and the control task • The switch ratio had a positive relationship in the full-feedback task only	Extraversion and • Sample size had a positive relationship in the costly sampling task and the costly control task • The switch ratio had a positive relationship in the costly partial-feedback task
Neuroticism and • Sample size did not have any relationship in any task • The switch ratio did not have any relationship in any task	Neuroticism and • Sample size did not have any relationship in any task • The switch ratio had a positive relationship in the costly partial-feedback task
Openness to Experience and • Sample size had a negative relationship in the sampling task and a positive relationship in the control task • The switch ratio had a negative relationship in the control task and the full-feedback task	Openness to Experience and • Sample size did not have any relationship in any task • The switch ratio had a negative relationship in the costly sampling task, the costly control task, and the costly partial-feedback task
Conscientiousness and • Sample size had a positive relationship in the sampling task • The switch ratio had a negative relationship in the control task and the full-feedback task	Conscientiousness and • Sample size had no relationship in any task • The switch ratio had a negative relationship in the costly full-feedback task
Agreeableness and • Sample size had a positive relationship in the sampling task	Agreeableness and • The switch ratio had a negative relationship in the costly full-feedback task

Openness to Experience had the second most consistent relationship with search behaviours between two experiments. Specifically, it had a negative

relationship with the switch ratio in the non-costly control task and the non-costly full-feedback task as well as in the costly sampling task, the costly control task, and the costly partial-feedback task, which may suggest consistency between Openness to Experience and a lesser switch ratio. However, Openness to Experience did not show consistency in its relationship with sample size since it did not have any relationship with sample size in Experiment 2 and in Experiment 1 it had a negative relationship with sample size in the sampling task and a positive relationship in the control task. Thus, Openness to Experience may not have a consistent impact on sample size although it may have a consistent impact on the switch ratio.

Conscientiousness showed some very minor consistency with search behaviours in Experiment 1 and Experiment 2. Specifically, Conscientiousness had a negative relationship with the switch ratio in the non-costly control task and the non-costly full-feedback task as well as in the costly full-feedback task. Thus, Conscientiousness may show some consistency in reducing the switch ratio. However, Conscientiousness did not show consistency in its relationship with sample size since it only had a positive relationship with sample size in the non-costly sampling task.

Finally, neither Neuroticism nor Agreeableness showed any consistency with search behaviours in Experiment 1 and Experiment 2. Neuroticism did not have any relationship with sample size in any task and only had a positive relationship with the switch ratio in the costly partial-feedback task. Agreeableness had a positive relationship with sample size in the non-costly sampling task and a negative relationship with the switch ratio in the costly full-feedback task.

3.4. Discussion

The four decisions from experience tasks including the sampling task, control task, partial-feedback task, and the full-feedback task used in Experiment 1 and the costly versions used in Experiment 2 allowed for stability in information search behaviour between individuals to be investigated in a broad manner. These four tasks varied between each other on the dimensions of exploration (whether sampling provides partial or full information) and exploitation (whether exploration and exploitation can be conducted simultaneously or whether they are in conflict). Nonetheless each task allowed for the measurement of the same information search behaviours: sampling (measured by counting how many samples participants took) in the sampling task and control task, and switching (calculated by taking the ratio between the number is switches between options and the maximum possible amount or $n - 1$, where n is the number of samples) in all four tasks. Since

the same decision problems were used in all four tasks it was straightforward to test whether information search behaviours correlated across tasks. The specific behaviours that were used as indications of information search behaviour were sampling in the sampling task and control task and switching in the sampling task and partial-feedback task since switching in the control task and full-feedback task were indications of a general tendency for switching and exploitation respectively. Combined with the IPIP-NEO-120 personality questionnaire, it was possible to further investigate whether stability in information search behaviour could be correlated and partially explained by the Big Five factors of personality or their more specific personality facets. In addition, the inclusion of information search costs in Experiment 2 allowed for testing whether the information search behaviours would remain consistent even when they could be detrimental.

The results from Experiment 1 suggest that as a whole information search behaviours correlated across tasks. Specifically, sample size in the sampling task had a positive relationship with sample size in the control task and the switch ratio in the sampling task had a positive correlation with the switch ratio in the partial-feedback task. Furthermore, sample size and the switch ratio in the sampling task had a negative correlation, which is consistent with the results of Hills and Hertwig (2010). The information search behaviours also seemed to be related to personality. Specifically, Extraversion had a positive relationship with sampling in both the sampling task and the control task while Openness to Experience had a negative relationship with sampling in the sampling task and a positive relationship with sampling in the control task (explained by different magnitudes of effects on the facet level). In addition Openness to Experience and Conscientiousness had a negative relationship with the switch ratio in the control task, which may indicate they reduce erratic switching.

The results from Experiment 2 are not as clear as those from Experiment 1 although as a whole they also suggest information search behaviours correlated across tasks. The lesser clarity may be due to a substantial reduction in the sample sizes in the costly sampling task and costly control task and the switch ratios in the partial-feedback task and control task the effect of outliers. For example the sample size in the costly sampling task had a negative correlation with the samples in the costly control task and the switch ratio in the costly sampling task had a negative correlation with the switch ratio in the partial-feedback task (although this correlation was very weak). However, the sample size in the costly sampling task still had a strong negative correlation with the switch ratio in the costly sampling task. The information search behaviours also seemed to be related to personality.

Specifically, Extraversion had a positive relationship with sample size in both the costly sampling task and the costly control task. In addition Openness to Experience had a negative relationship with switch ratio in the costly sampling task, the costly control task, and the costly partial-feedback task.

When comparing the results from Experiment 1 and Experiment 2 it seems Extraversion has a consistent positive relationship with sampling while Openness to Experience has a consistent negative relationship with switching. This provides evidence for some consistency in information search behaviour despite a different search environment. Given higher sample size had a positive relationship with payoffs in Experiment 1 while higher sample size and higher switching had a negative relationship with payoffs in Experiment 2 it can also be concluded that individuals with higher Extraversion perform better when information search is costless and worse when information search is costly and that individuals with higher Openness to Experience perform better when search is costly. A reason individuals exhibiting higher amounts of information search and individuals exhibiting lower amounts of information search coexist may therefore be partially explained by variation in information search costs in the real world (Wolf & Weissing, 2010).

Overall, the results of this study show that personality, particularly Extraversion and Openness to Experience, can impact the information search behaviours of individuals. Thus, individuals differ in how they search for information beyond differences in traits such as memory capacity (Rakow et al., 2008), numerical skills and rational thinking (Lejarraga, 2010). Such differences can also be consequential given their impact on subsequent decision-making. In addition the results of this study suggest overlap in information search behaviours between different decisions from experience tasks such as the sampling task and partial-feedback task, which are partly explained by the personality traits of the participants. However, further research is needed to for example see how personality can influence the information search behaviours of individuals in groups (Lejarraga, Lejarraga, & Gonzalez, 2014) and prior to non-monetary decisions such as medical decisions (Lejarraga et al., 2016).

Chapter 4. Intellectual Leveraging: Social Learning May Lead to Larger Populations But Greater Fragility

4.1. Introduction

It has for long been taken for granted that the cost savings afforded by social learning alone will not provide benefits to a species (Boyd et al., 2011). Rogers demonstrated that while social learners, who learn about a temporally varying environment indirectly through learning from others, can avoid the costs associated with individual learning, learning about the environment from personal experience, their long-term fitness is the same as the fitness of individual learners, as it is subject to negative frequency dependence (Rogers, 1988). This result is highly robust, holding as long as the only benefit of social learning is that is it less costly (Boyd & Richerson, 1995). Since social learning is considered to have been central to the success of humans (Boyd et al., 2011; Laland, 2017) the result that social learning will not inherently increase the fitness of a species has been termed Rogers' paradox (Enquist et al., 2007).

Prior research has focussed on finding conditions where Roger's paradox does not arise where social learning instead increases long-term population fitness. These include the introduction of hybrid learners capable of using both individual learning and social learning (Kameda & Nakanishi, 2002, 2003; Enquist et al., 2007; Kharratzadeh et al., 2017); allowing social learning to enhance the accuracy or efficiency of individual learning (Boyd & Richerson, 1995); allowing cumulative improvements to culture, i.e. socially learned information, across generations (Ehn & Laland, 2012; Enquist & Ghirlanda, 2007; Ohtsuki et al., 2017); modifying the modelled environment by adding risky payoffs in foraging (Rendell, Boyd, Cownden, et al., 2010; Arbilly et al., 2011) or adding spatial structure to the models (Ohtsuki et al., 2017; Rendell, Fogarty, & Laland, 2010; Kobayashi & Ohtsuki, 2014; Kobayashi, Wakano, & Ohtsuki, 2019). However, if social learning can impact a population beyond increasing the fitness of those engaging in it then it could prove beneficial to a population even if subject to negative frequency dependence.

Models building on Rogers' original model make a key assumption that the fitness effect of behaviours learned by individuals are independent of their frequency. In an environment with limited resources, however, this does not seem likely as resources consumed by one individual reduce the resources available to others. In such circumstances individuals requiring fewer resources than others (e.g. social learners due to their lower learning costs) could be able to indirectly

benefit others even if they themselves ultimately do not benefit in terms of fitness as at equilibrium all individuals would be expected to have the same fitness (Brown, Hall, & Sibly, 2018). Support for such a notion exists since in producer-scrounger games, which closely relate to models with individual learners and social learners, in which the presence of scroungers may indirectly benefit a population by regulating its growth thus allowing it to grow larger (Coolen, Giraldeau, & Vickery, 2007). Population size has also generally been excluded from Rogers type models, which may limit some findings since recent studies have suggested that explicitly modelling population size may lead to different conclusions than when population size is kept constant (Huang, Hauert, & Traulsen, 2015; Constable et al., 2016; Gokhale & Hauert, 2016). Instead of focusing on equilibrium fitness we therefore analyse the impact the presence of social learning can have on population size.

In contrast with previous studies, including some that have considered population size (Rendell, Fogarty, & Laland, 2010; Lehmann & Feldman, 2009), we demonstrate that under very general assumptions for models with density dependence, populations making use of social learning may grow greater in size than populations only making use of individual learning even if the fitness of both populations are the same if social learning has less impact on the consumption of resources than individual learning does. This is possible precisely because social learners require fewer resources to maintain the same mean fitness as individual learners. However, we also show that if social learning has a greater impact on the consumption of resources then it may reduce the size of a population even if used flexibly such as by critical social learners. We also show that populations with social learners may simultaneously be more extinction-prone because social learners leverage the knowledge of a small proportion of individual learners.

4.2. Population Growth Model With Two Types of Learners

Here we describe a model of population growth with only individual learners and social learners as in Rogers' original model. We first describe a general version of the model and then show a theorem that demonstrates social learners can impact the equilibrium size of a population based on their effect on per capita resource consumption. We then demonstrate these results with a logistic version of the general model. Finally, using a stochastic version of the logistic model, we show a population with social learners may be more susceptible to extinction.

4.2.1. General Model Description

To demonstrate the population level effects of social learning, consider a model of density-dependent population growth taking elements from Rogers' original model. In our model we assume a population of organisms lives in an environment the state of which determines the strategy required for acquiring resources (e.g. where to find food). An individual obtaining accurate information about the environment gains a benefit, b, reflecting how many resources they acquire and consume, which together with learning costs determine their fitness. Individuals exclusively learn about the environment either through individual learning or social learning with the choice of learning strategy being genetically determined and inherited by offspring. For simplicity individuals are assumed to reproduce asexually such that genetic complexities involved with which learning strategies are inherited can be ignored where the number of offspring is determined by the fitness of the parent. Resources in the environment are limited such that only a limited population can be sustained. However, individual learners and social learners may differ in their per capita resource consumption such that their impact on equilibrium population size may differ.

We first consider a population consisting only of individual learners, which we refer to as a pure population. Individual learners learn about the environment directly and are assumed to always obtain accurate information. Let $n_{i,t}$ be the number of individual learners at time t. Suppose the per capita growth rate of individual learners is $g(\omega_i, n_{i,t})$ where $\omega_i \in (0,1)$ is the fitness of individual learners, which is increasing in the benefit of accurate information, b, and decreasing in the cost of individual learning (e.g. amount of effort and risks taken to learn information), c_i, such that $\omega_i = h(b, c_i)$. We assume the per capita population growth, $g(\omega_i, n_{i,t})$, is an increasing function of fitness, ω_i, and a decreasing function of population size, $n_{i,t}$, reflecting the effect of the population approaching the carrying capacity of the environment. It follows that population size changes over time as follows:

$$\frac{\partial n_{i,t}}{\partial t} = g(\omega_i, n_{i,t}) n_{i,t}. \tag{4.1}$$

If $g(\omega_i, 0) > 0$ a population of individual learners will grow until it reaches a stable equilibrium at $n^*_{i,p}$, where $g(\omega_i, n^*_{i,p}) = 0$.

Consider now a population of individual learners that has converged to its equilibrium population size $n^*_{i,p}$. A mutation then occurs and a small number of social learners appear. Social learning is assumed to be less costly than individual

learning and to be used to learn from a randomly chosen individual in the population as in Rogers' original model. For simplicity, however, social learners learn from individuals from their own generation and only gain useful information when learning from an individual learner unlike in Rogers' model (our model may therefore be viewed as a producer-scrounger model). Therefore, the fitness of social learners is initially high, when they can learn from a high proportion of individual learners, but declines as the proportion of social learners grows. Specifically, the fitness of social learners, $\omega_{s,t} \in (0,1)$, is decreasing in the proportion of social learners to individual learners, $\frac{n_{s,t}}{n_{i,t}}$, increasing in the benefit of accurate information, b, and decreasing in the cost of social learning, c_s, such that $\omega_{s,t} = h(\frac{n_{s,t}}{n_{i,t}}, b, c_s)$, where $h(0, b, c_s) > \omega_i$ if $c_s < c_i$ (social learners have higher fitness than individual learners when rare) and $h(\infty, b, c_s) < \omega_i$ (social learners have lower fitness than individual learners when common). Finally, we assume that after learning from an individual learner, social learners may choose to compete with them for resources directly and either choose to share in big finds or steal (forms of kleptoparasitism).

To model the population with both individual learners and social learners, which we refer to as a mixed population, let $n_{i,t}$ and $n_{s,t}$ be the number of individual and social learners at time t respectively. Population growth is again an increasing function of fitness and a decreasing function of total population size, but we now allow for the possibility that social learning may have a greater or lesser impact on growth rates than individual learning does, through a differing impact on per capita resource consumption. Specifically, $n_{i,t}$ and $n_{s,t}$change as follows:

$$\frac{\partial n_{i,t}}{\partial t} = g\left(\omega_i, n_{i,t} + r n_{s,t}\right) n_{i,t}, \tag{4.2}$$

$$\frac{\partial n_{s,t}}{\partial t} = g\left(\omega_{s,t}, n_{i,t} + r n_{s,t}\right) n_{s,t}, \tag{4.3}$$

where r is the per capita impact social learners have on resource consumption compared with individual learners, which is decreasing in the proportion of social learners to individual learners, $\frac{n_{s,t}}{n_{i,t}}$, and increasing in the form of kleptoparasitism displayed by social learners, $s \in (0,2)$, where $s < 1$ indicates generally sharing big finds by individual learners that they could not fully exploit themselves (scramble kleptoparasitism), $s = 1$ indicates not engaging in kleptoparasitism, and $s > 1$ indicates stealing or forcibly gaining exclusive access to food (aggressive kleptoparasitism), such that $r = h(\frac{n_{s,t}}{n_{i,t}}, s)$. Theorem 4.1 then shows that the impact the presence of social learners has on equilibrium population size depends on the value of r:

4.2.2. Theorem 4.1 and Proof

Let $n_{i,p}^*$ be the equilibrium size a pure population consisting only of individual learners converges to and let n_m^* be the equilibrium size a mixed population with individual learners and social learners converges to. Then $n_m^* = \frac{n_{i,p}^*}{q_{i,m}^* + r^*(1-q_{i,m}^*)}$, where $q_{i,m}^*$ is the equilibrium fraction of individual learners in the mixed population and r^* is the per capita impact social learners have on resource consumption at equilibrium. Thus, i) whenever $r^* < 1$, $n_m^* > n_{i,p}^*$, ii) whenever $r^* = 1$, $n_m^* = n_{i,p}^*$, and iii) whenever $r^* > 1$, $n_m^* < n_{i,p}^*$. In all cases, $\omega_s = \omega_i$ at equilibrium, and unless $r^* = 0$, $n_m^* q_{i,m}^* < n_{i,p}^*$ i.e., there are fewer individual learners when social learners are introduced.

Proof. There is a unique positive solution, for any $\omega_i \in (0,1)$, to the equation $\frac{\partial n_{i,t}}{\partial t} = g(\omega_i, n_{i,t}) n_{i,t} = 0$ whenever $g(\omega_i, n_{i,t})$, is a strictly decreasing function of $n_{i,t}$ for which $g(\omega_i, 0) > 0$ as well as $\lim_{x\to\infty} g(\omega_i, n_{i,t}) < 0$. Under these conditions, $n_{i,t}$ converges to $n_{i,p}^*$ at which $g(\omega_i, \mathrm{n}_{\mathrm{i,p}}^*) = 0$ unless $n_{i,t=0} = 0$.

To solve for the population sizes at equilibrium for the case with social learners we set the population growth derivatives from equation 4.2 and equation 4.3 equal to zero:

$$\frac{\partial n_{i,t}}{\partial t} = g(\omega_i, n_{i,t} + r n_{s,t}) n_{i,t} = 0, \tag{4.4}$$

$$\frac{\partial n_{s,t}}{\partial t} = g(\omega_{s,t}, n_{i,t} + r n_{s,t}) n_{s,t} = 0. \tag{4.5}$$

A non-zero solution exists at $n_{i,t} = n_{i,m}^*$, $n_{s,t} = n_{s,m}^*$ and $r = r^*$ such that

$$g(\omega_i, n_{i,m}^* + r^* n_{s,m}^*) = 0, \tag{4.6}$$

$$g(\omega_{s,t}, n_{i,m}^* + r^* n_{s,m}^*) = 0. \tag{4.7}$$

If there is a unique equilibrium value ω^* at which $g(\omega^*, n_{i,t}) = 0$ for any $n_{i,t}$, then it follows from equation 4.6 and equation 4.7 that $\omega^* = \omega_i = \omega_{s,t} = h(b, c_i) = h(\frac{n_{s,m}^*}{n_{i,m}^*}, b, c_s)$. This equation, in turn, determines the equilibrium proportion of individual learners in the mixed population, $q_{i,m}^*$, such that $h(\frac{(1-q_{i,m}^*)}{q_{i,m}^*}, b, c_s) = \omega_i$. Since $h(\frac{(1-q_{i,m}^*)}{q_{i,m}^*}, b, c_s)$ is decreasing in the proportion of individual learners, with $h(0, b, c_s) > \omega_i$ if $c_s < c_i$, and with $h(\infty, b, c_s) < \omega_i$, there is a unique value at which $h(\frac{(1-q_{i,m}^*)}{q_{i,m}^*}, b, c_s) = \omega_i$.

If there is a unique value, $n_{i,p}^*$, at which $g(\omega_i, n_{i,p}^*) = 0$ for any $\omega_i \in (0,1)$ then it also follows from equation 4.6 that $n_{i,m}^* + r^* n_{s,m}^* = n_{i,p}^*$. This can be written as $n_m^* q_{i,m}^* + r^* n_m^*(1 - q_{i,m}^*) = n_{i,p}^*$. Solving this equation for n_m^* we get

$$n_m^* = \frac{n_{i,p}^*}{q_{i,m}^* + r^*(1 - q_{i,m}^*)}. \tag{4.8}$$

It follows that, whenever $r^* < 1$, $n_m^* > n_{i,p}^*$, ii) whenever $r^* = 1$, $n_m^* = n_{i,p}^*$, and iii) whenever $r^* > 1$, $n_m^* < n_{i,p}^*$. Note also that the equilibrium number of individual learners in the mixed population is $n_m^* q_{i,m}^* = n_{i,p}^*/(1 + \frac{r^*(1-q_{i,m}^*)}{q_{i,m}^*})$, which is less than $n_{i,p}^*$ unless $r^* = 0$ such that $n_m^* q_{i,m}^* = n_{i,p}^*$.

The intuition is that when $r^* < 1$, social learners have less impact on "effective population density" (i.e., $n_{i,m}^* + r^* n_{s,m}^*$) than individual learners do, through having a lesser per capita impact on population level resource consumption, allowing for a larger population size. For example, if $r^* = 0$, i.e., social learners solely rely on prey that individual learners catch but cannot consume all by themselves and which would otherwise be wasted, and $\omega_i = 0.5$ then using $n_m^* q_{i,m}^* = n_{i,p}^*$ we see the population grows (1/0.5) = 2 times larger. With only individual learners, population growth stops at $n_{i,p}^*$ at which point $g(\omega_i, n_{i,p}^*) = 0$. In a population with social learners, the number of individual learners stops growing, according to equation 4.2, when $g(\omega_i, n_{i,t} + r n_{s,t}) = 0$, or $g\left(\omega_i, \mathrm{n}_m^* q_{i,m}^* + r^* \mathrm{n}_m^*(1 - q_{i,m}^*)\right) = 0$. If there is only one solution to the equation $g(\omega_i, n_{i,t} + r^* n_{s,t}) = 0$, then $n_{i,p}^*$ has to equal $q_{i,m}^* + r^* \mathrm{n}_m^*(1 - q_{i,m}^*)$. Solving for n_m^* gives us the expression in Theorem 4.1.

4.2.3. Fitness and Per Capita Resource Consumption of Social Learners

Theorem 4.1 shows the presence of social learners may change the equilibrium size of a population even if it does not change the equilibrium fitness of the population. The key to this result is the assumption that both the fitness and per capita resource consumption of social learners depends on the proportion of social learners in the population, such that $\omega_{s,t} = h(\frac{n_{s,t}}{n_{i,t}}, b, c_s)$, and $r = h(\frac{n_{s,t}}{n_{i,t}}, s)$. Thus, as the number of social learners grows, both their fitness and per capita resource consumption decrease until their fitness is equal to the fitness of individual learners. Despite consuming fewer resources per capita at equilibrium, social learners are able to maintain the same average fitness as individual learners, due to the low cost of social learning (consequently while not all social learners will find useful

information and thus resources the ones that do will have a higher fitness than individual learners do).

Social learners may also impact per capita resource consumption through how they interact with individual learners once they have learned from them. Suppose first that social learners eat the remains of prey that individual learners cannot fully consume themselves or which otherwise would waste away (e.g. Jolles, Ostojić, & Clayton, 2013; Harel et al., 2017). Such social learners do not consume extra resources, beyond what individual learners would have done, and hence do not increase per capita resource consumption as much as individual learners do if individual learners only hunt for new prey and never share in finds by other individual learners. When there are few social learners, and many individual learners, social learners can easily find prey without much effort, but when there are many social learners finding an individual learner with a fresh prey takes more effort. Thus, the fitness of social learners depends on the ratio of social learners to individual ones and declines when there are many social learners. Even with many social learners, however, their per capita impact on resource consumption may remain below that of individual learners if social learners continue to eat only the remains from individual learners. Alternatively, social learners may choose to gain exclusive access to resources found by an individual learner such that the resources cannot be fully exploited. In such a case the per capita impact of social learners on effective resource consumption may be higher than the impact individual learners would have.

4.2.4. Logistic Population Growth Model and Results

To illustrate the population level effects of social learning, let us fill out the abstract general population growth model with a version of a logistic population growth. We first consider a population with only individual learners, which are subject to the assumptions described in the general model and the fitness of which is given by the equation $\omega_i = b - c_i$. Suppose the per capita birth rate, $\lambda_{i,t}$, and the per capita death rate, $\mu_{i,t}$, at time t are linear functions of fitness and population size as follows:

$$\lambda_{i,t} = \alpha\omega_i - \beta b n_{i,t}, \tag{4.9}$$

$$\mu_{i,t} = (1 - \omega_i) + \delta b n_{i,t}. \tag{4.10}$$

where β and δ are the base impact of the total resource consumption by the population on the birth rate and death rate respectively, and α is the base impact of fitness on the birth rate, It follows that the per capita growth rate equals $g(\omega_i, n_{i,t}) =$

$\lambda_{i,t} - \mu_{i,t} = \theta - (\beta + \delta) b n_{i,t}$, where $\theta = (\alpha + 1)\omega_i - 1$. Whenever $\theta > 0$ and $n_{i,t=0} > 0$ the population grows in a logistic fashion to the unique equilibrium at $n^*_{i,p} = \theta/(\beta + \delta)$.

Suppose we now introduce a small number of social learners, which are subject to the assumptions described in the general model. The fitness of social learners is given by the equation $\omega_{s,t} = b n_{i,t}/(n_{i,t} + n_{s,t}) - c_s$. Suppose the per capita birth and death rates of individual are as follows:

$$\lambda_{i,t} = \alpha\omega_i - \beta b(n_{i,t} + r n_{s,t}), \tag{4.11}$$

$$\mu_{i,t} = (1 - \omega_i) + \delta b(n_{i,t} + r n_{s,t}), \tag{4.12}$$

where $r = s n_{i,t}/(n_{i,t} + n_{s,t})$. Similarly, the births and death rates of social learners are as follows:

$$\lambda_{s,t} = \alpha\omega_{s,t} - \beta b(n_{i,t} + r n_{s,t}), \tag{4.13}$$

$$\mu_{s,t} = (1 - \omega_{s,t}) + \delta b(n_{i,t} + r n_{s,t}). \tag{4.14}$$

Suppose $n^*_{i,p} = \theta/(\beta + \delta)$ and a small number of social learners are introduced, with fitness $\omega_{s,t} = b n_{i,t}/(n_{i,t} + n_{s,t}) - c_s$. If $\omega_i < 1$, social learners initially have higher fitness than individual learners and will thus grow in number. From equation 4.8 we see that, at equilibrium, the total population with social learners is $\mathrm{n}^*_m = n^*_{i,p}/(q^*_{i,m} + r^*(1 - q^*_{i,m})$. Moreover, if $b = 1$ (which we assume throughout this study) then $q^*_{i,m} = \omega_i$ given $\omega_{s,t} = b n_{i,t}/(n_{i,t} + n_{s,t})$ and $\omega_i = \omega_{s,t}$ at equilibrium. Hence, the equilibrium size of a mixed population with individual learners and social learners can be rewritten as:

$$\mathrm{n}^*_m = \frac{\theta}{(\beta+\delta)(\omega_i + (1-\omega_i) r^*)}. \tag{4.15}$$

If $\omega_i < 1$, social learners initially have a higher fitness than individual learners and thus grow in number resulting in an overall increase in population size. When $r^* < 1$ the increase in population size is permanent (Figure 4.1A) because one social learner impacts effective population density less than one individual learners does through reducing per capita resource consumption. When $r^* = 1$ population size initially grows but eventually reverts back when fitnesses equalize (Figure 4.1B), and when $r^* > 1_i$ population size declines (Figure 4.1C). In all cases, fitnesses equalize in equilibrium, i.e., $\omega_s = \omega_i$. The results thus show that despite Rogers' paradox, social learning can result in a permanent increase to population size if $r^* < 1$. Furthermore, given the direct relationship between the fitness of social learners and their per capita impact on resource consumption, their presence is likely to increase population size in most cases. Thus, while it is possible for a mixed population to revert to equal size as a pure population or even decline in size

compared to it, this is only possible if social learners are sufficiently disruptive such that $s > 1$.

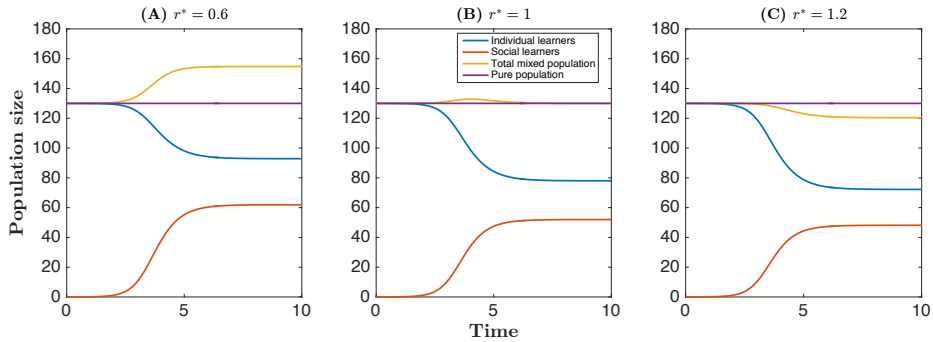

Figure. 4.1. Effect of social learners on population size depending on their impact on per capita resource consumption. **(A)** The population grows larger when social learners decrease the per capita resource usage: $r^* = 0.6$ ($s = 1$). **(B)** The population grows initially but eventually falls back when social learners do not change the per capita resource usage: $r^* = 1$ ($s = 5/3$). **(C)** The population declines when social learners increase the per capita resource usage: $r^* = 1.2$ ($s = 2$). While shown in the same figures the pure population and mixed population were modelled separately. In all cases, $b = 1$, $c_i = 0.4$, $\alpha = 5$, $\beta = \delta = 0.01$, and $n_{i,t=0} = n^*_{i,p}$. In addition in the mixed populations $n_{s,t=0} = 1$ and $c_s = 0$.

4.2.5. Stochastic Population Growth Model and Results

Because social learners rely on "leveraging" the knowledge of individual learners, but simultaneously reduce the number of individual learners, a population with both individual and social learners is more fragile than a population of individual learners only. Specifically, whenever $r^* > 0$ there are fewer individual learners, in equilibrium, in a mixed population than in a pure population (Theorem 4.1). To examine extinction probabilities, we introduce a stochastic version of the model: we assume that births and death each follow a Poisson process with the per capita birth and death rates specified in equations 4.9 to 4.14 (constrained to be positive).

We simulate a birth and death process in continuous time. Extinction occurs if total population size falls to zero (there are no mutations or immigrations in this model). Consider the case of a population with only individual learners first. The birth rate of such a population is given by $\lambda_{i,t} = Max[\alpha\omega_i - \beta b n_{i,t}, 0]$ and the death rate is given by $\mu_{i,t} = (1 - \omega_i) + \delta b n_{i,t}$. We start the simulations with the number of individual learners at "quasi-equilibrium" at the positive population size at which the birth rate equals the death rate, i.e., $n_{i,t=0} = n^*_{i,p} = \theta/(\beta + \delta)$, where $\theta = (\alpha +$

$1)\omega_i - 1$. We simulate the birth and death process as follows: at a given number of individual learners, $n_{i,t}$, one of two events can occur: birth or death. The time until the next event is exponentially distributed with rate $\lambda_{i,t}n_{i,t} + \mu_{i,t}n_{i,t}$ and the probability of a birth is $\lambda_{i,t}n_{i,t}/(\lambda_{i,t}n_{i,t} + \mu_{i,t}n_{i,t})$.

Consider next a mixed population including social learners. There are two subpopulations: individual learners and social learners. The per capita birth rate of the individual learner subpopulation is given by $\lambda_{i,t} = Max\ [\alpha\omega_i - \beta b(n_{i,t} + rn_{s,t}),0]$ and their per capita death rate is given by $\mu_{i,t} = (1 - \omega_i) + \delta(n_{i,t} + rn_{s,t})$. The per capita birth rate of the social learner subpopulation is give by $\lambda_{s,t} = \mathrm{Max}\big[\alpha\omega_i - \beta b(n_{i,t} + rn_{s,t}),0\big]$ and their per capita death rate is given by $\mu_{s,t} = (1 - \omega_s) + \delta(n_{i,t} + rn_{s,t})$, where $\omega_{s,t} = bn_{i,t}/\big(n_{i,t} + n_{s,t}\big) - c_s$. Note that if the subpopulation of individual learners goes extinct such that $n_{i,t} = 0$, then $\omega_{s,t} = 0$ and the birth rate for social learners falls to zero, implying that social learners will also eventually go extinct.

We simulate the birth and death process for the mixed population as follows: at a given number of individual and social learners, $n_{i,t} + n_{s,t}$, four events can occur: the birth or death of an individual learner or the birth or death of a social learner. The time until the next event is exponentially distributed with rate $\lambda_{i,t}n_{i,t} + \lambda_{s,t}n_{s,t} + \mu_{i,t}n_{i,t} + \mu_{s,t}n_{s,t}$ and the probability of a given event is proportional to its rate, i.e., the probability of a birth of an individual learner is$\lambda_{i,t}n_{i,t}$ divided by the sum of the rates, $\lambda_{i,t}n_{i,t} + \lambda_{s,t}n_{s,t} + \mu_{i,t}n_{i,t} + \mu_{s,t}n_{s,t}$.

We start the simulations with the mixed population at "quasi-equilibrium" i.e., at the positive population size at which the birth rates equal the death rates, given by $n_m^* = \theta/((\beta + \delta)(\omega_i + (1 - \omega_i)r^*))$ where $\theta = (\alpha + 1)\omega_i - 1$. The initial number of individual learners is therefore given by $\omega_i n_m^*$ and the initial number of social learners is given by $(1 - \omega_i)n_m^*$. The intention is to compare the fragility of i) a pure population consisting only of individual learners that has grown to its equilibrium size to ii) a mixed population with individual learners and social learners that has grown to its equilibrium size.

The stochastic model shows that a population with social learners is more likely to go extinct than a population without social learners: despite its advantages, intellectual leveraging can be dangerous. The risk of extinction is particularly high when the presence of social learners drives the number of individual learners very low (Figure 4.2C). However, the results also show that the lower r^* is the greater the number of individual learners in the mixed population is and thus the less likely

the population is to go extinct (Figure 4.2A and Figure 4.2B). Note that r^* is low precisely when ω_i is low (such that the proportion of individual learners in the population is low) and intellectual leveraging by social learners is most advantageous in boosting population size (see Theorem 4.1). The per capita impact social learners have on resource consumption therefore both allows for a larger population while simultaneously somewhat offsetting the increased probability of extinction of the mixed population by allowing for a larger number of individual learners to remain in the population. For example when $\omega_i = 0.4$ the average size of a mixed population remains greater than the average size of a pure population for 1000 periods of time unless $r^* > 0.6$ (see Table 4.1).

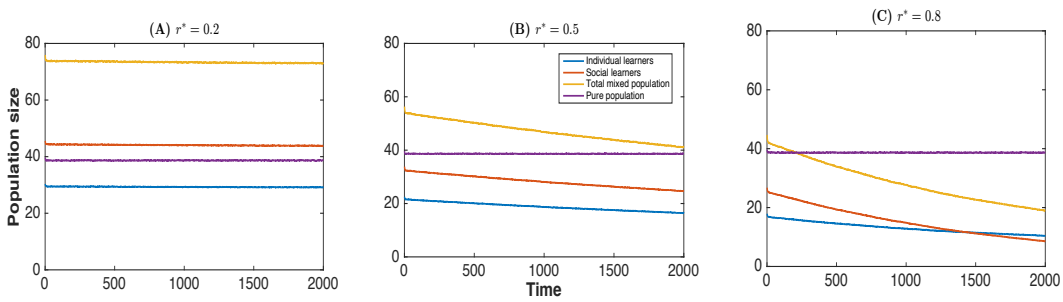

Figure 4.2. Fragility of populations with social learners in relation to the impact social learners have on per capita resource consumption. **(A)** Mean population size when social learners have low impact on resource consumption: $r^* = 0.2$ $(s = 0.5)$. **(B)** Mean population size when social learners have a moderate impact on resource consumption: $r^* = 0.5$ $(s = 1.25)$. **(C)** Mean population size when social learners have high impact on resource consumption: $r^* = 0.8$ $(s = 2)$. In all cases, mean population sizes were averaged over 10000 simulations and $b = 1$, $c_i = 0.6$, $\alpha = 3.5$, $\beta = \delta = 0.01$. For the pure population $n_{i,t=0} = n^*_{i,p}$. In addition in the mixed populations $n_{i,t=0} = \omega_i n^*_m$, $n_{s,t=0} = (1 - \omega_i) n^*_m$ and $c_s = 0$.

Table 4.1. Mean population sizes and proportion of extinctions for different values of r^*

r^*	s	Mean Population sizes at $t = 1000$				Proportion of extinctions at or before period 1000	
		$n_{i,t=1000}$	$n_{s,t=1000}$	Mixed population	Pure population	Mixed population	Pure population
0.0	0.00	38.7	58.2	96.9	38.8	0.00	0.00
0.1	0.25	33.4	50.3	83.7	38.6	0.00	0.00
0.2	0.50	29.4	44.1	73.5	38.7	0.01	0.00
0.3	0.75	25.9	38.9	64.8	38.8	0.02	0.00
0.4	1.00	22.1	33.2	55.3	38.6	0.07	0.00
0.5	1.25	18.7	28.2	46.9	38.6	0.13	0.00
0.6	1.50	19.3	22.5	41.8	38.7	0.12	0.00
0.7	1.75	12.8	18.9	31.6	38.8	0.30	0.00
0.8	2.00	12.9	14.7	27.6	38.6	0.33	0.00

Note: r^* is per capita impact of social learners on resource consumption at equilibrium, s is the form of kleptoparasitism displayed by social learners, $n_{i,t=1000}$ is the number of individual learners in the mixed population at $t = 1000$, $n_{s,t=1000}$ is the number of social learners in the mixed population at $t = 1000$, the mixed population consists of $n_{i,t=1000}$ and $n_{s,t=1000}$ combined, and the pure population consists of only individual learners simulated separately from the mixed population. Mean population sizes at $t = 1000$ and the proportion of extinctions occurring at or before $t = 1000$ for different values of r^* were acquired from 10000 simulations each, with $b = 1$, $c_i = 0.6$, $\alpha = 3.5$, $\beta = \delta = 0.01$. For the pure population $n_{i,t=0} = n^*_{i,p}$. In addition in the mixed populations $n_{i,t=0} = \omega_i n^*_m$, $n_{s,t=0} = (1 - \omega_i) n^*_m$ and $c_s = 0$.

4.3. Population Growth Model With A Range of Learners

Thus far we have assumed individuals will engage solely in individual learning or social learning. However, it is also possible for individuals to instead engage in some combination of both forms of learning such that they consistently spend some proportion of their time on social learning and the rest on individual learning. For example an individual could spend 70 per cent of their time on social learning and 30 per cent on individual learning. Multiple types of learners could then exist where each type of learner divides their time between social learning and individual learning differently from other types of learners. Would a population consisting of such a range of learner types be affected similarly by the differing effect of social learning on per capita resource consumption as a population with only pure individual learners and pure social learners would be? We can show that the results for both populations are qualitatively the same.

4.3.1. General Model Description

Suppose there are m types of learners and $n_{j,t}$ is the number of a type j learner at time t. A type j learner spends a proportion, $q_{i,j}$, of their time on individual learning and the rest, $1 - q_{i,j}$, on social learning. The fitness acquired through individual learning, $\omega_i \in (0,1)$, is an increasing function of the benefit of acquiring accurate information, b, and a decreasing function of the cost of individual learning, c_i, such that $\omega_i = h(b, c_i)$. The fitness acquired through social learning, $\omega_{s,t} \in (0,1)$, is an increasing function of the proportion of the population conducting individual learning at any given time, $\sum_{j=1}^{m} q_{i,j}\, n_{j,t} / \sum_{j=1}^{m} n_{j,t}$, an increasing function of the benefit of acquiring accurate information, b, and a decreasing function of the cost of individual learning, c_s, such that $\omega_{s,t} = h(I, b, c_s)$, where $I = \sum_{j=1}^{m} q_{i,j}\, n_{j,t} / \sum_{j=1}^{m} n_{j,t}$. We also assume $h(1, b, c_s) > \omega_i$ if $c_s < c_i$, and assume $h(0, b, c_s) < \omega_i$. The fitness of a type j learner at time t is then given by

$$\omega_{j,t} = \omega_i q_{i,j} + (1 - q_{i,j})\omega_{s,t}. \tag{4.16}$$

The growth rate of a type j learner is an increasing function of their fitness, $\omega_{j,t}$, as well as a decreasing function of the per capita impact of the population on resource consumption, $z = \sum_{j=1}^{m} q_{i,j}\, n_{j,t} + r \sum_{j=1}^{m} (1 - q_{i,j})\, n_{j,t}$, where r is the impact of social learning on resource consumption compared with individual learning. The impact of social learning on resource consumption is an increasing function of the proportion of the population conducting individual learning at a given time, I, and an increasing function of the form of kleptoparasitism displayed by learners while engaging in social learning, $s \in (0,2)$, where $s < 1$ indicates generally sharing big finds by other learners that they could not fully exploit themselves (scramble kleptoparasitism), $s = 1$ indicates not engaging in kleptoparasitism, and $s > 1$ indicates stealing or forcibly gaining exclusive access to food (aggressive kleptoparasitism), such that $r = h(I, s)$. The growth of a type j learner is therefore given by

$$\frac{\partial n_{j,t}}{\partial t} = g(\omega_{j,t}, z) n_{j,t}. \tag{4.17}$$

We assume the population consists of several types j learners (or only one type j learner) that engage in individual learning, $q_{i,j}$, a sufficiently low proportion of the time such that I can be low enough for $h(I, b, c_s) \leq \omega_i$. In fact, the alternative would not be sustainable as long as new types of learners could arise through mutation. Specifically, if I is sufficiently high that $h(I, b, c_s) > \omega_i$ is always true with the existing types of learners in the population, then if a type j learner with a lower $q_{i,j}$ than any existing type has arises through mutation, it would have a higher fitness than any other type and therefore grow in number. Consequently, I would

decrease in value and this process would repeat until $h(I, b, c_s) = \omega_i$. Given such a population Theorem 4.2 shows that equilibrium population size depends on the value of r.

4.3.2. Theorem 4.2 and Proof

Let $n_{i,p}^*$ be the equilibrium size a pure population consisting only of individual learners converges to and let n_m^* be the equilibrium size a mixed population with m types of learners. Further, let $q_{i,j}$ and $1 - q_{i,j}$ denote the proportion of time a type j learner spends on individual learning and social learning respectively. Then $n_m^* = \frac{n_{i,p}^*}{r^* + (1 - r^*)x}$, where r^* is the per capita impact social learning has on resource consumption at equilibrium and x is a parameter with a value between 0 and 1. Thus, i) whenever $r^* < 1$, $n_m^* > n_{i,p}^*$, ii) whenever $r^* = 1$, $n_m^* = n_{i,p}^*$, and iii) whenever $r^* > 1$, $n_m^* < n_{i,p}^*$. In all cases, $\omega_s = \omega_i$ at equilibrium.

Proof. At a non-zero equilibrium $g(\omega_{j,t}, z) = 0$ for all j. If there is a unique value y such that $g(y, z) = 0$ for each value z, then it follows that the fitnesses, $\omega_{j,t}$, of all types j must be identical. From equation 4.16 we can see that for all $\omega_{j,t}$ to be equal it must be the case that $\omega_{s,t} = \omega_i$. Thus, the fitness of all learner types is equal to ω_i such that $g(\omega_i, z) = 0$. It follows that $z = n_{i,p}^*$ since the size to which a pure population consisting only of individual learners converges to at equilibrium, $n_{i,p}^*$, is defined as the value at which $g(\omega_i, n_{i,p}^*) = 0$. Given $z = n_{i,p}^*$ it then follows that

$$\begin{aligned} n_{i,p}^* &= \sum_{j=1}^{m} q_{i,j}\, n_{j,t} + r \sum_{j=1}^{m} (1 - q_{i,j})\, n_{j,t} \\ &= r \sum_{j=1}^{m} n_{j,t} + (1 - r) \sum_{j=1}^{m} q_{i,j}\, n_{j,t}. \end{aligned} \tag{4.18}$$

Since $\sum_{j=1}^{m} q_{i,j}\, n_{j,t} < \sum_{j=1}^{m} n_{j,t}$, if some $q_{i,j} < 1$, $\sum_{j=1}^{m} q_{i,j}\, n_{j,t}$ can be written as $x \sum_{j=1}^{m} n_{j,t}$, where $0 < x < 1$. In addition at equilibrium $\sum_{j=1}^{m} n_{j,t}$ can be written as n_m^* and $r = r^*$. Thus, we have

$$\begin{aligned} n_{i,p}^* &= r^* n_m^* + (1 - r^*) x n_m^* \\ &= n_m^* (r^* + (1 - r^*) x), \end{aligned} \tag{4.19}$$

which can be rearranged to give

$$n_m^* = \frac{n_{i,p}^*}{r^* + (1 - r^*) x}. \tag{4.20}$$

From equation 4.20 we can see that whenever $r^* < 1$, then $r^* + (1 - r^*)x < 1$, and thus $n_m^* > n_{i,p}^*$. Whenever, $r^* = 1$, then $r^* + (1 - r^*)x = 1$, and thus $n_m^* = n_{i,p}^*$. Finally, whenever, $r^* > 1$, then $r^* + (1 - r^*)x > 1$, and thus $n_m^* < n_{i,p}^*$.

4.3.3. Logistic Population Growth Model and Results

To illustrate the impact of a differing impact of social learning on a population with many types of learners ranging in the proportion of the time they spend on social learning, we develop a logistic growth version of the general model. Suppose there are 101 types of learners, ranging in the proportion of the time they engage in individual learning from $q_{i,j=0} = 0$ to $q_{i,j=101} = 1$ in increments of 0.01. The fitness acquired through individual learning is given by the benefit of acquiring accurate information, b, minus the cost of individual learning, c_i, such that $\omega_i = b - c_i$. The fitness acquired through social learning is given by the benefit of accurate information multiplied by the proportion of the population conducting individual learning at any given time, $b \sum_{j=1}^{m} q_{i,j}\, n_{j,t} / \sum_{j=1}^{m} n_{j,t}$, minus the cost of social learning, c_s, such that $\omega_{s,t} = b \sum_{j=1}^{m} q_{i,j}\, n_{j,t} / \sum_{j=1}^{m} n_{j,t} - c_s$. The growth rate of a type j learner at time t is given by

$$\frac{\partial n_{j,t}}{\partial t} = \lambda_{j,t} - \mu_{j,t}, \tag{4.21}$$

where $\lambda_{j,t}$ is the birth rate and $\mu_{j,t}$ is the death rate. The birth rate is given by

$$\lambda_{j,t} = \alpha \omega_{j,t} - \beta z, \tag{4.22}$$

where α is the base impact of fitness on the birth rate, β is the base impact of population size on the birth rate and $z = \sum_{j=1}^{101} q_{i,j}\, n_{j,t} + r \sum_{j=1}^{101} (1 - q_{i,j})\, n_{j,t}$. The death rate is given by

$$\mu_{j,t} = \left(1 - \omega_{j,t}\right) + \delta \sum_{j=1}^{101} n_{j,t}. \tag{4.23}$$

The impact of r^* on equilibrium population size can now be illustrated as in Figure 4.3 where a population with only individual learners is compared with a population with 101 types of learners. The population with only individual learners starts at its equilibrium size while the population with 101 types of learners starts with an additional 0.01 for each of the 100 learner types that engage in some amount of social learning. Note that while 0.01 individuals is not a realistic value for the number of individuals, it was chosen to allow for the illustration of smooth logistic growth. When $r^* < 1$ a population with learner types making use of social learning will permanently grow greater in size than a population with only individual learners (see Figure 4.3A). When $r^* = 1$ then a population with learner types making use of social learning initially grows greater in size than a population with only individual learners but eventually falls to be equal in size at equilibrium (see Figure 4.3B). Finally, when $r^* < 1$ a population with learner types making use of social learning may initially grow greater in size than a population with only

individual learners but will eventually fall to be lesser in size at equilibrium (see Figure 4.3C).

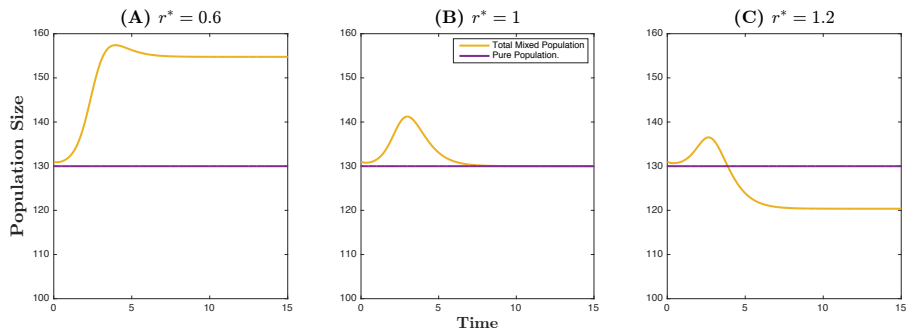

Figure 4.3. Effect of social learning on population size depending on its impact on per capita resource consumption in a population with 101 types of learners. **(A)** The population grows larger when social learning decreases the per capita resource consumption: $r^* = 0.6$ ($s = 1$). **(B)** The population grows initially but eventually falls back when social learning does not change the per capita resource consumption: $r^* = 1$ ($s = 5/3$). **(C)** The population declines when social learning increases the per capita resource consumption: $r^* = 1.2$ ($s = 2$). While shown in the same figures the pure population and mixed population were modelled separately. The mixed population consisted of 101 types of learners ranging from 0 to 1 in 0.01 increments in the proportion of time used on individual learning. In all cases, $b = 1$, $c_i = 0.4$, $\alpha = 5$, $\beta = \delta = 0.01$, and $n_{i,t=0} = n_{j=101,t=0} = n^*_{i,p}$. In addition in the mixed populations $n_{j=0,t=0}$ to $n_{j=100,t=0}$ were set to 0.01 and $c_s = 0$. Note that for simplicity $r = r^*$ throughout the growth of the mixed populations.

4.4. Discussion

The benefits provided by social learning in our model require it to have less impact on resource consumption than individual learning does. This is possible because social learners consume fewer resources per capita than individual learners do at equilibrium since social learners do not always acquire useful information and thus do not always acquire resources. This may be a realistic assumption as social learning can demonstrably be cheaper than individual learning in animals (Kendal et al., 2018, Galef & Laland, 2005), which suggests individuals making use of social learning can consume fewer resources than individuals only making use of individual learning learners while maintaining equal fitness. For example, individuals making use of social learning to learn which types of locations will provide them with the most food without having to expend energy actively learning it through individual

learning, will be able to maintain the same fitness as individual learners while eating less. However, despite lesser learning costs individuals making use of social learning may have a higher impact on resource usage compared with individual making use of individual learning. If individuals making use of social learning act as scroungers (Lehmann & Feldman, 2009) and engage in scramble kleptoparasitism (Giraldeau & Caraco, 2000), the simultaneous exploitation of resources found by others characterised by little or no aggression, then their impact on producers (individual making use of individual learning) will be minimal allowing the population to grow. However, if individuals making use of social learning engage in aggressive kleptoparasitism, actively denying or reducing the access of the producers to the food they have found, the population size may decline with the introduction of social learning even if the cost of social learning is low. We suggest social learning may have a sufficiently lesser impact on resource usage than individual learning does that the presence of individuals making use of social learning in a population will have a substantial impact on population size. However, our study does not investigate the degree to which this is the case in reality and it will have to remain the subject of future research.

We assumed that population sizes combine additively in the per capita population growth function, i.e., $g(\omega_{i,t}, n_{i,t} + rn_{s,t})$. What if the impact of population size were non-linear, such as $g(\omega_{i,t}, n_{i,t}^2 + rn_{s,t}^2)$? The presence of non-linearities can change the results, but only because they introduce benefits to diversification or specialization; benefits that do not depend on social learning per se. For example, suppose the birth date depends on the squared population sizes as follows: $g(\omega_{i,t}, n_{i,t}^2 + rn_{s,t}^2)$. In this case, introducing social learners may increase population size even if *r = 1*. The reason is that there is a benefit to diversification due to the convexity of the growth rate function: $g(\omega_{i,t}, 100^2) < g(\omega_{i,t}, 50^2 + 50^2)$. It follows that a mixed population will have a higher growth rate than a pure population, but this conclusion holds for any mixture and does not depend on social versus individual learning.

Our resolution to Roger's paradox shows that the lesser cost of social learning may even by itself provide value for a species in terms of population size if social learners simultaneously consume fewer resources than individual learners do. Such an increase could provide benefits of its own as research suggests larger populations are more capable of creating adaptive culture (Kline & Boyd, 2010; Derex et al., 2013; Kobayashi, Ohtsuki, & Wakano, 2016; Powell, Shennan, & Thomas, 2009). Our results may also offer theoretical support for the possible

coexistence of individual learners and social learners, which is supported by experimental evidence (e.g. Molleman, van den Berg, & Weissing, 2014; Duffy et al., 2019; Kameda & Nakanishi, 2002). Prior research has found social learners able to increase population size but only when the cost of individual learning and social learning are equal and when social learners spend more time learning from others than individual learners do inventing new technologies (Lehmann & Feldman, 2009). Research on producer-scroungers games, which are closely tied to models with individual learners and social learners, has also suggested that the presence of scroungers (similar to individuals using social learning) can increase population size (Coolen et al., 2007). However, this result was made possible by scroungers preventing the population from growing too large such that a greater amount of food was retained in the long run allowing for a greater population size to be sustained. Our result therefore differs in showing that the cost difference between individual learning and social learning may be a crucial factor for making social learning beneficial. However, our results simultaneously suggest that intellectual leveraging by social learners may make a species more susceptible to extinction through a reduction in the number of individual learners although this is largely mitigated by the generally simultaneous low per capita impact social learners have on resource consumption.

Chapter 5. Heterogeneity in Search Behaviours Limited by Need to Develop Absorptive Capacity

5.1. Introduction

Social learning, learning from others, is a widely exhibited behaviour in nature and considered to have been crucial to human ecological success. Despite this, it has long been recognised that in a temporally varying environment social learning is not inherently beneficial as its benefits may be subject to negative frequency dependence (Rogers, 1988; Boyd & Richerson, 1995). Specifically, the higher the proportion of social learning in a population the less useful it becomes as proportionately fewer individuals will be directly learning about the environment through individual learning. This result mirrors the well-known frequency dependence present in producer-scrounger games used to model animal foraging behaviours (Barnard & Sibly, 1981; Giraldeau et al., 1994). In these games producers search for food while scroungers take advantage of food found by producers. Given the close resemblance between models of social learning and producer-scrounger games individual learners may be considered information producers while social learners may be considered information scroungers for modelling purposes (Laland, 2004; Lehmann & Feldman, 2009; Rendell, Fogarty, & Laland, 2010).

Various ways of reducing or removing the frequency dependence associated with social learning have been proposed. Adaptive use of social learning is one way of allowing it to remain beneficial. Specifically, if individuals use social learning when it proves beneficial and switch to individual learning otherwise, or the reverse, they may retain higher fitness than individuals that have fixed learning strategies (Kameda & Nakanishi, 2002, 2003; Enquist et al., 2007). Social learning may also retain its benefits if it allows for the learning of information that is added to cumulatively every generation (Ehn & Laland, 2012; Enquist & Ghirlanda, 2007; Ohtsuki et al., 2017). Alternatively, social learning may also be used to simply enhance the effectiveness of individual learning (Boyd & Richerson, 1995). If the reverse were true, if individual learning were instead used to enhance the effectiveness of social learning, would the benefits of social learning similarly be retained at equilibrium?

Enhancing social learning through individual learning could take place if some level of understanding is first required to be able to learn effectively from others. In organizational research this concept has been termed absorptive capacity and has

been defined as the capability to identify, assimilate and exploit knowledge from the environment (Cohen & Levinthal, 1990). Absorptive capacity has mostly been considered in the context of how companies seek to understand and incorporate external knowledge (Lewin, Massini, & Peeters, 2011; Sun & Anderson, 2010; Volberda, Foss, & Lyles, 2010). Specifically, the research has suggested that companies conduct research and development not only to develop innovations but to also develop their absorptive capacity such that they can more readily use new technologies and ideas from outside the company. Absorptive capacity has also been considered on the individual level (e.g. Enkel et al., 2017; Zhao & Anand, 2009) but not as much and not in the context of social learning specifically. Research does suggest through that individuals can vary in their level of absorptive capacity caused for example by their experiences and how open they are to new experiences (Yildiz et al., 2019). In this study, however, we will use a simplified concept of individual level absorptive capacity where the absorptive capacity of an individual is entirely subject to how much individual learning they conduct and this absorptive capacity in turn affects how effectively the individual can make use of social learning.

In this study we develop a population growth model with a mixture of learner types where learners vary in the proportion of their learning time they use on individual learning over social learning. We demonstrate that just as in Rogers' original model, the proportion of social learning conducted on the population level increases until the fitness acquired from social learning is equal to the fitness acquired from individual learning. We then show that by adding absorptive capacity to the model, the fitness of this mixed population will remain higher than for a pure population consisting only of individual learners. Thus, even without flexibly switching between individual learning and social learning, the benefits of social learning may be retained. We also show that doing so reduces the range of learner types over time such that the population eventually converges on a single type of learner.

5.2. Social Learning and the Impact of Free Riding

To illustrate how social learning can naturally become free riding through excessive use and thus remove its benefits, consider the following logistic population growth model. Suppose a population of n individuals lives in an environment that is constantly changing. Every period of time, t, the individuals in the population have to learn information about the environment, which if learned successfully confers a benefit, b, to the individual that learned it (e.g. through ability to find food) while

failing to learn the information confers no benefit. The information can be learned through individual learning (learning by oneself) or social learning (learning from others) or some combination of both. We assume the different forms of learning are mutually exclusive such that only one type of learning can be performed at a time. Specifically, we assume there are j learning strategies varying in the proportion of learning time spent on individual learning, $q_{i,j}$, and the proportion of learning time spent on social learning, $1 - q_{i,j}$, where $q_{i,j} = \frac{j}{100}$ and j is an integer between 0 and 100. We assume the learning strategy used by an individual is genetically determined such that they use it consistently, and thus we consider individuals as type j learners ranging from type 0 ($q_{i,j=0} = 0$, pure social learner) to type 100 ($q_{i,j=100} = 1$, pure individual learner).

5.2.1. Fitness Functions

Individual learning allows individuals to learn information reliably but at a cost of time and effort, c_i, such that fitness acquired through individual learning, $\omega_i \in (0,1)$, is given by

$$\omega_i = b - c_i. \tag{5.1}$$

Social learning meanwhile allows the cost of individual learning to be avoided through acquiring information from others. Social learning thus has the potential to provide higher fitness than individual learning if a sufficiently informed individual is found. However, if a sufficiently informed individual is not found social learning will provide lesser fitness than individual learning. The fitness acquired through social learning is therefore frequency dependent: it depends on the frequency of informed individuals in the population. For simplicity, we assume the amount of information that can be learned from another individual through social learning is wholly dependent on how much individual learning the individual being learned from has conducted. Thus, the effectiveness of social learning at time t is subject to the average proportion of individual learning conducted in the population given by

$$q_{i,P,t} = \frac{\sum_{j=1}^{101} q_{i,j} n_{j,t}}{\sum_{j=1}^{101} n_{j,t}}, \tag{5.2}$$

where $n_{j,t}$ is the number of type j learners in the population at time t. Assuming social learning has no costs of its own, the fitness acquired through social learning at time t is then given by

$$\omega_{s,t} = b q_{i,P,t}. \tag{5.3}$$

Given the fitness acquired through individual learning and social learning the fitness of a type j learner at time t is given by

$$\omega_{j,t} = q_{i,j}\omega_i + \left(1 - q_{i,j}\right)\omega_{s,t}. \tag{5.4}$$

The fitness of a type j learner is therefore given by the proportion of time they spend on individual learning and social learning, where the proportions depend on genetically determined preferences of the learner type. Thus, we assume a trade off between the two forms of learning. If such a trade off did not exist then all learners would simply perform both forms of learning simultaneously. However, this may not always be feasible as it is reasonable to assume focusing on a specific form of learning would reduce the amount of attention on another form of learning. Furthermore, while engaging in individual learning a learner may have fewer individuals around them to learn from, which would reduce the effectiveness of simultaneous social learning. Thus, assuming a trade off between individual learning and social learning is justified.

5.2.2. Population Growth Functions

The per capita growth rate of type j learners at time t is subject to their birth rate, $\lambda_{j,t}$, and death rate, $\mu_{j,t}$. The growth of type j learners is therefore given by

$$\frac{\partial n_{j,t}}{\partial t} = \lambda_{j,t} n_{j,t} - \mu_{j,t} n_{j,t}. \tag{5.5}$$

We assume the birth rate of type j learners increases as a function of their fitness and decreases as a function of the size of the population (reflecting the population reaching the carrying capacity of the environment) such that

$$\lambda_{j,t} = \alpha\omega_{j,t} - \beta \sum_{j=1}^{101} n_{j,t}, \tag{5.6}$$

where α is the base impact of fitness on the birth rate and β is the base impact of population size on the birth rate. We assume the death rate type j learners decreases as a function of their fitness and increases as a function of the size of the population such that

$$\mu_{j,t} = \left(1 - \omega_{j,t}\right) + \delta \sum_{j=1}^{101} n_{j,t}, \tag{5.7}$$

where δ is the base impact of population size on the death rate.

5.2.3. Results

We assume a population of n individuals is initially divided evenly in number between the 101 learner types. We then simulate how the number of different types of learners in this mixed population evolves over time based on the growth rates of the different learner types and how this affects the average fitness of the population compared to a pure population consisting only of individual learners. The results show that the mixed population will grow until the fitness provided by individual learning and social learning are equal such that social learning no longer provides a

benefit for individuals beyond solely engaging in individual learning. Specifically, whether $\omega_i = 0.4$ as in Figure 5.1A, $\omega_i = 0.6$ as in Figure 5.1B, or $\omega_i = 0.8$ as in Figure 5.1C, the average fitness of a mixed population quickly converges to the average fitness of a pure population.

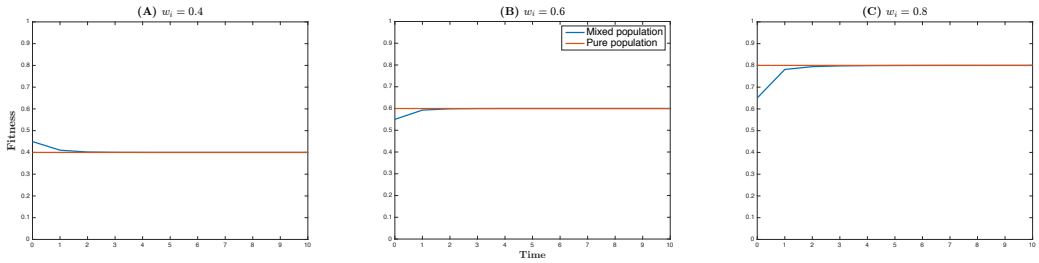

Figure 5.1. The average fitness of a mixed population with 101 types of learners and the average fitness of a pure population with only individual learners equalise regardless of fitness provided by individual learning. **(A)** Fitness from individual learning is relatively low: $\omega_i = 0.4$ $(c_i = 0.6)$. **(B)** Fitness from individual learning is relatively high: $\omega_i = 0.6$ $(c_i = 0.4)$. **(C)** Fitness from individual learning is very high: $\omega_i = 0.8$ $(c_i = 0.2)$. In all cases, and $b = 1$, $\alpha = 20$, $\beta = \delta = 0.01$. Mixed populations started with 1 member each and the pure population stated with 1 individual learner. The two populations were modelled separately.

Although the fitness of a mixed population and a pure population equalize regardless of the fitness provided by individual learning, ω_i, the numbers of each type of learner in the mixed population can substantially change depending on its value. Specifically, a relatively low fitness from individual learning ($\omega_i = 0.4$), somewhat favours learner types using more social learning such that they grow greater in number (see Figure 5.2A). A relatively high fitness from individual learning ($\omega_i = 0.6$) somewhat favours learner types using more individual learning such that they grow greater in number (see Figure 5.2B). Finally, a very high fitness from individual learning ($\omega_i = 0.8$) strongly favours learner types using more individual learning such that they grow substantially greater in number (see Figure 5.2C). In all of these cases, however, some learners of all types coexist since they all have the same fitness at equilibrium. The equal fitness of all the learner types at equilibrium is proved in Theorem 5.1.

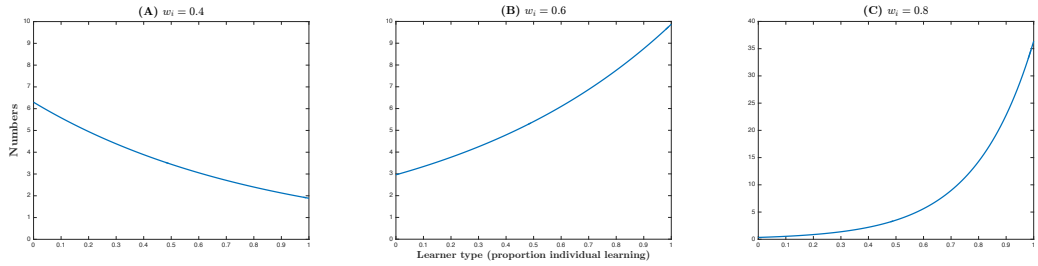

Figure 5.2. Numbers for learners depending on fitness provided by individual learning in a mixed population with 101 types of learners. **(A)** Fitness from individual learning is relatively low: $\omega_i = 0.4$ $(c_i = 0.6)$. **(B)** Fitness from individual learning is relatively high: $\omega_i = 0.6$ $(c_i = 0.4)$. **(C)** Fitness from individual learning is very high: $\omega_i = 0.8$ $(c_i = 0.2)$. In all cases the numbers shown are after 100 periods, all types of learners started at 1 member each, and $b = 1$, $\alpha = 20$, $\beta = \delta = 0.01$.

5.2.4. Theorem 5.1 and Proof

Let the fitness of a type j learner be $\omega_{j,t} = q_{i,j}\omega_i + \left(1 - q_{i,j}\right)\omega_{s,t}$, *where* $q_{i,j}$ *is the proportion of time they spend on individual learning,* $\omega_i = b - c_i$ *is the fitness provided by individual learning given by the benefit of learning accurate information,* b, *minus the cost of individual learning,* c_i, *and* $\omega_{s,t} = bq_{i,P,t}$ *is the fitness provided by social learning given by the benefit of learning accurate information multiplied by the proportion of the population conducting individual learning at time* t, $q_{i,P,t} = \frac{\sum_{j=1}^{101} q_{i,j}n_{j,t}}{\sum_{j=1}^{101} n_{j,t}}$, *where* $n_{j,t}$ *is the number of type j learners at time* t. *Then the fitness of any type j learner at equilibrium,* ω_j^*, *will be equal to the fitness acquired through individual learning* ω_i.

Proof. We combine equation 5.5 with equation 5.6 and equation 5.7 and solve for equilibrium fitness by setting the derivative equal to zero:

$$\forall_j: \frac{\partial n_{j,t}}{\partial t} = (\alpha\omega_{j,t} - \beta N)n_{j,t} - ((1 - \omega_{j,t}) + \delta N)n_{j,t} = 0, \tag{5.8}$$

where $N = \sum_{j=1}^{101} n_{j,t}$. For any *type j learner for which* $n_{j,t} > 0$ we then have

$$\alpha\omega_j^* - \beta N = (1 - \omega_j^*) + \delta N,$$

$$\rightarrow \omega_j^* = \frac{1+(b+d)N}{1+k}, \tag{5.9}$$

where ω_j^* is $\omega_{j,t}$ at equilibrium. Given $\omega_{j,t} = q_{i,j}\omega_i + \left(1 - q_{i,j}\right)\omega_{s,t}$ we also have for any *type j learner*

$$q_{i,j}\omega_i + \left(1 - q_{i,j}\right)\omega_{s,t} = \frac{1+(b+d)N}{1+k}. \tag{5.10}$$

Equation 5.9 implies the fitness of all types j learners is equal at equilibrium. Equation 5.10 implies that at equilibrium $\omega_i = \omega_{s,t}$, which together with equation 5.9 further implies at equilibrium $\omega_j^* = \omega_i$.

5.3. Absorptive Capacity Reducing Free-riding Through Social Learning

To learn effectively from others an individual may first need to have some understanding of what they are trying to learn from them. To represent this we assume the proportion of time an individual spends on individual learning will influence the effectiveness of their social learning. Specifically, we assume the effectiveness of social learning is subject to absorptive capacity, $f(q_{i,j})$, which is increasing in the amount of individual learning conducted by a type j learner such that

$$f(q_{i,j}) = 1 - a(1 - q_{i,j})^2, \tag{5.11}$$

where a is a parameter regulating how much the proportion of learning time spent on individual learning by a type j learner influences their absorptive capacity. When $a = 0$ absorptive capacity is unrelated to the proportion of time spent on individual learning while when $a > 0$ absorptive capacity is reduced in relation to the value of a. We can now combine equation 5.11 with equation 5.4 to show the impact absorptive capacity has on the fitness of a type

$$\omega_{j,t} = q_{i,j}\omega_i + (1 - q_{i,j})f(q_{i,j})\omega_{s,t}. \tag{5.12}$$

5.3.1. Results

As before we assume a mixed population of n individuals is initially divided evenly in number between the 101 learner types and we again simulate how the fitness and number of different types of learners in the population evolves over time. This time, however, we vary the effect individual learning has on absorptive capacity to see its impact on the learners in the mixed population. We also show the effect of varying the amount of time the population has to evolve. In each case we perform two sets of simulations where we set the benefit of individual learning to $\omega_i = 0.5$ or $\omega_i = 0.1$ respectively. We then compare the results to a similar mixed population in which learners do not need to develop absorptive capacity through individual learning, which thus has the same fitness as a pure population with only individual learners (see Figure 5.1).

The results show that when individual learning has an impact on absorptive capacity the average fitness of the mixed population remains greater than if

individual learning does not have an impact on absorptive capacity. However, the extent of the impact individual learning has on absorptive capacity has a lesser impact on the fitness of the mixed population after 100 periods than it does on the proportion of individual learning and types of learners in the population. Specifically, when $\omega_i = 0.5$ and the impact of individual learning on absorptive capacity is relatively low ($a = 0.5$) the average fitness of learners is 0.53 (see Figure 5.3A) while the proportion of the population using individual learning at any given time is

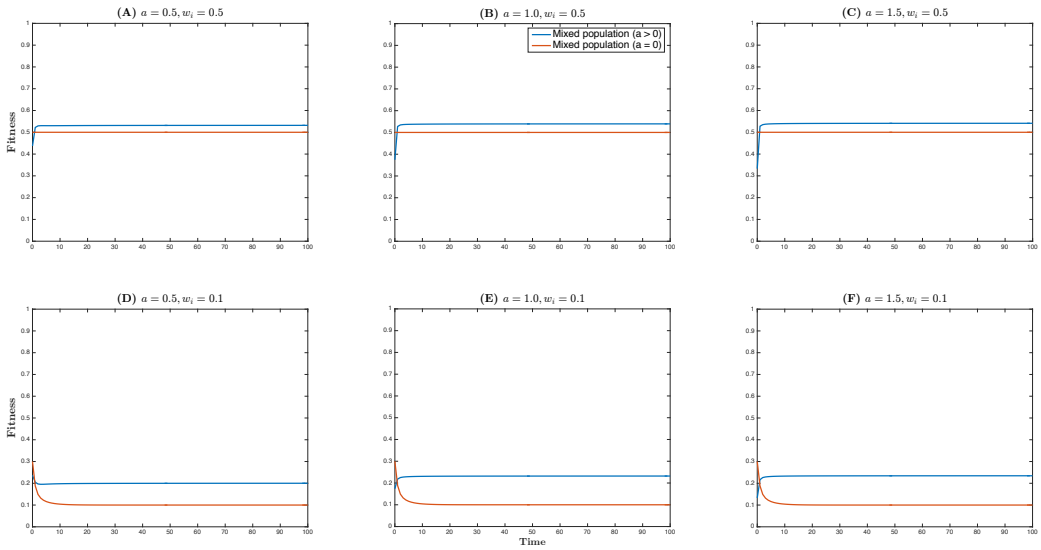

Figure 5.3. The average fitness of a mixed population with 101 types of learners subject to absorptive capacity remains greater than the average fitness of a similar population not subject to absorptive capacity. **(A)** Impact of individual learning on absorptive capacity is low and fitness provided by individual learning is moderate: $a = 0.5$ and $\omega_i = 0.5$ $(c_i = 0.5)$. **(B)** Impact of individual learning on absorptive capacity is moderate and fitness provided by individual learning is moderate: $a = 1.0$ and $\omega_i = 0.5$ $(c_i = 0.5)$. **(C)** Impact of individual learning on absorptive capacity is high and fitness provided by individual learning is moderate: $a = 1.5$ and $\omega_i = 0.5$ $(c_i = 0.5)$. **(D)** Impact of individual learning on absorptive capacity is low and fitness provided by individual learning is low: $a = 0.5$ and $\omega_i = 0.1$ $(c_i = 0.9)$. **(E)** Impact of individual learning on absorptive capacity is moderate and fitness provided by individual learning is low: $a = 1.0$ and $\omega_i = 0.1$ $(c_i = 0.9)$. **(F)** Impact of individual learning on absorptive capacity is high and fitness provided by individual learning is low: $a = 1.5$ and $\omega_i = 0.1$ $(c_i = 0.9)$. In all cases the numbers shown are after 100 periods, all types of learners started at 1 member each, $b = 1$, $\alpha = 20$, $\beta = \delta = 0.01$, and for the mixed population not subject to absorptive capacity $a = 0$. The two populations were modelled separately.

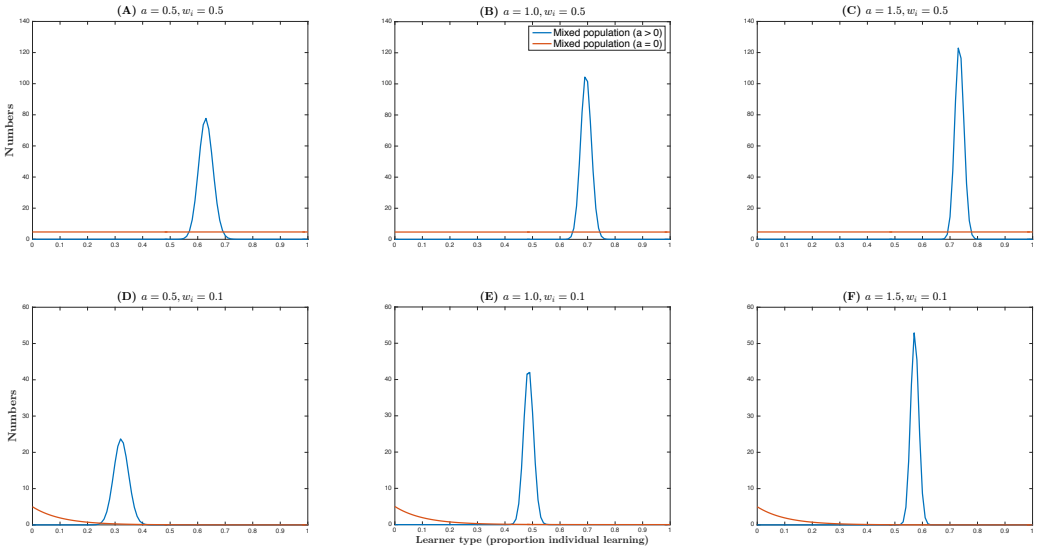

Figure 5.4. Numbers for learners depending on impact of individual learning on absorptive capacity in a mixed population with 101 types of learners subject to absorptive capacity compared to a population not subject to absorptive capacity. **(A)** Impact of individual learning on absorptive capacity is low and fitness provided by individual learning is moderate: $a = 0.5$ and $\omega_i = 0.5$ $(c_i = 0.5)$. **(B)** Impact of individual learning on absorptive capacity is moderate and fitness provided by individual learning is moderate: $a = 1.0$ and $\omega_i = 0.5$ $(c_i = 0.5)$. **(C)** Impact of individual learning on absorptive capacity is high and fitness provided by individual learning is moderate: $a = 1.5$ and $\omega_i = 0.5$ $(c_i = 0.5)$. **(D)** Impact of individual learning on absorptive capacity is low and fitness provided by individual learning is low: $a = 0.5$ and $\omega_i = 0.1$ $(c_i = 0.9)$. **(E)** Impact of individual learning on absorptive capacity is moderate and fitness provided by individual learning is low: $a = 1.0$ and $\omega_i = 0.1$ $(c_i = 0.9)$. **(F)** Impact of individual learning on absorptive capacity is high and fitness provided by individual learning is low: $a = 1.5$ and $\omega_i = 0.1$ $(c_i = 0.9)$. In all cases the numbers shown are after 100 periods, all types of learners started at 1 member each, and $b = 1$, $\alpha = 20$, $\beta = \delta = 0.01$, and for the mixed population not subject to absorptive capacity $a = 0$. The two populations were modelled separately.

0.63 (see Figure 5.4A). When the impact of individual learning on absorptive capacity is moderate $(a = 1.0)$ the average fitness of learners is 0.54 (see Figure 5.3B) while the proportion of the population using individual learning at any given time is 0.69 (see Figure 5.4B). Finally, when the impact of individual learning on absorptive capacity is relatively high $(a = 1.5)$ the average fitness of learners is 0.54 (see Figure 5.3C) while the proportion of the population using individual learning at

any given time is 0.73 (see Figure 5.4C). Note that in all of these cases the fitness and proportion of individual learning in the mixed population where learners do not need to develop absorptive capacity is equal to the fitness acquired from individual learning $\omega_i = 0.5$. In addition the numbers for the different types of learners in this population are equal since neither types using more individual learning nor types using more social learning are favoured, as they would if $\omega_i > 0.5$ or $\omega_i < 0.5$ (see Figure 5.2).

The impact requiring individual learning to develop absorptive capacity has on the fitness and proportion of individual learning in a mixed population is even greater when the fitness provided by individual learning is low. Specifically, when $\omega_i = 0.1$ and the impact of individual learning on absorptive capacity is relatively low ($a = 0.5$) the average fitness of learners is 0.20 (see Figure 5.3D) while the proportion of the population using individual learning at any given time is 0.32 (see Figure 5.4D). When the impact of individual learning on absorptive capacity is moderate ($a = 1.0$) the average fitness of learners is 0.23 (see Figure 5.3E) while the proportion of the population using individual learning at any given time is 0.49 (see Figure 5.4E). Finally, when the impact of individual learning on absorptive capacity is relatively high ($a = 1.5$) the average fitness of learners is 0.23 (see Figure 5.3F) while the proportion of the population using individual learning at any given time is 0.57 (see Figure 5.4F). Note that in all of these cases the fitness and proportion of individual learning in the mixed population where learners do not need to develop absorptive capacity is again equal to the fitness acquired from individual learning $\omega_i = 0.1$. However, in contrast to when $\omega_i = 0.5$, learner types using more social learning are now strongly favoured such that these types of learners have greater numbers than learner types using more individual learning. Thus, requiring individual learning to develop absorptive capacity has a greater impact when $\omega_i = 0.1$ than when $\omega_i = 0.5$ since it makes learning strategies relying mostly on social learning unviable, which affects more learners when $\omega_i = 0.1$.

The greater the amount of time the mixed population has to evolve also affects the number of different types of learners remaining in the population. However, proportion of the population engaging in individual learning and the fitness of the population do not substantially change over time. Specifically, when $\omega_i = 0.5$ and the amount of time that has take place is relatively low ($t = 100$) the average fitness of learners is 0.53 (see Figure 5.5A) while the proportion of the population using individual learning at any given time is 0.63 (see Figure 5.6A). When a moderate amount of time has taken place ($t = 1000$) the average fitness of learners

is 0.53 (see Figure 5.5B) while the proportion of the population using individual learning at any given time is 0.63 (see Figure 5.6B). Finally, when the amount of time that has take place is relatively high ($t = 2000$) the average fitness of learners is 0.53 (see Figure 5.5C) while the proportion of the population using individual learning at any given time is 0.63 (see Figure 5.6C). Although the average fitness and the proportion of individual learning do not change much over time, the results

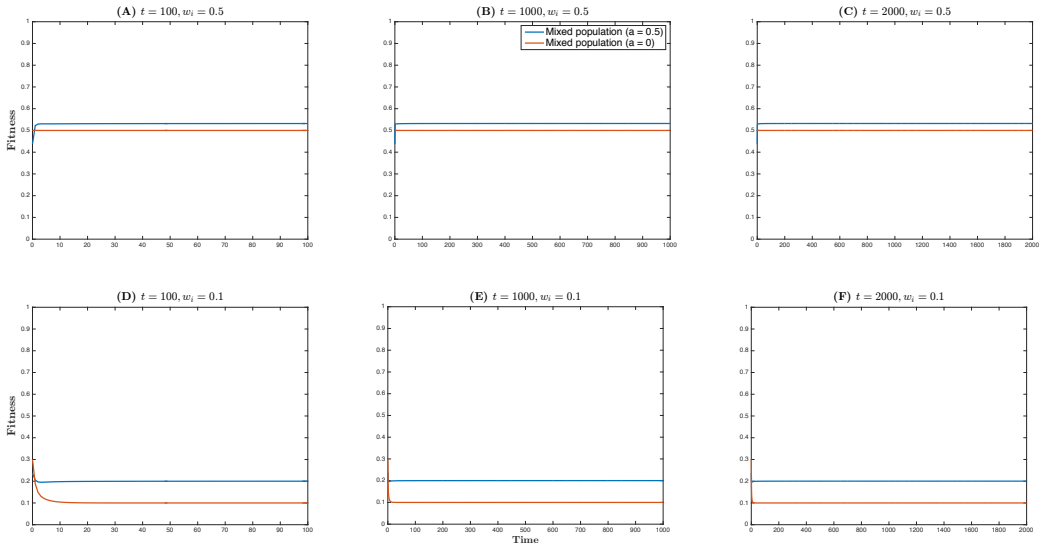

Figure 5.5. Average fitness for learners depending on number of periods in a mixed population with 101 types of learners subject to absorptive capacity compared to a similar population not subject to absorptive capacity. **(A)** Fitness for learners when a low amount of time has taken place and fitness provided by individual learning is moderate: $t = 100$ and $\omega_i = 0.5$ $(c_i = 0.5)$. **(B)** Fitness for learners when a moderate amount of time has taken place and fitness provided by individual learning is moderate: $t = 1000$ and $\omega_i = 0.5$ $(c_i = 0.5)$. **(C)** Fitness for learners when a high amount of time has taken place and fitness provided by individual learning is moderate: $t = 2000$ and $\omega_i = 0.5$ $(c_i = 0.5)$. **(D)** Fitness for learners when a low amount of time has taken place and fitness provided by individual learning is low: $t = 100$ and $\omega_i = 0.1$ $(c_i = 0.9)$. **(E)** Fitness for learners when a moderate amount of time has taken place and fitness provided by individual learning is low: $t = 1000$ and $\omega_i = 0.1$ $(c_i = 0.9)$. **(F)** Fitness for learners when a high amount of time has taken place and fitness provided by individual learning is low: $t = 2000$ and $\omega_i = 0.1$ $(c_i = 0.9)$. In all cases all types of learners started at 1 member each, and $b = 1$, $\alpha = 20$, and $\beta = \delta = 0.01$. For the mixed population subject to absorptive capacity $a = 0.5$ and for the mixed population not subject to absorptive capacity $a = 0$. The two populations were modelled separately.

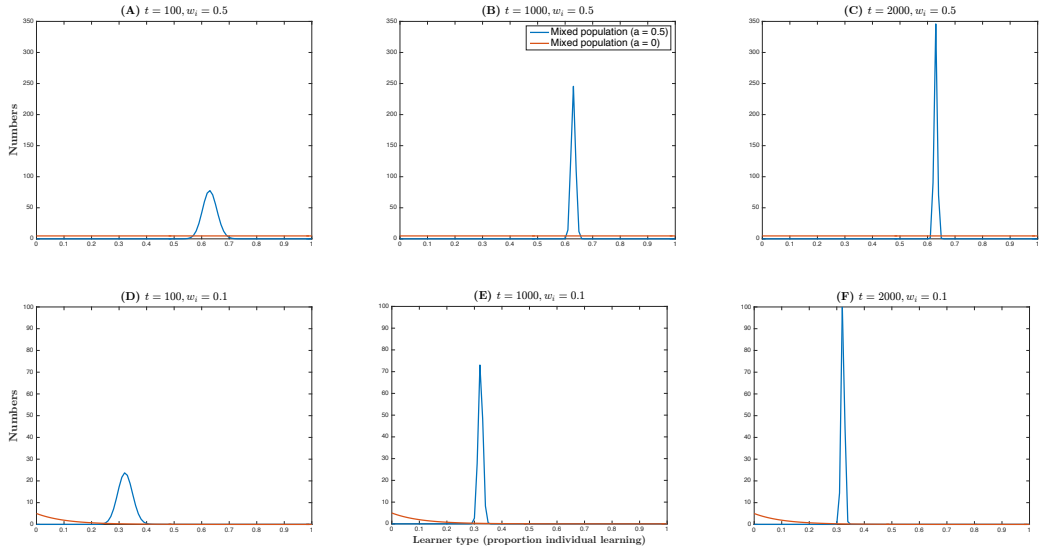

Figure 5.6. Numbers for learners depending on number of periods in a mixed population with 101 types of learners compared to a similar population not subject to absorptive capacity. **(A)** Numbers for learners when a low amount of time has taken place and fitness provided by individual learning is moderate: $t = 100$ and $\omega_i = 0.5$ $(c_i = 0.5)$. **(B)** Numbers for learners when a moderate amount of time has taken place and fitness provided by individual learning is moderate: $t = 1000$ and $\omega_i = 0.5$ $(c_i = 0.5)$. **(C)** Numbers for learners when a high amount of time has taken place and fitness provided by individual learning is moderate: $t = 2000$ and $\omega_i = 0.5$ $(c_i = 0.5)$. **(D)** Numbers for learners when a low amount of time has taken place and fitness provided by individual learning is low: $t = 100$ and $\omega_i = 0.1$ $(c_i = 0.9)$. **(E)** Numbers for learners when a moderate amount of time has taken place and fitness provided by individual learning is low: $t = 1000$ and $\omega_i = 0.1$ $(c_i = 0.9)$. **(F)** Numbers for learners when a high amount of time has taken place and fitness provided by individual learning is low: $t = 2000$ and $\omega_i = 0.1$ $(c_i = 0.9)$. In all cases all types of learners started at 1 member each, and $b = 1$, $\alpha = 20$, and $\beta = \delta = 0.01$. For the mixed population subject to absorptive capacity $a = 0.5$ and for the mixed population not subject to absorptive capacity $a = 0$. The two populations were modelled separately.

do show a convergence towards a single type of learner over time, which has higher fitness than a pure individual learner.

As when the fitness provided by individual learning is moderate, the proportion of the mixed population engaging in individual learning and the fitness of the population do not substantially change over time when the fitness provided by individual learning is low. Specifically, when $\omega_i = 0.1$ and the amount of time that

has take place is relatively low ($t = 100$) the average fitness of learners is 0.20 (see Figure 5.5D) while the proportion of the population using individual learning at any given time is 0.32 (see Figure 5.6D). When a moderate amount of time has taken place ($t = 1000$) the average fitness of learners is 0.20 (see Figure 5.5E) while the proportion of the population using individual learning at any given time is 0.32 (see Figure 5.6E). Finally, when the amount of time that has take place is relatively high ($t = 2000$) the average fitness of learners is 0.20 (see Figure 5.5F) while the proportion of the population using individual learning at any given time is 0.32 (see Figure 5.6F). As before though the results show a convergence towards a single type of learner over time, which has higher fitness than a pure individual learner. This result can also be expressed as Theorem 5.2.

5.3.2. Theorem 5.2 and Proof

Let $f(q_{i,j})$ represent some continuous absorptive capacity function increasing in the amount of individual learning conducted by a type j learner, $q_{i,j}$, at a decreasing rate such that $\frac{\partial^2 f(q_{i,j})}{\partial q_{i,j}^2} < 0$. Furthermore, let the fitness of a type j learner be $\omega_{j,t} = q_{i,j}\omega_i + (1 - q_{i,j})\, f(q_{i,j})\omega_{s,t}$, where the fitness acquired through individual learning, ω_i, is given by the benefit of useful information, b, minus the cost of individual learning, c_i, such that $\omega_i = b - c_i$, and the fitness acquired through social learning at time t, $\omega_{s,t}$, is given by the benefit of useful information and the proportion of the population conducting individual learning at time t, $q_{i,P,t}$, such that $\omega_{s,t} = bq_{i,P,t}$. Suppose the proportion of individual learning in the population, $q_{i,P,t}$, converges to $q_{i,P}^*$ at equilibrium such that only one type of learner survives due to all others having lower fitness. Then the fitness of the population at equilibrium, ω_j^*, will be higher than fitness acquired through individual learning ω_i.

Proof. When $q_{i,P,t} = q_{i,P}^*$ the fitness of the only remaining type *j* learner in the population is given by $\omega_j^* = q_{i,j}\omega_i + (1 - q_{i,j})\, f(q_{i,j})bq_{i,P}^*$. To find the proportion of learning time the remaining type *j* learners spend on individual learning that maximises ω_j^* we take the derivative of ω_j^* with respect to $q_{i,j}$ such that

$$\frac{\partial \omega_j^*}{\partial q_{i,j}} = \omega_i - f(q_{i,j})bq_{i,P}^* + (1 - q_{i,j})f'(q_{i,j})bq_{i,P}^*. \tag{5.13}$$

This is a maximum since the second-order condition holds

$$\frac{\partial^2 \omega_j^*}{\partial q_{i,j}^2} = -2f'(q_{i,j})bq_{i,P}^* + (1 - q_{i,j})f''(q_{i,j})bq_{i,P}^* < 0. \tag{5.14}$$

Given the entire population consists of type *j* learners at equilibrium we can set $q_{i,j} = q_{i,P}^*$ in equation 5.13 and thus get

$$\frac{\partial \omega_j^*}{\partial q_{i,j}}_{q_{i,j}=q_{i,P}^*} = \omega_i - f(q_{i,P}^*)bq_{i,P}^* + (1 - q_{i,P}^*)f'(q_{i,P}^*)bq_{i,P}^*. \quad (5.15)$$

The value of $q_{i,P}^*$ can now be found by setting the equation equal to zero and solving for $q_{i,P}^*$:

$$\frac{\partial \omega_j^*}{\partial q_{i,j}}_{q_{i,j}=q_{i,P}^*} = \omega_i - f(q_{i,P}^*)bq_{i,P}^* + (1 - q_{i,P}^*)f'(q_{i,P}^*)bq_{i,P}^* = 0. \quad (5.16)$$

$$\rightarrow \omega_i = f(q_{i,P}^*)bq_{i,P}^* - (1 - q_{i,P}^*)f'(q_{i,P}^*)bq_{i,P}^*. \quad (5.17)$$

To show that an interior solution $q_{i,P}^* \in (0,1)$ exists to this equation, let $h(q_{i,P}^*) = f(q_{i,P}^*)bq_{i,P}^* - (1 - q_{i,P}^*)f'(q_{i,P}^*)bq_{i,P}^*$. Note that $h(0) = 0$ and $h(1) = f(1)b$. Since $h(q_{i,P}^*)$ is a continuous function it must become equal in value to ω_i between $h(0) = 0$ and $h(1) = f(1)b > \omega_i$ for some $q_{i,P}^* \in (0,1)$.

The fitness of the population at equilibrium is $\omega_j^* = q_{i,P}^*\omega_i + (1 - q_{i,P}^*)\, f(q_{i,P}^*)bq_{i,P}^*$, which is greater than ω_i whenever $f(q_{i,P}^*)bq_{i,P}^* > \omega_i$. The first order condition in equation 5.16 implies

$$f(q_{i,P}^*)bq_{i,P}^* = \omega_i + (1 - q_{i,P}^*)f'(q_{i,P}^*)bq_{i,P}^* > \omega_i. \quad (5.18)$$

Therefore, the fitness of the population at equilibrium, ω_j^*, is greater than the fitness acquired only from individual learning, ω_i. Note that the approach taken in this proof involved deriving the evolutionary stable state with a continuous state space (Rice, 2004).

5.4. Discussion

Our results show that if social learners have to conduct some individual learning to develop their absorptive capacity and thereby be able to use social learning effectively, a population will converge toward types of learners that use more individual learning. Thus, social learners are unable to free ride to the same extent as they would otherwise and the fitness provided by social learning will remain higher than the fitness provided by individual learning. It is important to note that although no learner in the population is flexible in their use of social learning and individual learning as critical social learners for example would be (Enquist et al., 2007), the fitness of the population can nonetheless remain higher than for a population not making use of social learning. Since flexibility in using social learning and individual learning may involve cognitive and other costs, our result may perhaps apply more widely than models requiring such flexibility from individuals.

Our results also show that over a sufficient amount of time the population will converge on a single type of learner. This is possibly not realistic. Animal foraging studies for example routinely show that individuals differ in their foraging behaviours

including in how they use social information (Kurvers et al., 2010; González-Bernal, Brown, & Shine, 2014). A possible explanation for this apparent discrepancy between the prediction of our model and reality is that we assume the benefit of individual learning is static over multiple generations. If the benefit of individual learning instead changed from generation to generation then a wider range of learner types could be retained even while still benefitting from the reduction of free riding by social learners.

Finally, our results suggest that Rogers' paradox may inherently be a lesser issue for populations that have to learn more complex information. Learning more complex information (e.g. how to build a bow) through social learning is likely more difficult than learning simpler information (e.g. how to open nuts), which would mean that the more complex the information that has to be learned the more individual learning individuals will have to engage in. Since much of human knowledge may be viewed as complex in nature, it is possible that the need to develop absorptive capacity to better understand it has resulted in humans spending more time on individual learning, which then further increased the complexity of information as technology progressively developed. Such a feedback loop between the complexity of technology and the need to understand it may have been crucial in the evolution of mankind.

Chapter 6. Conclusion

This thesis adopted a three-paper format to investigate whether individuals exhibit stability in their information search behaviours as well as how such behaviours may arise. Specifically, Chapter 3 used two decisions from experience experiments (a version with no information search costs and a version where information search was costly) to investigate whether stable differences in search behaviours between individuals exist. This was done by seeing whether the Big Five factors of personality, which themselves are stable over a person's lifetime, had a relationship with information search behaviours. Chapter 4 developed a model exploring how even simple forms of social learning may provide benefits to a population through reducing its per capita resource consumption rate and may thus contribute to allowing different types of information searchers to coexist. Chapter 5 developed a model investigating the effects having to develop absorptive capacity through individual learning would have on the benefits provided by social learning at equilibrium.

The results from Chapter 3 suggest individuals do exhibit stability in their information search behaviours and that this stability may even impact their performance in tasks where greater or lesser amounts of search may be more beneficial. Specifically, of the Big Five factors of personality both Extraversion and Openness to Experience had relatively consistent relationships with information search behaviours. Extraversion most consistently had a positive relationship with sample size, which may indicate a relationship with information search effort at least in regards to payoffs. Meanwhile, Openness to Experience most consistently had a negative relationship with switching between options, which may indicate a relationship with more focused information search. This stability in information search was shown to be consequential as greater information search was beneficial in the non-costly experimental tasks while excessive information search could be detrimental in the costly experimental tasks. Since the cost of information search may vary in reality, the results offer some evidence towards the possibility of different types of in information search behaviours coexisting as a result of providing equal payoffs on average (Wolf & Weissing, 2010).

The model developed in Chapter 4 demonstrated that populations making use of social learning may grow larger due to lesser per capita resource requirements as a consequence of lesser learning costs. Crucially, this is possible even though individuals do not flexibly change between individual learning and social learning but instead have fixed probabilities for their use. Thus, social learning may be

beneficial even when subject to negative frequency dependence. This contrasts with previous studies that have assumed social learning needs to be used flexibly for it to provide long-term benefits to a population (e.g. Enquist et al., 2007). It also suggests that populations with different types of learners may be more likely to exist than often thought, particularly if flexible use of social learning and individual learning incurs costs of its own. This remains true even though stochastic simulations show populations with social learners may be somewhat more likely to go extinct than populations with only individual learners. The reason for this is that while populations with a large proportion of social learners are more likely to go extinct, these same populations benefit the most from the reduction in per capita resource consumption, which can largely offset the probability of extinction.

The results from Chapter 5 suggest that when developing absorptive capacity requires a greater use of individual learning, a greater amount of individual learning will be conducted in the population than would otherwise. This allows for the equilibrium fitness of the population to be higher than for a population where social learning does not require the development of absorptive capacity. An additional consequence of requiring individual learning to develop absorptive capacity is that a population in which this is that case will tend to converge towards a single type of learner thus reducing heterogeneity in search behaviours in the population. This in turn suggests that the relationship between individual learning and absorptive capacity may not be very strong such that converge takes a long time. Indeed, the relationship between individual learning and absorptive capacity may only be particularly strong when the information learned from others through social learning is complex in nature. Alternatively the model used in Chapter 5 may be missing an important element. For example, if the effectiveness of individual learning varies sufficiently between periods the population may not converge on a single type of learner. Instead, the need to develop absorptive capacity through individual learning may instead simply reduce the range of learner types.

There are several possible future directions for research on stable differences in information search behaviour. For example the decisions from experience tasks in Chapter 3 only investigated information search in a non-social context. However, in reality a lot of information search takes place while surrounded by others, which may substantially change what forms of information search are possible and optimal (e.g. social learning as investigated in Chapters 4 and 5). Thus, examining impact of personality on the information search behaviours of individuals in decisions from experience in a social context would be beneficial. Specifically, the relationship between personality and information search behaviours could be studied in a

context where groups cooperate in their information search (Lejarraga et al., 2014), where groups compete for payoffs (Phillips et al., 2014) or where individuals receive their payoffs independently but may observe the information search and payoffs others receive (Yechiam, Druyan, & Ert, 2008).

Examining differences in information search behaviours between individuals with non-monetary choice alternatives is another possible avenue for research. For example medical decisions are arguably of greater consequence than monetary decisions and thus it may be useful to examine whether individuals consistently differ in how they conduct information search. Specifically, the relationship between personality and stability in information search behaviours in decisions from experience with medical gambles could be examined (Lejarraga et al., 2016). This could prove particularly important as such research has found individuals to gather considerably less information prior to choices between medical gambles than between monetary gambles. Gaining a greater understanding of this discrepancy could for example be used to help in how medical information is provided to individuals.

To summarize, this thesis investigated reasons for stable differences in information search behaviours between individuals and its consequences. Overall, the results suggest differences in personality, changes in the environment resulting in multiple information search strategies providing equal benefits on average, and frequency dependence of information search behaviours such as social learning help explain the existence of these stable differences in information search behaviours.

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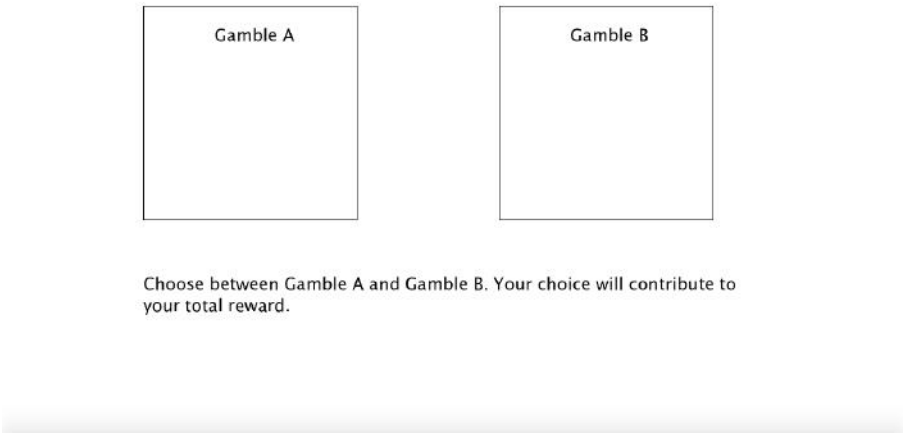
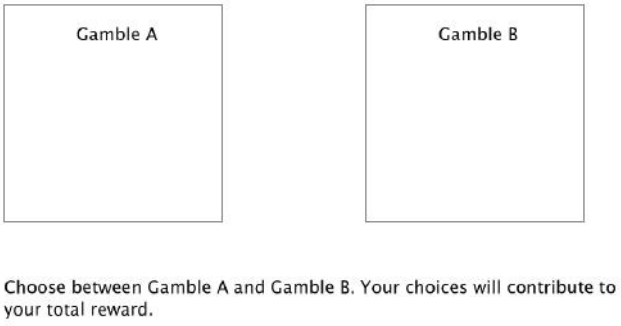
Appendix A. Details of Experiments in Chapter 3

A.1. Instructions Provided to Participants in Experiment 1

Table A.1: Instructions and screens displayed to participants during experiment 1

Task	Task instructions and screens displayed during the task
Sampling task	In the following task you will be asked to sample from and then choose between a series of pairs of gambles. Each gamble is associated with a button presented to you on the screen. By pressing on a button you will receive a sample from the associated gamble. These samples will not determine your rewards but will allow you to learn about the gambles. You are encouraged to take as many samples as you feel you need to be confident about making a choice determining your reward. Once you feel ready to make a choice you may press on the 'Make a Choice' button on the bottom right corner of the screen. You will then be able to make a choice determining your reward from that round by choosing one of the gambles. After your choice you will be presented with the next pair of gambles and the above process will repeat.  
Partial-feedback task	In the following task you will be asked to make a series of choices between each pair of gambles you will be presented with. Each gamble is associated with a button presented to you on the screen. By pressing on the buttons you will receive rewards dependent on the associated gambles. Note that each choice will contribute to your total reward.

After making a set number of choices between a pair of gambles you will be presented with the next pair of gambles and the above process will repeat.

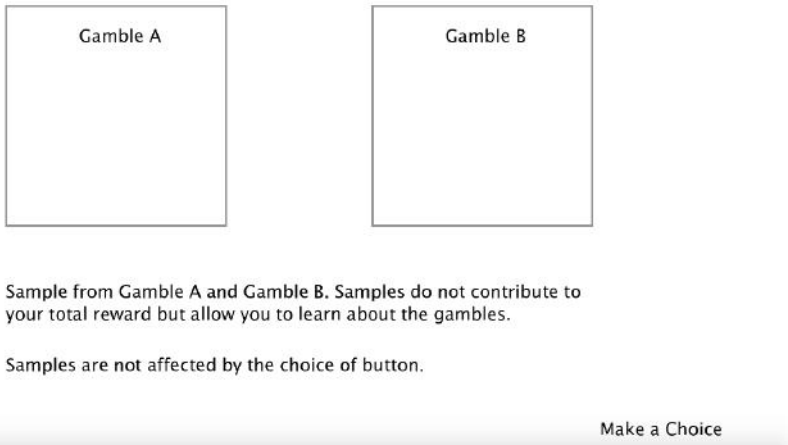


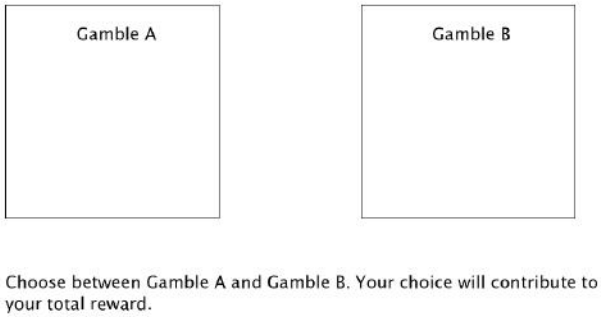
Control task

In the following task you will be asked to sample from and then choose between a series of pairs of gambles. Each gamble is associated with a button presented to you on the screen. By pressing on either button you will receive samples from both gambles. The choice of button does not influence the samples you receive. These samples will not determine your rewards but will allow you to learn about the gambles. You are encouraged to take as many samples as you feel you need to be confident about making a choice determining your reward.

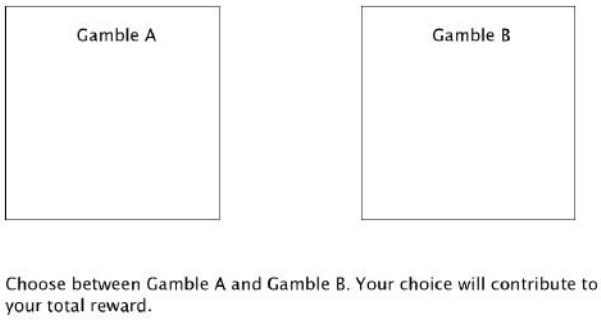
Once you feel ready to make a choice you may press on the 'Make a Choice' button on the bottom right corner of the screen. You will then be able to make a choice determining your reward from that round by choosing one of the gambles.

After your choice you will be presented with the next pair of gambles and the above process will repeat.





Full-feedback task	In the following task you will be asked to make a series of choices between each pair of gambles you will be presented with. Each gamble is associated with a button presented to you on the screen. By pressing a button you will receive a reward dependent on the associated gamble. You will also be presented with the reward you could have received from the other gamble. Note that each choice will contribute to your total reward. After making a set number of choices between a pair of gambles you will be presented with the next pair of gambles and the above process will repeat.



Note. Task instructions were shown on a screen prior to the start of the task. Participants would then be shown a screen with two squares that could be clicked for the purposes of receiving samples (sampling task and control task) or making payoff-consequential choices (partial-feedback task and full-feedback task). In the sampling task and the control task participants would also be taken to a separate screen after they were ready to make their choice.

A.2. Results Tables for Experiment 1

A.2.1. Relationship Between Personality and Sample Size

Table A.2: Regressions of the relationship between personality factors and sample size in the sampling task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Neuroticism	0.964	1.864	0.748	-0.622	3.202	-2.667
	(2.815)	(0.978)	(1.276)	(2.359)	(2.714)	(6.074)
Extraversion	-2.314	3.761**	2.607**	0.309	1.812	-4.778
	(3.075)	(1.255)	(0.986)	(1.935)	(2.483)	(5.370)
Agreeableness	4.734	-0.119	2.438*	7.264***	9.987**	14.888*
	(2.813)	(0.989)	(1.204)	(1.988)	(3.516)	(6.205)
Openness to experience	-5.536	-2.270**	-3.628**	-2.613	-10.722**	-17.325**
	(3.551)	(0.802)	(1.265)	(2.244)	(3.765)	(6.231)
Conscientiousness	5.927*	0.328	1.449	4.157*	8.086*	12.622
	(2.804)	(0.677)	(0.998)	(2.085)	(3.284)	(7.436)
Risk aversion	0.022	-0.032	-0.050	0.141	0.224	0.236
	(0.167)	(0.033)	(0.074)	(0.118)	(0.166)	(0.313)
Age	-0.752	0.359	-0.084	-0.857	-2.200**	-1.240
	(0.696)	(0.189)	(0.383)	(0.669)	(0.825)	(0.941)
Female	-5.224*	-3.101***	-4.670***	-6.997***	-10.187***	-16.709***
	(2.473)	(0.819)	(1.223)	(2.048)	(2.967)	(4.864)
Education	2.377	1.303*	2.373	3.480	6.133	4.050
	(3.697)	(0.616)	(2.334)	(3.634)	(3.626)	(7.955)
Quantitative background dummy	-2.184	-2.665**	-0.749	5.067*	4.525	0.378
	(5.652)	(0.835)	(1.138)	(1.985)	(3.380)	(5.344)
Treatment 2 dummy	2.687	6.990**	10.051***	11.131***	9.843***	-1.878
	(3.091)	(2.208)	(1.259)	(2.288)	(2.904)	(12.421)
Treatment 3 dummy	12.996***	3.344***	4.207*	15.053***	27.988***	30.217*
	(3.922)	(0.749)	(1.822)	(2.949)	(3.918)	(12.378)
Treatment 4 dummy	9.090*	0.046	3.846*	9.900***	16.287**	30.856*
	(3.841)	(0.720)	(1.811)	(2.131)	(5.323)	(13.272)
Constant	23.209	-14.192	-5.637	-10.791	12.102	46.654
	(23.236)	(7.671)	(12.540)	(22.623)	(25.768)	(50.467)
Observations	648	648	648	648	648	648
Adjusted/Pseudo	0.012	0.0281	0.0699	0.0645	0.0655	0.0654

R-squared	
F-statistic	3.689
	(p<0.001)

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown.

Table A.3: Regressions of the relationship between personality facets and sample size in the sampling task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Anxiety (N1)	0.586	-2.853***	-2.623*	-0.239	3.458	2.201
	(2.934)	(0.645)	(1.314)	(2.438)	(2.620)	(7.900)
Anger (N2)	3.959	0.947*	1.248	3.216	4.333*	-0.589
	(2.549)	(0.456)	(0.928)	(1.722)	(1.851)	(5.582)
Depression (N3)	3.820	0.054	1.354	-0.248	2.876	5.141
	(2.442)	(0.560)	(1.141)	(2.118)	(2.276)	(6.863)
Self-consciousness (N4)	11.141***	-0.003	0.381	5.618**	11.209***	10.192
	(3.185)	(0.559)	(1.139)	(2.114)	(2.273)	(6.852)
Immoderation (N5)	0.012	0.716	-0.441	-2.801	4.191*	4.801
	(2.275)	(0.518)	(1.055)	(1.958)	(2.104)	(6.344)
Vulnerability (N6)	3.958	1.994**	2.946*	6.161*	0.259	-4.860
	(2.454)	(0.712)	(1.450)	(2.691)	(2.893)	(8.722)
Friendliness (E1)	3.585	1.697*	1.745	5.029	5.288	2.057
	(3.128)	(0.717)	(1.461)	(2.711)	(2.914)	(8.786)
Gregariousness (E2)	4.511	0.866	0.863	-0.267	2.043	8.379
	(2.311)	(0.508)	(1.034)	(1.920)	(2.063)	(6.221)
Assertiveness (E3)	7.392**	-1.119	0.140	4.550*	6.975**	9.880
	(2.827)	(0.607)	(1.236)	(2.295)	(2.466)	(7.436)
Activity Level (E4)	-9.867***	-0.217	-0.720	-1.371	-7.133*	-7.781
	(2.871)	(0.705)	(1.436)	(2.665)	(2.864)	(8.636)
Excitement Seeking (E5)	-11.556*	-1.490*	-1.680	-6.352*	-7.657**	-9.309
	(4.708)	(0.726)	(1.478)	(2.744)	(2.949)	(8.892)
Cheerfulness (E6)	-1.139	-4.358***	-3.974**	-0.742	4.485	7.488
	(4.396)	(0.634)	(1.291)	(2.396)	(2.576)	(7.765)
Imagination (O1)	3.314	1.841***	3.110**	2.582	2.427	4.236
	(2.256)	(0.491)	(0.999)	(1.855)	(1.994)	(6.011)
Artistic Interests (O2)	-6.675**	-2.732***	-3.918***	-6.496***	-5.214**	-9.028
	(2.457)	(0.416)	(0.847)	(1.572)	(1.689)	(5.093)
Emotionality (O3)	-10.106***	-4.753***	-6.821***	-7.730**	-6.729**	-7.905
	(2.681)	(0.630)	(1.284)	(2.383)	(2.561)	(7.721)
Adventurousness (O4)	12.453***	4.042***	5.117***	9.205***	9.554***	5.964

	(2.969)	(0.630)	(1.283)	(2.382)	(2.560)	(7.719)
Intellect (O5)	0.296	1.216*	1.254	4.427*	2.985	-0.878
	(2.629)	(0.523)	(1.065)	(1.976)	(2.124)	(6.405)
Liberalism (O6)	-3.011	-2.153***	-2.010	-3.533	-3.040	-4.618
	(3.106)	(0.642)	(1.308)	(2.427)	(2.608)	(7.864)
Trust (A1)	1.048	2.540***	1.827	4.194*	-1.015	-1.938
	(1.944)	(0.500)	(1.017)	(1.888)	(2.029)	(6.119)
Morality (A2)	2.088	2.156***	3.075**	1.865	2.401	-6.420
	(2.696)	(0.527)	(1.073)	(1.991)	(2.140)	(6.453)
Altruism (A3)	2.945	3.634***	4.885**	-2.922	-2.997	-0.659
	(3.252)	(0.790)	(1.610)	(2.987)	(3.211)	(9.682)
Cooperation (A4)	1.147	0.590	0.671	0.421	1.378	2.596
	(4.132)	(0.688)	(1.402)	(2.602)	(2.797)	(8.433)
Modesty (A5)	-7.504*	-4.765***	-5.260***	-4.152	0.168	12.170
	(3.438)	(0.637)	(1.296)	(2.406)	(2.586)	(7.797)
Sympathy (A6)	1.924	0.376	1.452	1.366	-0.692	3.577
	(2.613)	(0.576)	(1.174)	(2.178)	(2.341)	(7.058)
Self-Efficacy (C1)	2.180	0.011	-2.891	-0.009	6.360	13.284
	(3.285)	(0.887)	(1.806)	(3.352)	(3.603)	(10.862)
Orderliness (C2)	0.350	-0.458	-1.363	-4.931**	-0.920	5.933
	(2.416)	(0.419)	(0.853)	(1.583)	(1.702)	(5.130)
Dutifulness (C3)	10.736***	3.852***	5.253***	9.779***	9.233***	13.329
	(2.890)	(0.677)	(1.379)	(2.559)	(2.751)	(8.294)
Achievement-Striving (C4)	-0.443	2.637***	4.387***	2.032	-0.255	-7.614
	(3.761)	(0.623)	(1.269)	(2.356)	(2.532)	(7.635)
Self-Discipline (C5)	-2.955	-4.702***	-5.030**	-6.421*	-0.826	-1.808
	(3.475)	(0.812)	(1.653)	(3.068)	(3.298)	(9.944)
Cautiousness (C6)	3.129	0.751	1.379	2.378	4.399*	10.728
	(1.979)	(0.455)	(0.928)	(1.722)	(1.850)	(5.579)
Risk aversion	0.043	-0.134**	-0.071	-0.049	0.361*	0.307
	(0.185)	(0.041)	(0.083)	(0.154)	(0.166)	(0.500)
Age	-1.218	-1.083***	-0.750*	-0.824	-2.170**	-4.241
	(0.736)	(0.180)	(0.367)	(0.681)	(0.733)	(2.209)
Female	0.120	-0.752	-0.243	0.371	-6.865*	-6.889
	(3.226)	(0.809)	(1.647)	(3.057)	(3.286)	(9.908)
Education	3.706	1.174	1.233	2.470	7.628*	16.267
	(4.060)	(0.943)	(1.921)	(3.565)	(3.832)	(11.555)
Quantitative background dummy	-6.689	2.652**	4.331*	4.535	-2.605	-9.190
	(6.023)	(0.881)	(1.795)	(3.331)	(3.581)	(10.797)
Treatment 2 dummy	9.288**	9.833***	14.227***	19.426***	11.697**	-4.993
	(3.346)	(0.939)	(1.912)	(3.549)	(3.815)	(11.501)
Treatment 3 dummy	16.255***	6.785***	9.469***	14.614***	22.879***	20.946

	(4.282)	(0.936)	(1.907)	(3.539)	(3.804)	(11.470)
Treatment 4 dummy	6.141	6.130***	5.786**	6.033	9.013*	18.679
	(4.352)	(0.991)	(2.018)	(3.745)	(4.025)	(12.135)
Constant	-44.561	20.131**	-0.465	-26.649	-101.981***	-82.250
	(38.813)	(7.582)	(15.441)	(28.657)	(30.803)	(92.872)
Observations	648	648	648	648	648	648
Adjusted/Pseudo R-squared	0.099	0.128	0.165	0.162	0.184	0.19
F-statistic	5.731 (p<0.001)					

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown.

Table A.4: Regressions of the relationship between personality factors and sample size in the control task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Neuroticism	0.619	1.183	0.822	-0.548	0.447	-2.027
	(1.690)	(0.779)	(0.536)	(1.613)	(2.139)	(3.430)
Extraversion	1.546	2.479**	3.299***	-0.091	1.151	-1.530
	(1.705)	(0.891)	(0.715)	(1.555)	(2.034)	(3.710)
Agreeableness	-2.327	-2.066*	-1.442*	-2.059	-2.998	-6.043
	(1.624)	(0.851)	(0.653)	(1.248)	(2.137)	(3.595)
Openness to experience	2.849	1.165	1.928***	4.699**	9.405***	9.036*
	(1.764)	(0.829)	(0.544)	(1.480)	(2.505)	(4.395)
Conscientiousness	1.554	0.323	0.234	1.685	1.098	2.404
	(1.654)	(1.049)	(0.659)	(1.631)	(2.521)	(3.602)
Risk aversion	-0.123	0.024	0.062	-0.011	-0.028	-0.291
	(0.109)	(0.037)	(0.043)	(0.095)	(0.141)	(0.212)
Age	0.917	0.455	0.683***	1.461***	2.007*	1.828
	(0.501)	(0.289)	(0.198)	(0.403)	(0.813)	(0.995)
Female	-9.673***	-3.307***	-7.301***	-8.454***	-14.820***	-13.574***
	(1.772)	(0.969)	(0.733)	(1.765)	(2.093)	(3.946)
Education	-0.295	-1.601	-2.381**	-6.537**	-1.631	3.066
	(2.696)	(1.009)	(0.907)	(2.224)	(5.837)	(6.310)
Quantitative background dummy	-1.670	0.007	0.010	-1.977	-2.229	1.010
	(1.875)	(0.817)	(0.675)	(1.804)	(2.496)	(3.002)
Treatment 2 dummy	4.710*	1.939	1.134	2.611	11.401**	10.038*
	(2.088)	(1.018)	(1.113)	(2.064)	(4.072)	(3.926)

Treatment 3 dummy	0.123	-0.670	-2.249**	-3.110	1.678	1.620
	(1.958)	(0.916)	(0.784)	(1.694)	(3.115)	(4.809)
Treatment 4 dummy	-1.116	-0.779	-0.380	-0.960	3.253	-1.233
	(1.899)	(1.121)	(1.134)	(1.820)	(2.588)	(3.972)
Constant	-3.191	-12.177	-17.237**	-13.936	-36.590	8.999
	(15.747)	(10.611)	(6.205)	(16.497)	(22.853)	(30.645)
Observations	648	648	648	648	648	648
Adjusted/Pseudo R-squared	0.062	0.0618	0.0962	0.0604	0.0672	0.081
F-statistic	4.922					
	(p<0.001)					

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown.

Table A.5: Regressions of the relationship between personality facets and sample size in the control task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Anxiety (N1)	2.218	1.556**	1.543	2.357	5.742*	4.449
	(1.518)	(0.477)	(1.070)	(1.780)	(2.831)	(4.303)
Anger (N2)	-0.848	-1.459***	-0.148	-0.209	1.167	3.494
	(1.229)	(0.337)	(0.756)	(1.258)	(2.000)	(3.040)
Depression (N3)	-0.256	0.685	-0.042	-0.988	-1.464	-0.062
	(1.325)	(0.415)	(0.930)	(1.547)	(2.459)	(3.738)
Self-consciousness (N4)	3.154	0.570	1.688	3.827*	6.629**	6.669
	(1.610)	(0.414)	(0.928)	(1.544)	(2.455)	(3.732)
Immoderation (N5)	1.803	0.908*	0.279	1.609	5.335*	5.285
	(1.213)	(0.383)	(0.860)	(1.430)	(2.273)	(3.456)
Vulnerability (N6)	3.199	0.402	2.184	1.737	1.216	-0.934
	(1.646)	(0.527)	(1.182)	(1.966)	(3.125)	(4.751)
Friendliness (E1)	0.701	-0.082	0.144	-0.172	-0.800	-0.097
	(1.964)	(0.531)	(1.190)	(1.980)	(3.148)	(4.785)
Gregariousness (E2)	1.964	1.454***	1.161	2.975*	5.887**	6.084
	(1.273)	(0.376)	(0.843)	(1.402)	(2.229)	(3.389)
Assertiveness (E3)	2.280	-1.162**	-0.146	1.772	6.347*	4.550
	(1.708)	(0.449)	(1.008)	(1.676)	(2.664)	(4.050)
Activity Level (E4)	-3.588	1.831***	-0.504	-3.053	-9.126**	-10.631*
	(1.850)	(0.522)	(1.170)	(1.946)	(3.094)	(4.704)
Excitement Seeking (E5)	-5.133*	-0.959	-1.540	-2.661	-5.677	-7.848
	(2.415)	(0.537)	(1.205)	(2.004)	(3.186)	(4.844)

Cheerfulness (E6)	0.703	-0.281	0.570	1.302	-0.399	0.991
	(1.386)	(0.469)	(1.052)	(1.750)	(2.782)	(4.230)
Imagination (O1)	2.553	1.436***	1.280	2.671*	6.305**	4.076
	(1.358)	(0.363)	(0.814)	(1.355)	(2.154)	(3.274)
Artistic Interests (O2)	-2.791*	-1.239***	-1.421*	-2.729*	-4.641*	-3.785
	(1.266)	(0.308)	(0.690)	(1.148)	(1.825)	(2.774)
Emotionality (O3)	-4.903**	-1.847***	-4.756***	-3.964*	-6.146*	-5.118
	(1.542)	(0.467)	(1.046)	(1.740)	(2.766)	(4.206)
Adventurousness (O4)	6.579**	1.032*	3.124**	2.278	6.880*	6.787
	(2.063)	(0.466)	(1.046)	(1.739)	(2.765)	(4.204)
Intellect (O5)	4.500**	2.718***	3.804***	5.967***	7.522**	9.672**
	(1.723)	(0.387)	(0.868)	(1.443)	(2.295)	(3.489)
Liberalism (O6)	-1.572	-0.033	0.387	-0.008	-2.223	-2.097
	(1.719)	(0.475)	(1.065)	(1.772)	(2.818)	(4.283)
Trust (A1)	0.733	0.756*	1.145	1.678	2.810	-0.217
	(1.336)	(0.370)	(0.829)	(1.379)	(2.192)	(3.333)
Morality (A2)	-0.556	0.594	0.357	0.593	-1.893	-4.234
	(1.522)	(0.390)	(0.874)	(1.454)	(2.312)	(3.515)
Altruism (A3)	0.885	1.192*	0.318	-2.631	-0.888	-2.448
	(1.921)	(0.585)	(1.312)	(2.182)	(3.469)	(5.274)
Cooperation (A4)	-4.631*	-1.356**	-1.359	-4.836*	-7.542*	-4.861
	(2.046)	(0.510)	(1.143)	(1.901)	(3.021)	(4.593)
Modesty (A5)	-2.894*	-1.991***	-2.729*	-1.948	-2.621	-3.945
	(1.429)	(0.471)	(1.056)	(1.757)	(2.794)	(4.247)
Sympathy (A6)	-0.305	-2.033***	-0.672	-1.049	0.788	1.597
	(1.405)	(0.426)	(0.956)	(1.591)	(2.529)	(3.845)
Self-Efficacy (C1)	-2.653	-0.226	-0.018	-1.005	-1.365	-1.246
	(2.208)	(0.656)	(1.472)	(2.448)	(3.892)	(5.917)
Orderliness (C2)	-0.825	-0.804**	-0.747	-1.326	-0.856	-2.923
	(1.233)	(0.310)	(0.695)	(1.156)	(1.838)	(2.794)
Dutifulness (C3)	5.458*	0.507	1.500	3.696*	8.372**	9.092*
	(2.117)	(0.501)	(1.124)	(1.869)	(2.972)	(4.518)
Achievement-Striving (C4)	4.006**	1.256**	1.530	5.813***	5.063	5.849
	(1.402)	(0.461)	(1.034)	(1.721)	(2.735)	(4.159)
Self-Discipline (C5)	-1.512	-1.771**	-1.791	-3.117	3.326	5.185
	(1.921)	(0.601)	(1.347)	(2.241)	(3.563)	(5.416)
Cautiousness (C6)	0.787	1.539***	1.433	1.836	1.121	-1.582
	(1.173)	(0.337)	(0.756)	(1.257)	(1.999)	(3.039)
Risk aversion	-0.157	-0.074*	-0.020	-0.083	-0.023	-0.143
	(0.126)	(0.030)	(0.068)	(0.113)	(0.179)	(0.272)
Age	0.972	0.796***	1.135***	0.825	1.077	1.683
	(0.496)	(0.133)	(0.299)	(0.498)	(0.791)	(1.203)
Female	-4.130*	-0.860	-2.976*	-3.647	-6.536	-9.049

	(1.970)	(0.599)	(1.342)	(2.233)	(3.550)	(5.397)
Education	-1.660	-5.734***	-5.848***	-4.065	0.581	13.124*
	(2.367)	(0.698)	(1.566)	(2.604)	(4.140)	(6.294)
Quantitative background dummy	-0.983	0.406	-0.681	-4.673	-3.768	-2.627
	(2.110)	(0.652)	(1.463)	(2.433)	(3.868)	(5.881)
Treatment 2 dummy	6.992**	1.255	1.633	5.368*	9.351*	14.332*
	(2.398)	(0.695)	(1.558)	(2.592)	(4.121)	(6.265)
Treatment 3 dummy	-0.499	-3.914***	-2.928	0.371	3.849	-2.096
	(2.380)	(0.693)	(1.554)	(2.585)	(4.109)	(6.247)
Treatment 4 dummy	-4.544	-4.073***	-2.881	-1.193	-6.068	-8.404
	(2.394)	(0.733)	(1.644)	(2.735)	(4.348)	(6.610)
Constant	-18.836	-10.278	-24.032	-21.862	-81.749*	-68.238
	(18.426)	(5.611)	(12.583)	(20.930)	(33.275)	(50.587)
Observations	648	648	648	648	648	648
Adjusted/Pseudo R-squared	0.141	0.157	0.162	0.143	0.184	0.23
F-statistic	5.172					
	(p<0.001)					

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown.

A.2.2. Relationship Between Personality and Switch Ratios

Table A.6: Regressions of the relationship between personality factors and switch ratios in the control task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Neuroticism	-0.030				0.002	-0.022
	(0.017)				(0.016)	(0.077)
Extraversion	-0.010				0.002	0.025
	(0.015)				(0.012)	(0.065)
Agreeableness	0.020				-0.009	0.033
	(0.018)				(0.014)	(0.071)
Openness to experience	-0.053*				-0.005	-0.095
	(0.022)				(0.017)	(0.097)
Conscientiousness	-0.039*				-0.012	-0.052
	(0.015)				(0.012)	(0.069)
Risk aversion	0.000				0.001	-0.002
	(0.001)				(0.001)	(0.003)
Age	0.001				0.003	-0.004
	(0.004)				(0.004)	(0.025)

Female	0.037*				0.010	0.045
	(0.017)				(0.020)	(0.067)
Education	-0.026				-0.019	-0.018
	(0.026)				(0.024)	(0.104)
Quantitative background dummy	-0.069**				-0.050	-0.439**
	(0.025)				(0.067)	(0.149)
Treatment 2 dummy	-0.011				0.002	-0.040
	(0.020)				(0.016)	(0.079)
Treatment 3 dummy	0.063**				0.091***	0.216*
	(0.021)				(0.025)	(0.107)
Treatment 4 dummy	0.019				0.007	0.017
	(0.020)				(0.016)	(0.073)
Constant	0.456**				0.073	1.055
	(0.149)				(0.165)	(0.730)
Observations	648				648	648
Adjusted/Pseudo R-squared	0.049				0.0476	0.163
F-statistic	3.469					
	(p<0.001)					

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown. Quantile regressions without sufficient data are omitted.

Table A.7: Regressions of the relationship between personality facets and switch ratios in the control task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Anxiety (N1)	-0.005				0.001	0.010
	(0.020)				(0.034)	(0.054)
Anger (N2)	-0.026				-0.007	-0.030
	(0.014)				(0.024)	(0.038)
Depression (N3)	-0.037**				-0.012	-0.030
	(0.013)				(0.029)	(0.047)
Self-consciousness (N4)	-0.015				0.012	-0.028
	(0.012)				(0.029)	(0.047)
Immoderation (N5)	-0.029				-0.044	-0.134**
	(0.016)				(0.027)	(0.044)
Vulnerability (N6)	0.007				0.018	-0.068
	(0.022)				(0.037)	(0.060)

Friendliness (E1)	-0.026	-0.023	-0.100
	(0.015)	(0.038)	(0.061)
Gregariousness (E2)	-0.007	0.012	0.014
	(0.014)	(0.027)	(0.043)
Assertiveness (E3)	0.002	0.020	0.048
	(0.018)	(0.032)	(0.051)
Activity Level (E4)	-0.020	-0.051	-0.138*
	(0.017)	(0.037)	(0.059)
Excitement Seeking (E5)	0.033	0.010	0.070
	(0.022)	(0.038)	(0.061)
Cheerfulness (E6)	-0.020	-0.003	0.033
	(0.019)	(0.033)	(0.053)
Imagination (O1)	-0.015	0.003	0.000
	(0.012)	(0.026)	(0.041)
Artistic Interests (O2)	0.029**	0.017	0.037
	(0.010)	(0.022)	(0.035)
Emotionality (O3)	0.034	0.006	0.087
	(0.018)	(0.033)	(0.053)
Adventurousness (O4)	-0.009	0.004	-0.066
	(0.016)	(0.033)	(0.053)
Intellect (O5)	-0.056***	-0.031	-0.134**
	(0.016)	(0.027)	(0.044)
Liberalism (O6)	-0.044**	-0.059	-0.158**
	(0.016)	(0.034)	(0.054)
Trust (A1)	-0.008	0.002	0.085*
	(0.012)	(0.026)	(0.042)
Morality (A2)	0.042*	0.028	0.074
	(0.017)	(0.028)	(0.044)
Altruism (A3)	-0.004	0.005	-0.001
	(0.025)	(0.042)	(0.067)
Cooperation (A4)	-0.043	-0.029	-0.047
	(0.023)	(0.036)	(0.058)
Modesty (A5)	0.031	-0.004	0.122*
	(0.022)	(0.033)	(0.054)
Sympathy (A6)	-0.004	0.007	-0.011
	(0.015)	(0.030)	(0.049)
Self-Efficacy (C1)	0.076**	0.034	0.141
	(0.026)	(0.047)	(0.075)
Orderliness (C2)	-0.008	-0.019	-0.012
	(0.011)	(0.022)	(0.035)
Dutifulness (C3)	-0.011	-0.012	-0.021
	(0.021)	(0.036)	(0.057)
Achievement-Striving	-0.075***	-0.049	-0.169**

(C4)			
	(0.018)	(0.033)	(0.053)
Self-Discipline (C5)	0.031	0.028	0.055
	(0.022)	(0.043)	(0.069)
Cautiousness (C6)	-0.022*	-0.004	0.013
	(0.009)	(0.024)	(0.038)
Risk aversion	0.000	0.000	0.000
	(0.001)	(0.002)	(0.003)
Age	-0.001	0.001	-0.005
	(0.005)	(0.009)	(0.015)
Female	-0.020	-0.007	-0.108
	(0.024)	(0.043)	(0.068)
Education	-0.003	-0.005	0.113
	(0.030)	(0.050)	(0.080)
Quantitative background dummy	-0.112***	-0.091	-0.425***
	(0.025)	(0.046)	(0.074)
Treatment 2 dummy	-0.048	0.007	-0.189*
	(0.027)	(0.049)	(0.079)
Treatment 3 dummy	0.086**	0.118*	0.392***
	(0.029)	(0.049)	(0.079)
Treatment 4 dummy	0.018	0.045	0.087
	(0.028)	(0.052)	(0.084)
Constant	0.783**	0.531	1.600*
	(0.253)	(0.398)	(0.640)
Observations	648	648	648
Adjusted/Pseudo R-squared	0.116	0.0975	0.32
F-statistic	2.616		
	(p<0.001)		

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown. Quantile regressions without sufficient data are omitted.

Table A.8: Regressions of the relationship between personality factors and switch ratios in the sampling task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Neuroticism	-0.011	-0.002	0.007	-0.003	0.017	-0.037
	(0.031)	(0.006)	(0.005)	(0.026)	(0.042)	(0.087)
Extraversion	-0.059	0.000	0.005	-0.004	-0.104*	-0.134
	(0.035)	(0.005)	(0.006)	(0.021)	(0.049)	(0.136)
Agreeableness	-0.018	0.000	-0.009	-0.027	0.029	-0.008
	(0.032)	(0.005)	(0.005)	(0.023)	(0.058)	(0.037)

Openness to experience	0.016	0.005	-0.003	-0.030	0.055	0.060
	(0.036)	(0.005)	(0.005)	(0.021)	(0.072)	(0.074)
Conscientiousness	-0.015	0.003	0.002	-0.018	-0.008	0.004
	(0.032)	(0.005)	(0.005)	(0.022)	(0.041)	(0.048)
Risk aversion	-0.003	0.000	-0.001*	-0.003*	-0.002	0.001
	(0.002)	0.000	0.000	(0.001)	(0.003)	(0.003)
Switch ratio (control task)	0.466***	0.039	0.412***	0.790***	0.514***	0.056
	(0.072)	(0.069)	(0.120)	(0.045)	(0.108)	(0.134)
Age	-0.004	0.002	0.001	0.003	0.002	-0.017
	(0.008)	(0.001)	(0.001)	(0.004)	(0.018)	(0.019)
Female	0.128***	0.008*	0.023***	0.079***	0.138**	0.091
	(0.036)	(0.004)	(0.006)	(0.022)	(0.053)	(0.097)
Education	-0.043	-0.016***	-0.009	-0.033	-0.087	-0.028
	(0.043)	(0.003)	(0.009)	(0.026)	(0.111)	(0.067)
Quantitative background dummy	-0.046	0.000	-0.004	-0.021	-0.040	0.016
	(0.041)	(0.005)	(0.012)	(0.027)	(0.056)	(0.082)
Treatment 2 dummy	-0.235***	0.011	-0.018	-0.198*	-0.611***	-0.217
	(0.043)	(0.009)	(0.010)	(0.087)	(0.070)	(0.133)
Treatment 3 dummy	-0.203***	-0.002	-0.029*	-0.199*	-0.431***	-0.080
	(0.044)	(0.009)	(0.012)	(0.088)	(0.069)	(0.071)
Treatment 4 dummy	-0.225***	-0.006	-0.021*	-0.214*	-0.526***	-0.018
	(0.042)	(0.010)	(0.010)	(0.087)	(0.096)	(0.077)
Constant	0.971**	-0.008	0.076	0.643**	1.075*	1.680*
	(0.313)	(0.050)	(0.059)	(0.238)	(0.446)	(0.714)
Observations	648	648	648	648	648	648
Adjusted/Pseudo R-squared	0.135	0.0118	0.0298	0.101	0.175	0.0039
F-statistic	9.747					
	(p<0.001)					

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown.

Table A.9: Regressions of the relationship between personality facets and switch ratios in the sampling task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Anxiety (N1)	-0.003	-0.004	0.004	0.012	0.092	0.123***

	(0.030)	(0.009)	(0.015)	(0.053)	(0.061)	(0.032)
Anger (N2)	-0.037	0.005	-0.007	-0.056	-0.082	-0.185***
	(0.022)	(0.007)	(0.011)	(0.038)	(0.043)	(0.022)
Depression (N3)	-0.068*	-0.012	-0.014	-0.074	-0.085	-0.155***
	(0.028)	(0.008)	(0.013)	(0.047)	(0.053)	(0.028)
Self-consciousness (N4)	-0.095***	-0.012	-0.029*	-0.066	-0.124*	-0.145***
	(0.026)	(0.008)	(0.013)	(0.046)	(0.053)	(0.027)
Immoderation (N5)	-0.013	0.003	0.009	0.013	0.085	-0.178***
	(0.026)	(0.008)	(0.012)	(0.043)	(0.049)	(0.025)
Vulnerability (N6)	0.005	0.008	0.001	-0.001	-0.090	0.076*
	(0.037)	(0.010)	(0.017)	(0.059)	(0.067)	(0.035)
Friendliness (E1)	-0.024	0.001	-0.011	0.010	-0.118	-0.321***
	(0.039)	(0.010)	(0.017)	(0.059)	(0.068)	(0.035)
Gregariousness (E2)	-0.051*	-0.025***	-0.026*	-0.071	-0.075	-0.093***
	(0.025)	(0.007)	(0.012)	(0.042)	(0.048)	(0.025)
Assertiveness (E3)	-0.146***	-0.039***	-0.053***	-0.132**	-0.082	-0.023
	(0.029)	(0.009)	(0.014)	(0.050)	(0.057)	(0.030)
Activity Level (E4)	0.042	0.014	0.016	0.065	0.099	0.120***
	(0.031)	(0.010)	(0.017)	(0.058)	(0.067)	(0.035)
Excitement Seeking (E5)	0.053	0.015	0.021	0.106	0.069	0.227***
	(0.032)	(0.011)	(0.017)	(0.060)	(0.069)	(0.036)
Cheerfulness (E6)	0.058*	0.029**	0.036*	0.029	0.181**	0.141***
	(0.029)	(0.009)	(0.015)	(0.052)	(0.060)	(0.031)
Imagination (O1)	-0.059**	-0.019**	-0.032**	-0.052	-0.047	-0.018
	(0.022)	(0.007)	(0.012)	(0.041)	(0.046)	(0.024)
Artistic Interests (O2)	0.043*	0.016**	0.026**	0.034	0.096*	0.023
	(0.021)	(0.006)	(0.010)	(0.035)	(0.039)	(0.020)
Emotionality (O3)	0.137***	0.020*	0.029	0.115*	0.246***	0.245***
	(0.031)	(0.009)	(0.015)	(0.052)	(0.060)	(0.031)
Adventurousness (O4)	-0.111***	0.005	-0.015	-0.110*	-0.199***	-0.135***
	(0.030)	(0.009)	(0.015)	(0.052)	(0.060)	(0.031)
Intellect (O5)	-0.027	-0.007	-0.019	-0.020	-0.067	-0.036
	(0.027)	(0.008)	(0.012)	(0.044)	(0.050)	(0.026)
Liberalism (O6)	-0.018	-0.012	-0.018	0.023	0.041	-0.011
	(0.029)	(0.009)	(0.015)	(0.053)	(0.061)	(0.032)
Trust (A1)	-0.061*	-0.019**	-0.014	-0.053	-0.119*	0.020
	(0.025)	(0.007)	(0.012)	(0.041)	(0.047)	(0.024)
Morality (A2)	-0.053	0.011	0.008	-0.077	-0.098	0.033
	(0.028)	(0.008)	(0.012)	(0.044)	(0.050)	(0.026)
Altruism (A3)	-0.010	-0.003	-0.020	0.047	-0.002	-0.297***
	(0.040)	(0.011)	(0.019)	(0.065)	(0.075)	(0.039)
Cooperation (A4)	0.041	0.006	-0.009	0.001	0.042	-0.102**

	(0.038)	(0.010)	(0.016)	(0.057)	(0.065)	(0.034)
Modesty (A5)	0.032	0.000	0.014	0.017	0.128*	0.232***
	(0.032)	(0.009)	(0.015)	(0.053)	(0.060)	(0.031)
Sympathy (A6)	0.066*	0.018*	0.018	-0.009	0.014	0.126***
	(0.026)	(0.008)	(0.014)	(0.048)	(0.054)	(0.028)
Self-Efficacy (C1)	-0.014	0.011	0.014	0.003	-0.045	0.042
	(0.040)	(0.013)	(0.021)	(0.074)	(0.084)	(0.044)
Orderliness (C2)	0.032	0.007	0.005	0.023	0.033	-0.100***
	(0.019)	(0.006)	(0.010)	(0.035)	(0.040)	(0.021)
Dutifulness (C3)	-0.102**	-0.006	-0.009	-0.083	-0.214***	-0.209***
	(0.032)	(0.010)	(0.016)	(0.056)	(0.064)	(0.033)
Achievement-Striving (C4)	-0.099***	-0.037***	-0.043**	-0.100	-0.185**	-0.126***
	(0.028)	(0.009)	(0.015)	(0.052)	(0.060)	(0.031)
Self-Discipline (C5)	0.113**	0.014	0.038*	0.100	0.250**	0.247***
	(0.036)	(0.012)	(0.019)	(0.067)	(0.077)	(0.040)
Cautiousness (C6)	-0.022	-0.001	0.000	0.011	0.039	-0.017
	(0.020)	(0.007)	(0.011)	(0.038)	(0.043)	(0.022)
Risk aversion	-0.003	0.000	-0.001	0.001	0.006	-0.006**
	(0.002)	(0.001)	(0.001)	(0.003)	(0.004)	(0.002)
Switch ratio (control task)	0.355***	0.048*	0.371***	0.553***	0.290*	0.000
	(0.067)	(0.022)	(0.035)	(0.123)	(0.140)	(0.073)
Age	-0.006	0.002	0.003	0.006	0.004	-0.003
	(0.009)	(0.003)	(0.004)	(0.015)	(0.017)	(0.009)
Female	0.042	-0.026*	-0.029	0.064	0.027	-0.058
	(0.041)	(0.012)	(0.019)	(0.067)	(0.076)	(0.040)
Education	-0.037	-0.015	-0.030	-0.078	-0.089	-0.009
	(0.049)	(0.014)	(0.022)	(0.078)	(0.089)	(0.046)
Quantitative background dummy	-0.025	-0.030*	-0.041	-0.047	-0.030	-0.017
	(0.045)	(0.013)	(0.021)	(0.074)	(0.085)	(0.044)
Treatment 2 dummy	-0.322***	-0.018	-0.071**	-0.287***	-0.562***	-0.493***
	(0.052)	(0.014)	(0.022)	(0.078)	(0.089)	(0.046)
Treatment 3 dummy	-0.246***	-0.030*	-0.061**	-0.201*	-0.358***	-0.281***
	(0.051)	(0.014)	(0.022)	(0.078)	(0.089)	(0.046)
Treatment 4 dummy	-0.177***	-0.013	-0.028	-0.130	-0.242**	-0.273***
	(0.049)	(0.014)	(0.023)	(0.082)	(0.094)	(0.049)
Constant	1.976***	0.088	0.419*	1.245*	1.324	3.025***
	(0.395)	(0.111)	(0.180)	(0.634)	(0.724)	(0.376)
Observations	648	648	648	648	648	648
Adjusted/Pseudo R-squared	0.264	0.0399	0.0672	0.174	0.328	0.208
F-statistic	11.83					

	(p<0.001)

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown.

Table A.10: Regressions of the relationship between personality factors and switch ratios in the partial-feedback task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Neuroticism	-0.008	-0.009	0.000	0.001	-0.019	-0.027
	(0.016)	(0.012)	(0.010)	(0.019)	(0.030)	(0.047)
Extraversion	-0.018	-0.018	-0.022*	-0.023	-0.035	-0.007
	(0.018)	(0.010)	(0.010)	(0.018)	(0.029)	(0.045)
Agreeableness	-0.018	0.018	0.020	0.005	-0.047	-0.090
	(0.019)	(0.009)	(0.012)	(0.021)	(0.038)	(0.051)
Openness to experience	-0.011	-0.018	-0.026*	-0.007	-0.067	-0.010
	(0.022)	(0.009)	(0.012)	(0.021)	(0.040)	(0.041)
Conscientiousness	-0.030	-0.010	-0.011	-0.038	-0.044	-0.015
	(0.017)	(0.011)	(0.011)	(0.020)	(0.032)	(0.035)
Risk aversion	0.000	0.001	0.000	0.001	-0.003	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Switch ratio (control task)	0.011	-0.022	-0.044	-0.006	0.107	0.192*
	(0.042)	(0.019)	(0.029)	(0.048)	(0.119)	(0.080)
Age	-0.001	0.003	0.004	0.000	0.003	-0.014
	(0.005)	(0.002)	(0.003)	(0.004)	(0.009)	(0.011)
Female	0.018	-0.010	-0.003	0.010	0.055	-0.005
	(0.020)	(0.009)	(0.012)	(0.021)	(0.038)	(0.045)
Education	0.023	0.004	0.010	0.044	0.001	0.082
	(0.023)	(0.016)	(0.016)	(0.034)	(0.041)	(0.057)
Quantitative background dummy	-0.002	-0.030	-0.044***	-0.006	-0.010	0.038
	(0.021)	(0.020)	(0.012)	(0.023)	(0.038)	(0.062)
Treatment 2 dummy	0.040	0.007	0.025	0.045	0.017	0.038
	(0.022)	(0.016)	(0.015)	(0.027)	(0.036)	(0.044)
Treatment 3 dummy	0.018	0.018	0.030	0.011	0.003	0.094
	(0.023)	(0.013)	(0.016)	(0.027)	(0.040)	(0.051)
Treatment 4 dummy	-0.006	0.000	-0.014	-0.014	-0.095	0.053
	(0.022)	(0.010)	(0.014)	(0.025)	(0.052)	(0.067)
Constant	0.523**	0.114	0.173	0.332	1.092***	1.239**
	(0.180)	(0.094)	(0.107)	(0.177)	(0.292)	(0.377)

Observations	648	648	648	648	648	648
Adjusted/Pseudo R-squared	0.001	0.0195	0.0348	0.0234	0.0302	0.0294
F-statistic	1.226 (p=0.251)					

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown.

Table A.11: Regressions of the relationship between personality facets and switch ratios in the partial-feedback task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Anxiety (N1)	0.014	-0.009	0.030*	0.016	-0.025	-0.059
	(0.021)	(0.011)	(0.013)	(0.024)	(0.029)	(0.047)
Anger (N2)	-0.004	0.019*	-0.002	0.002	0.013	-0.040
	(0.014)	(0.008)	(0.009)	(0.017)	(0.021)	(0.033)
Depression (N3)	-0.013	0.000	-0.015	-0.038	-0.011	0.001
	(0.015)	(0.009)	(0.012)	(0.021)	(0.025)	(0.041)
Self-consciousness (N4)	-0.010	-0.001	-0.002	-0.004	-0.004	-0.060
	(0.015)	(0.009)	(0.011)	(0.021)	(0.025)	(0.041)
Immoderation (N5)	0.016	0.006	0.002	0.009	0.010	0.058
	(0.015)	(0.009)	(0.011)	(0.019)	(0.023)	(0.038)
Vulnerability (N6)	-0.004	-0.013	-0.026	-0.003	0.044	0.028
	(0.021)	(0.012)	(0.015)	(0.026)	(0.032)	(0.052)
Friendliness (E1)	0.011	-0.008	0.011	0.004	0.053	0.004
	(0.022)	(0.012)	(0.015)	(0.026)	(0.032)	(0.052)
Gregariousness (E2)	-0.021	-0.005	-0.026*	-0.020	-0.026	-0.016
	(0.015)	(0.008)	(0.010)	(0.019)	(0.023)	(0.037)
Assertiveness (E3)	-0.043*	-0.005	-0.020	-0.011	-0.058*	-0.098*
	(0.017)	(0.010)	(0.012)	(0.022)	(0.027)	(0.044)
Activity Level (E4)	0.001	0.015	0.024	0.005	-0.003	-0.047
	(0.020)	(0.012)	(0.014)	(0.026)	(0.032)	(0.051)
Excitement Seeking (E5)	0.036	-0.007	0.017	0.016	0.026	0.028
	(0.021)	(0.012)	(0.015)	(0.027)	(0.033)	(0.053)
Cheerfulness (E6)	-0.002	0.008	0.003	-0.009	-0.016	-0.026
	(0.017)	(0.011)	(0.013)	(0.023)	(0.029)	(0.046)
Imagination (O1)	-0.070***	-0.023**	-0.054***	-0.074***	-0.095***	-0.061
	(0.014)	(0.008)	(0.010)	(0.018)	(0.022)	(0.036)
Artistic Interests (O2)	0.012	0.021**	0.010	0.028	0.010	0.023
	(0.012)	(0.007)	(0.009)	(0.015)	(0.019)	(0.030)
Emotionality (O3)	0.034	-0.001	0.018	0.042	0.015	0.074
	(0.022)	(0.010)	(0.013)	(0.023)	(0.028)	(0.046)

Adventurousness (O4)	0.004	-0.008	0.008	0.016	-0.023	-0.020
	(0.017)	(0.010)	(0.013)	(0.023)	(0.028)	(0.046)
Intellect (O5)	-0.012	-0.013	-0.015	-0.037	-0.036	-0.067
	(0.016)	(0.009)	(0.011)	(0.019)	(0.024)	(0.038)
Liberalism (O6)	0.062***	0.031**	0.044**	0.074**	0.114***	0.088
	(0.018)	(0.011)	(0.013)	(0.024)	(0.029)	(0.047)
Trust (A1)	-0.024	0.002	-0.013	-0.031	-0.034	-0.041
	(0.015)	(0.008)	(0.010)	(0.018)	(0.022)	(0.036)
Morality (A2)	-0.029*	-0.022*	-0.012	-0.013	-0.028	-0.069
	(0.014)	(0.009)	(0.011)	(0.020)	(0.024)	(0.038)
Altruism (A3)	-0.033	-0.007	-0.006	-0.023	-0.060	-0.088
	(0.022)	(0.013)	(0.016)	(0.029)	(0.036)	(0.057)
Cooperation (A4)	0.024	0.012	0.000	0.009	0.040	0.012
	(0.021)	(0.011)	(0.014)	(0.025)	(0.031)	(0.050)
Modesty (A5)	-0.040*	0.013	0.007	-0.031	-0.057*	-0.042
	(0.018)	(0.011)	(0.013)	(0.023)	(0.029)	(0.046)
Sympathy (A6)	0.048**	0.012	0.010	0.033	0.074**	0.111**
	(0.015)	(0.010)	(0.012)	(0.021)	(0.026)	(0.042)
Self-Efficacy (C1)	-0.078**	0.003	-0.015	-0.068*	-0.117**	-0.095
	(0.026)	(0.015)	(0.018)	(0.033)	(0.040)	(0.065)
Orderliness (C2)	0.019	0.002	0.003	0.016	0.017	0.043
	(0.013)	(0.007)	(0.009)	(0.015)	(0.019)	(0.030)
Dutifulness (C3)	-0.013	-0.001	-0.017	0.005	-0.008	-0.001
	(0.019)	(0.011)	(0.014)	(0.025)	(0.030)	(0.049)
Achievement-Striving (C4)	0.006	0.013	-0.003	0.023	0.043	0.025
	(0.017)	(0.010)	(0.013)	(0.023)	(0.028)	(0.046)
Self-Discipline (C5)	0.019	-0.027*	-0.025	-0.022	0.048	0.096
	(0.024)	(0.013)	(0.017)	(0.030)	(0.037)	(0.059)
Cautiousness (C6)	-0.005	0.000	-0.002	-0.017	-0.037	-0.024
	(0.013)	(0.008)	(0.009)	(0.017)	(0.021)	(0.033)
Risk aversion	0.001	0.001	0.001	0.003	0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Switch ratio (control task)	0.013	-0.010	-0.051	-0.017	0.069	0.036
	(0.045)	(0.025)	(0.030)	(0.055)	(0.067)	(0.108)
Age	-0.007	0.008**	-0.002	-0.007	-0.008	-0.014
	(0.005)	(0.003)	(0.004)	(0.007)	(0.008)	(0.013)
Female	0.014	-0.028*	-0.018	0.005	-0.001	0.005
	(0.021)	(0.013)	(0.017)	(0.030)	(0.036)	(0.059)
Education	0.038	0.008	0.027	0.070*	0.071	0.054
	(0.025)	(0.016)	(0.019)	(0.035)	(0.042)	(0.068)
Quantitative background dummy	0.026	-0.034*	-0.050**	0.010	0.106**	0.145*

	(0.025)	(0.015)	(0.018)	(0.033)	(0.040)	(0.065)
Treatment 2 dummy	0.013	0.016	0.014	0.043	0.016	-0.002
	(0.026)	(0.016)	(0.019)	(0.035)	(0.042)	(0.068)
Treatment 3 dummy	-0.065*	-0.018	-0.017	-0.056	-0.109*	0.004
	(0.027)	(0.016)	(0.019)	(0.035)	(0.042)	(0.069)
Treatment 4 dummy	0.010	-0.010	0.006	-0.014	-0.047	0.003
	(0.029)	(0.016)	(0.020)	(0.036)	(0.045)	(0.072)
Constant	0.666**	-0.105	0.374*	0.559*	0.854*	1.625**
	(0.224)	(0.127)	(0.157)	(0.282)	(0.345)	(0.556)
Observations	648	648	648	648	648	648
Adjusted/Pseudo R-squared	0.090	0.074	0.0867	0.0999	0.154	0.180
F-statistic	4.056					
	(p<0.001)					

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown.

Table A.12: Regressions of the relationship between personality factors and switch ratios in the full-feedback task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Neuroticism	0.017	-0.003	0.005	0.019	0.014	0.006
	(0.014)	(0.006)	(0.012)	(0.017)	(0.022)	(0.027)
Extraversion	0.042**	0.011	0.040***	0.048**	0.059**	0.040
	(0.013)	(0.006)	(0.011)	(0.016)	(0.020)	(0.026)
Agreeableness	0.001	0.003	0.005	-0.008	0.016	0.002
	(0.015)	(0.006)	(0.012)	(0.018)	(0.022)	(0.032)
Openness to experience	-0.043**	-0.021**	-0.058***	-0.047*	-0.034	-0.031
	(0.016)	(0.007)	(0.013)	(0.019)	(0.023)	(0.032)
Conscientiousness	-0.028*	-0.010	-0.022*	-0.022	-0.054*	-0.042
	(0.013)	(0.007)	(0.011)	(0.017)	(0.021)	(0.025)
Risk aversion	0.000	0.000	0.000	0.001	0.001	0.001
	(0.001)	0.000	(0.001)	(0.001)	(0.001)	(0.002)
Switch ratio (control task)	0.050	0.005	0.008	0.061	0.041	0.142
	(0.030)	(0.023)	(0.033)	(0.037)	(0.044)	(0.085)
Age	-0.008*	-0.002	-0.004	-0.009**	-0.015**	-0.025*
	(0.003)	(0.002)	(0.003)	(0.003)	(0.006)	(0.010)
Female	0.040**	0.015	0.025*	0.051**	0.060**	0.029
	(0.015)	(0.008)	(0.012)	(0.018)	(0.023)	(0.033)
Education	0.021	0.014	0.016	0.013	0.021	0.075
	(0.019)	(0.009)	(0.015)	(0.020)	(0.030)	(0.044)
Quantitative	0.024	-0.011	-0.015	0.028	0.063**	0.104**

background dummy						
	(0.014)	(0.008)	(0.014)	(0.017)	(0.022)	(0.034)
Treatment 2 dummy	-0.011	0.003	0.006	0.030	0.014	-0.046
	(0.017)	(0.009)	(0.018)	(0.023)	(0.027)	(0.038)
Treatment 3 dummy	0.001	0.013	0.027	0.012	0.022	0.008
	(0.018)	(0.009)	(0.016)	(0.019)	(0.031)	(0.043)
Treatment 4 dummy	-0.025	-0.006	-0.008	-0.014	0.011	-0.035
	(0.017)	(0.009)	(0.017)	(0.019)	(0.029)	(0.050)
Constant	0.342*	0.122	0.249*	0.314*	0.473*	0.800*
	(0.140)	(0.063)	(0.101)	(0.147)	(0.212)	(0.324)
Observations	648	648	648	648	648	648
Adjusted/Pseudo R-squared	0.051	0.017	0.0262	0.043	0.0575	0.0712
F-statistic	3.102					
	(p<0.001)					

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown.

Table A.13: Regressions of the relationship between personality facets and switch ratios in the full-feedback task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Anxiety (N1)	0.002	0.004	0.011	0.034	0.003	-0.021
	(0.013)	(0.009)	(0.015)	(0.020)	(0.022)	(0.023)
Anger (N2)	0.011	-0.005	0.013	0.007	0.026	0.043**
	(0.010)	(0.007)	(0.010)	(0.014)	(0.016)	(0.017)
Depression (N3)	-0.018	-0.020*	-0.039**	-0.028	-0.006	0.024
	(0.011)	(0.008)	(0.013)	(0.017)	(0.019)	(0.020)
Self-consciousness (N4)	0.010	-0.001	-0.021	0.006	0.051**	0.091***
	(0.012)	(0.008)	(0.013)	(0.017)	(0.019)	(0.020)
Immoderation (N5)	0.001	0.009	0.000	-0.005	-0.002	0.033
	(0.011)	(0.008)	(0.012)	(0.016)	(0.018)	(0.019)
Vulnerability (N6)	0.001	-0.002	-0.003	-0.019	-0.015	-0.037
	(0.015)	(0.010)	(0.016)	(0.022)	(0.024)	(0.026)
Friendliness (E1)	0.040**	0.004	0.034*	0.074***	0.080**	0.083**
	(0.014)	(0.011)	(0.016)	(0.022)	(0.024)	(0.026)
Gregariousness (E2)	-0.015	-0.017*	-0.026*	-0.017	-0.019	0.006
	(0.010)	(0.007)	(0.012)	(0.016)	(0.017)	(0.018)
Assertiveness (E3)	-0.027*	-0.025**	-0.031*	-0.048**	-0.025	0.025
	(0.013)	(0.009)	(0.014)	(0.019)	(0.021)	(0.022)

Activity Level (E4)	0.004	0.020	0.025	0.008	-0.019	-0.071**
	(0.015)	(0.010)	(0.016)	(0.022)	(0.024)	(0.026)
Excitement Seeking (E5)	0.055***	0.026*	0.055**	0.052*	0.064**	0.037
	(0.016)	(0.011)	(0.017)	(0.022)	(0.025)	(0.026)
Cheerfulness (E6)	0.008	0.014	-0.003	-0.003	0.030	0.049*
	(0.013)	(0.009)	(0.015)	(0.019)	(0.022)	(0.023)
Imagination (O1)	-0.029**	-0.022**	-0.031**	-0.039**	-0.037*	-0.012
	(0.010)	(0.007)	(0.011)	(0.015)	(0.017)	(0.018)
Artistic Interests (O2)	0.027**	0.014*	0.014	0.021	0.036*	0.055***
	(0.009)	(0.006)	(0.010)	(0.013)	(0.014)	(0.015)
Emotionality (O3)	0.000	0.012	0.013	-0.003	-0.012	-0.010
	(0.013)	(0.009)	(0.014)	(0.019)	(0.021)	(0.023)
Adventurousness (O4)	-0.020	-0.009	-0.015	-0.019	-0.025	-0.041
	(0.014)	(0.009)	(0.014)	(0.019)	(0.021)	(0.023)
Intellect (O5)	-0.015	-0.001	-0.017	-0.024	-0.007	-0.018
	(0.013)	(0.008)	(0.012)	(0.016)	(0.018)	(0.019)
Liberalism (O6)	-0.008	0.007	0.022	0.031	-0.025	-0.033
	(0.014)	(0.009)	(0.015)	(0.020)	(0.022)	(0.024)
Trust (A1)	-0.021*	-0.001	-0.007	-0.015	-0.037*	-0.038*
	(0.010)	(0.007)	(0.011)	(0.015)	(0.017)	(0.018)
Morality (A2)	-0.024*	-0.003	-0.020	-0.028	-0.013	-0.037
	(0.010)	(0.008)	(0.012)	(0.016)	(0.018)	(0.019)
Altruism (A3)	0.013	0.011	0.043*	0.008	0.017	0.003
	(0.017)	(0.012)	(0.018)	(0.024)	(0.027)	(0.029)
Cooperation (A4)	0.042**	0.006	0.034*	0.049*	0.060*	0.065*
	(0.015)	(0.010)	(0.016)	(0.021)	(0.023)	(0.025)
Modesty (A5)	-0.002	0.003	-0.002	-0.035	-0.009	0.025
	(0.015)	(0.009)	(0.015)	(0.020)	(0.022)	(0.023)
Sympathy (A6)	-0.013	-0.020*	-0.031*	-0.009	-0.009	-0.016
	(0.013)	(0.008)	(0.013)	(0.018)	(0.020)	(0.021)
Self-Efficacy (C1)	-0.031	-0.021	-0.034	-0.034	-0.051	-0.073*
	(0.020)	(0.013)	(0.020)	(0.027)	(0.030)	(0.033)
Orderliness (C2)	-0.005	0.000	0.016	0.008	-0.005	0.025
	(0.010)	(0.006)	(0.010)	(0.013)	(0.014)	(0.015)
Dutifulness (C3)	0.011	-0.006	-0.014	0.003	0.007	0.004
	(0.014)	(0.010)	(0.016)	(0.021)	(0.023)	(0.025)
Achievement-Striving (C4)	0.011	-0.014	0.005	0.028	0.021	0.079***
	(0.013)	(0.009)	(0.014)	(0.019)	(0.021)	(0.023)
Self-Discipline (C5)	-0.001	0.011	-0.032	-0.038	0.003	0.028
	(0.019)	(0.012)	(0.019)	(0.025)	(0.028)	(0.030)
Cautiousness (C6)	-0.027**	-0.012	-0.010	-0.026	-0.041**	-0.041*
	(0.010)	(0.007)	(0.010)	(0.014)	(0.016)	(0.017)

Risk aversion	0.001	0.000	0.001	0.002	0.002	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Switch ratio (control task)	0.021	-0.009	0.010	0.059	-0.008	0.102
	(0.030)	(0.022)	(0.034)	(0.046)	(0.050)	(0.054)
Age	-0.010**	-0.002	-0.009*	-0.014*	-0.021***	-0.016*
	(0.003)	(0.003)	(0.004)	(0.006)	(0.006)	(0.007)
Female	0.016	0.009	0.005	0.033	0.025	-0.001
	(0.018)	(0.012)	(0.019)	(0.025)	(0.027)	(0.029)
Education	0.031	-0.006	0.030	0.037	0.084**	0.103**
	(0.021)	(0.014)	(0.022)	(0.029)	(0.032)	(0.034)
Quantitative background dummy	0.026	-0.013	-0.021	0.024	0.052	0.083*
	(0.018)	(0.013)	(0.021)	(0.027)	(0.030)	(0.033)
Treatment 2 dummy	-0.043*	-0.001	-0.026	-0.021	-0.050	-0.053
	(0.020)	(0.014)	(0.022)	(0.029)	(0.032)	(0.034)
Treatment 3 dummy	-0.015	0.016	-0.006	-0.061*	-0.007	0.071*
	(0.020)	(0.014)	(0.022)	(0.029)	(0.032)	(0.034)
Treatment 4 dummy	-0.032	-0.008	-0.023	-0.036	-0.004	0.017
	(0.021)	(0.014)	(0.023)	(0.030)	(0.034)	(0.036)
Constant	0.391*	0.189	0.355*	0.493*	0.366	-0.355
	(0.166)	(0.112)	(0.176)	(0.235)	(0.260)	(0.279)
Observations	648	648	648	648	648	648
Adjusted/Pseudo R-squared	0.14	0.0732	0.0999	0.138	0.176	0.203
F-statistic	4.346					
	(p<0.001)					

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown.

A.2.3. Relationship Between Search Behaviours and Payoffs

Table A.14: Regressions of the relationship between sample size and expected payoffs earned in the experimental tasks

Regressor	Sampling task	Sampling task	Control task	Control task
Number of samples	0.058**	0.060**	-0.045	-0.048
	(0.022)	(0.023)	(0.044)	(0.046)
Neuroticism		-0.058		0.025
		(2.378)		(2.393)
Extraversion		0.166		0.133
		(2.296)		(2.285)
Agreeableness		-0.280		-0.192
		(2.502)		(2.496)

Openness to experience		0.316		0.196
		(2.553)		(2.539)
Conscientiousness		-0.305		0.045
		(2.351)		(2.356)
Risk aversion		-0.004		-0.002
		(0.138)		(0.138)
Age		-0.005		0.035
		(0.626)		(0.619)
Female		0.188		-0.405
		(2.478)		(2.518)
Education		0.057		-0.098
		(3.195)		(3.237)
Quantitative background dummy		0.144		-0.034
		(2.859)		(2.882)
Treatment 2 dummy		-0.200		0.302
		(3.000)		(3.002)
Treatment 3 dummy		-0.753		0.129
		(2.984)		(2.950)
Treatment 4 dummy		-0.489		0.166
		(3.070)		(3.056)
Constant	0.949	1.814	3.446*	2.413
	(1.245)	(22.836)	(1.446)	(22.709)
Observations	648	648	648	648
Adjusted R-squared	0.005	-0.016	0	-0.021
F-statistic	6.973	0.502	1.031	0.0806
	(p<0.010)	(p=0.932)	(p=0.31)	(p=1.00)

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses.

Table A.15: Regressions of the relationship between switch ratios and expected payoffs earned in the experimental tasks

Regressor	Sampling task	Sampling task	Control task	Control task	Partial-feedback task	Partial-feedback task	Full-feedback task	Full-feedback task
Switch ratio	-1.075	-1.168	1.125	1.162	-7.358	-7.517	-12.354	-13.207
	(2.632)	(2.815)	(5.185)	(5.425)	(4.916)	(5.061)	(6.476)	(6.747)
Neuroticism		-0.029		0.030		-0.021		0.100
		(2.392)		(2.395)		(2.373)		(2.399)
Extraversion		-0.047		0.071		-0.190		0.479
		(2.300)		(2.290)		(2.271)		(2.306)
Agreeableness		-0.005		-0.103		-0.150		-0.004
		(2.507)		(2.498)		(2.472)		(2.484)
Openness to experience		-0.026		0.121		-0.046		-0.613

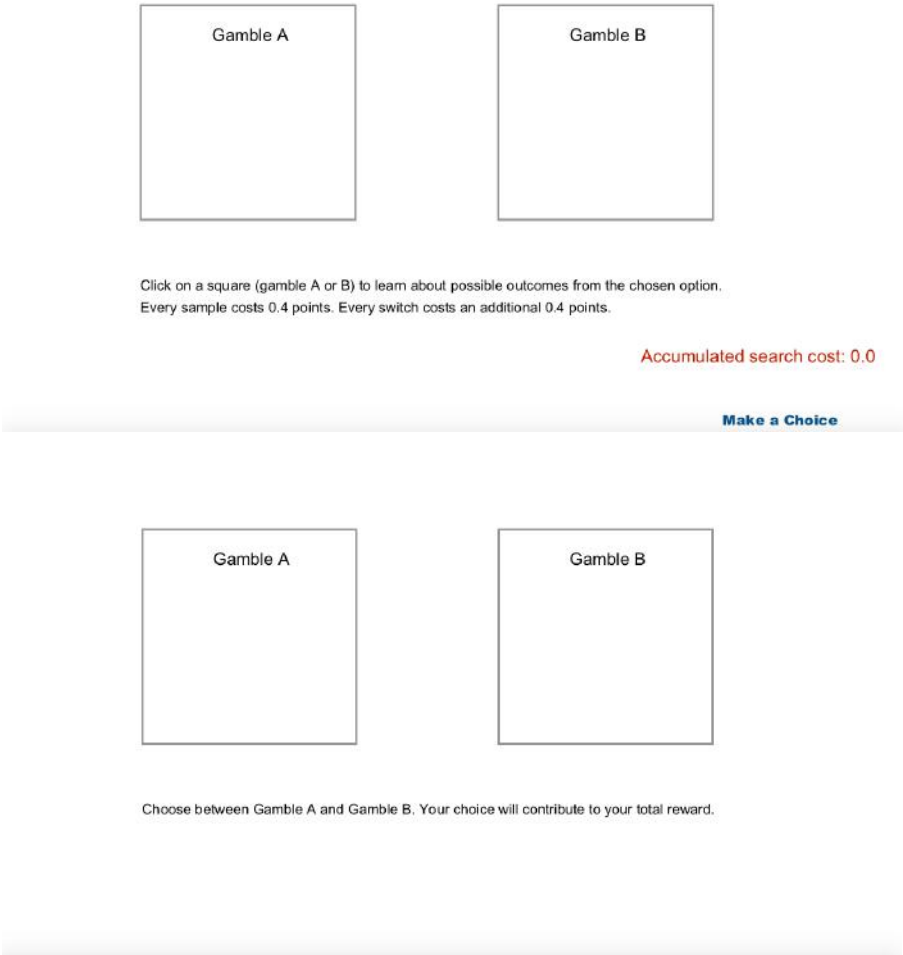
		(2.548)		(2.561)		(2.522)		(2.553)
Conscientiousness		0.012		0.015		-0.174		-0.367
		(2.349)		(2.362)		(2.334)		(2.335)
Risk aversion		-0.006		0.004		-0.003		0.007
		(0.139)		(0.138)		(0.138)		(0.137)
Age		-0.053		-0.011		0.006		-0.115
		(0.626)		(0.621)		(0.622)		(0.622)
Female		0.045		0.016		0.101		0.577
		(2.515)		(2.482)		(2.462)		(2.481)
Education		0.136		-0.053		0.177		0.288
		(3.217)		(3.238)		(3.200)		(3.205)
Quantitative background dummy		-0.078		0.126		-0.051		0.286
		(2.891)		(2.896)		(2.869)		(2.876)
Treatment 2 dummy		-0.319		0.088		0.251		-0.252
		(3.089)		(2.995)		(2.979)		(2.985)
Treatment 3 dummy		-0.175		0.050		0.079		-0.050
		(2.995)		(2.990)		(2.932)		(2.935)
Treatment 4 dummy		-0.195		0.198		-0.005		-0.339
		(3.130)		(3.052)		(3.040)		(3.028)
Constant	2.907*	4.590	2.467*	2.036	4.498**	6.205	5.006**	8.145
	(1.347)	(22.997)	(1.083)	(22.799)	(1.657)	(22.889)	(1.557)	(22.847)
Observations	648	648	648	648	648	648	648	648
Adjusted R-squared	-0.001	-0.022	-0.001	-0.022	0.002	-0.019	0.004	-0.016
F-statistic	0.167	0.0134	0.0471	0.00417	2.24	0.159	3.639	0.275
	0.683	1	0.828	1	0.135	1	0.0569	0.996

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses.

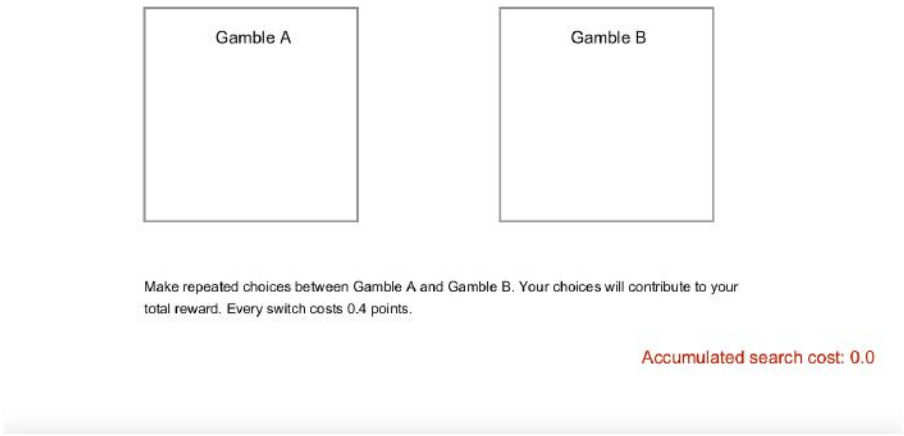
A.3. Instructions Provided to Participants in Experiment 2

Table A.16: Instructions and screens displayed to participants during experiment 2

Task	Task instructions and screens displayed during the task
Costly sampling task	In the following task you will be asked to choose between pairs of gambles. There are two phases in the task: 1. Click on a square (gamble A or B) to learn about possible outcomes from the chosen option. Each click or switch between gambles costs 0.4 points, which are subtracted from your winnings. No rewards are provided at this point. To move from phase 1 to phase 2 click on “Make a Choice”. 2. Select one of the options to receive your reward (10 points = £0.5). The above process will repeat 6 times with different pairs of gambles.



Costly partial-feedback task	In the following task you will be asked to make repeated choices between pairs of gambles. Click on a square (gamble A or B) to receive rewards (10 points = = £0.5) from the chosen option. Each switch costs 0.4 points, which is subtracted from your winnings. Keep making choices until you are presented with the next pair of gambles. The above process will repeat 6 times with different pairs of gambles.

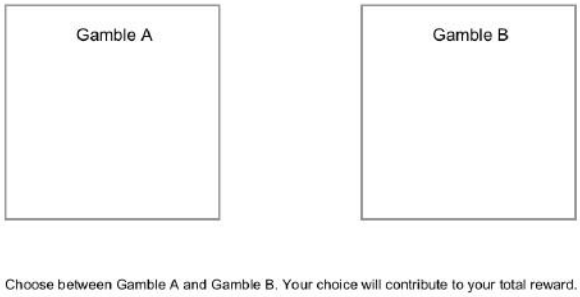


Costly control task

In the following task you will be asked to choose between pairs of gambles. There are two phases in the task:

1. Click on a square (gamble A or B) to learn about possible outcomes from both options. Each click or switch between gambles costs 0.4 points, which are subtracted from your winnings. No rewards are provided at this point. To move from phase 1 to phase 2 click on "Make a Choice".
2. Select one of the options to receive your reward (10 points = £0.5).

The above process will repeat 6 times with different pairs of gambles.



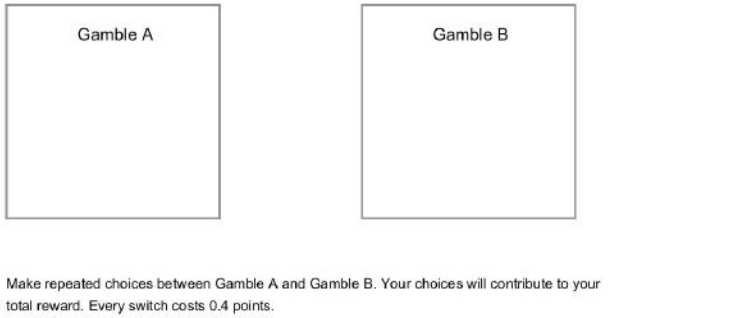
Costly full-feedback task

In the following task you will be asked to make repeated choices between pairs of gambles.

Click on a square (gamble A or B) to receive rewards (10 points = = £0.5) from the chosen option and to see how many points you could have received from the other option. Each switch costs 0.4 points, which is subtracted from your winnings.

Keep making choices until you are presented with the next pair of gambles.

The above process will repeat 6 times with different pairs of gambles.



Note. Task instructions were shown on a screen prior to the start of the task. Participants would then be shown a screen with two squares that could be clicked for the purposes of receiving samples (costly sampling task and costly control task) or making payoff-consequential choices (costly partial-feedback task and costly full-feedback task). In the costly sampling task and the costly control task participants would also be taken to a separate screen after they were ready to make their choice.

A.4. Results Tables for Experiment 2

A.4.1. Relationship Between Personality and Sample Size

Table A.17: Regressions of the relationship between personality factors and sample size in the costly sampling task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Neuroticism	2.913	0.000	0.000	-0.178	-0.725	-0.847
	(4.901)	(21.795)	(0.086)	(0.106)	(0.459)	(2.906)
Extraversion	5.517*	0.000	0.000	-0.144	1.231**	5.187*
	(2.293)	(21.183)	(0.099)	(0.096)	(0.468)	(2.588)
Agreeableness	-3.357	0.000	0.000	-0.014	-0.626	-2.938
	(1.992)	(1.590)	(0.076)	(0.121)	(0.435)	(1.801)
Openness to experience	0.315	0.000	0.000	-0.057	0.021	0.040
	(1.200)	(7.621)	(0.082)	(0.149)	(0.574)	(2.298)
Conscientiousness	-1.999	0.000	0.000	0.103	-0.479	-0.355
	(1.234)	(11.899)	(0.083)	(0.125)	(0.403)	(2.308)
Risk aversion	-1.512	0.000	0.000	0.048	0.136	-0.016
	(1.064)	(0.461)	(0.014)	(0.027)	(0.125)	(0.593)
Age	-0.086	0.000	0.000	-0.069**	-0.056	-0.472
	(0.375)	(1.470)	(0.033)	(0.022)	(0.066)	(0.502)
Female	2.145	0.000	0.000	-0.150	0.046	2.597
	(1.645)	(6.321)	(0.089)	(0.115)	(0.450)	(2.315)
Education	-0.410	0.000	0.000	0.320*	0.299	3.833
	(1.741)	(2.909)	(0.130)	(0.126)	(0.557)	(3.028)
Quantitative background dummy	0.642	0.000	0.000	0.374**	0.751	0.479
	(2.239)	(9.087)	(0.060)	(0.125)	(0.438)	(2.821)
Treatment 2 dummy	-7.693	0.000	1.000***	1.382***	1.880***	-2.593
	(4.332)	0.000	(0.086)	(0.214)	(0.528)	(7.319)
Treatment 3 dummy	-7.195*	0.000	0.000	0.069	-0.255	-3.417
	(3.628)	0.000	(0.143)	(0.079)	(0.522)	(7.567)
Treatment 4 dummy	-0.337	1.000	1.000***	1.900***	5.830***	7.318
	(4.560)	(238.154)	(0.096)	(0.332)	(0.761)	(7.840)
Constant	10.219	1.000	1.000	3.328***	5.022	12.273
	(14.215)	0.000	(0.679)	(0.729)	(3.873)	(16.930)
Observations	960	960	960	960	960	960
Adjusted/Pseudo	0.011	0.00301	0.0284	0.0157	0.0426	0.0482

R-squared	
F-statistic	2.403
	(p<0.010)

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown.

Table A.18: Regressions of the relationship between personality facets and sample size in the costly sampling task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Anxiety (N1)	-2.867*	0.281***	0.190*	0.230	-0.370	-1.476
	(1.325)	(0.044)	(0.084)	(0.234)	(0.686)	(2.237)
Anger (N2)	1.391	0.082*	0.124	0.076	-0.325	-1.179
	(2.325)	(0.034)	(0.065)	(0.182)	(0.535)	(1.744)
Depression (N3)	5.023	-0.150**	-0.135	0.036	0.805	2.430
	(4.006)	(0.048)	(0.091)	(0.255)	(0.748)	(2.438)
Self-consciousness (N4)	-0.386	0.086	0.020	0.024	0.106	-2.668
	(1.716)	(0.045)	(0.085)	(0.236)	(0.692)	(2.256)
Immoderation (N5)	-0.157	0.055	0.069	-0.091	0.573	2.204
	(2.170)	(0.038)	(0.073)	(0.203)	(0.598)	(1.947)
Vulnerability (N6)	-0.473	-0.201***	-0.154	-0.230	-1.071	-2.435
	(1.499)	(0.052)	(0.099)	(0.275)	(0.807)	(2.630)
Friendliness (E1)	0.200	0.015	0.023	0.586*	1.448	1.421
	(2.689)	(0.055)	(0.105)	(0.291)	(0.857)	(2.791)
Gregariousness (E2)	-1.169	0.043	0.008	-0.126	0.178	0.987
	(1.838)	(0.044)	(0.083)	(0.230)	(0.677)	(2.206)
Assertiveness (E3)	3.546	0.136***	-0.022	-0.247	-0.491	-1.377
	(3.936)	(0.041)	(0.078)	(0.218)	(0.641)	(2.090)
Activity Level (E4)	-2.956	-0.165**	-0.015	0.026	0.916	1.638
	(3.732)	(0.050)	(0.095)	(0.264)	(0.777)	(2.531)
Excitement Seeking (E5)	3.580	0.128**	0.336***	0.371	1.051	4.380
	(2.287)	(0.048)	(0.091)	(0.253)	(0.745)	(2.427)
Cheerfulness (E6)	8.942	-0.261***	-0.127	-0.222	-0.232	4.269
	(5.485)	(0.050)	(0.094)	(0.262)	(0.771)	(2.512)
Imagination (O1)	-6.320	-0.111**	-0.288***	-0.408	-0.476	-3.789
	(3.562)	(0.040)	(0.076)	(0.211)	(0.620)	(2.020)
Artistic Interests (O2)	7.083	0.143***	0.071	0.026	1.209*	3.523*
	(4.140)	(0.035)	(0.066)	(0.185)	(0.544)	(1.772)
Emotionality (O3)	-1.473	-0.145***	-0.039	-0.263	0.421	0.472
	(1.723)	(0.043)	(0.082)	(0.228)	(0.671)	(2.186)
Adventurousness (O4)	-5.991**	0.222***	0.236**	-0.162	-1.666*	-2.377

	(2.293)	(0.042)	(0.080)	(0.222)	(0.652)	(2.124)
Intellect (O5)	5.762*	0.041	0.116	0.391	1.117	2.204
	(2.356)	(0.039)	(0.075)	(0.208)	(0.611)	(1.991)
Liberalism (O6)	-3.902**	-0.141***	-0.224**	-0.070	-1.073	-6.634**
	(1.411)	(0.040)	(0.076)	(0.212)	(0.622)	(2.028)
Trust (A1)	-6.429*	0.110**	-0.011	-0.178	-0.763	-3.818
	(3.092)	(0.041)	(0.078)	(0.217)	(0.638)	(2.078)
Morality (A2)	7.246*	-0.207***	0.129	0.326	0.364	3.231
	(3.366)	(0.049)	(0.093)	(0.259)	(0.760)	(2.476)
Altruism (A3)	-8.234*	-0.080	-0.122	0.158	-1.486	-7.914**
	(3.195)	(0.059)	(0.113)	(0.314)	(0.922)	(3.005)
Cooperation (A4)	-3.009*	0.078	-0.141	-0.101	0.363	-1.918
	(1.471)	(0.047)	(0.090)	(0.250)	(0.734)	(2.392)
Modesty (A5)	-2.130	0.094*	0.097	0.263	0.296	1.497
	(2.115)	(0.040)	(0.075)	(0.210)	(0.617)	(2.010)
Sympathy (A6)	5.652	0.285***	0.131	-0.302	-0.616	1.761
	(3.430)	(0.048)	(0.092)	(0.256)	(0.752)	(2.452)
Self-Efficacy (C1)	-1.117	-0.119*	0.133	0.454	0.383	-0.245
	(2.122)	(0.059)	(0.111)	(0.310)	(0.911)	(2.969)
Orderliness (C2)	-1.940	-0.002	0.040	0.088	0.268	-0.713
	(2.117)	(0.030)	(0.056)	(0.156)	(0.458)	(1.494)
Dutifulness (C3)	4.323	-0.070	-0.281**	-0.136	0.419	2.197
	(4.235)	(0.056)	(0.106)	(0.295)	(0.867)	(2.825)
Achievement-Striving (C4)	-2.089	-0.166**	-0.212*	-0.457	-1.078	3.225
	(2.420)	(0.051)	(0.096)	(0.268)	(0.789)	(2.570)
Self-Discipline (C5)	-0.671	0.182***	0.072	0.111	-0.054	-3.307
	(1.503)	(0.054)	(0.102)	(0.283)	(0.832)	(2.711)
Cautiousness (C6)	-2.647	0.005	0.120	-0.068	-0.524	-0.170
	(1.524)	(0.033)	(0.063)	(0.176)	(0.518)	(1.688)
Risk aversion	-1.034	0.009	0.026	0.027	0.096	0.340
	(0.645)	(0.014)	(0.026)	(0.071)	(0.210)	(0.684)
Age	-0.335	0.001	-0.034	-0.068	-0.042	-0.859
	(0.534)	(0.010)	(0.020)	(0.055)	(0.162)	(0.527)
Female	2.741	-0.292***	-0.354***	0.063	0.007	-0.234
	(2.257)	(0.054)	(0.103)	(0.286)	(0.840)	(2.738)
Education	-0.569	0.056	0.312*	0.408	0.224	4.176
	(2.686)	(0.068)	(0.130)	(0.362)	(1.064)	(3.468)
Quantitative background dummy	3.085	0.331***	0.175	0.376	2.502**	-3.823
	(2.872)	(0.057)	(0.107)	(0.299)	(0.880)	(2.866)
Treatment 2 dummy	-9.400	0.511***	0.748***	1.284***	2.521*	-2.634
	(5.520)	(0.066)	(0.125)	(0.349)	(1.027)	(3.347)
Treatment 3 dummy	-2.421	0.270***	0.176	0.276	0.393	-4.971

	(1.827)	(0.074)	(0.141)	(0.394)	(1.158)	(3.772)
Treatment 4 dummy	0.220	0.741***	0.978***	1.949***	6.068***	5.121
	(4.302)	(0.068)	(0.130)	(0.362)	(1.064)	(3.467)
Constant	21.731	0.339	1.291	1.966	3.405	43.675
	(15.005)	(0.500)	(0.948)	(2.640)	(7.762)	(25.292)
Observations	960	960	960	960	960	960
Adjusted/Pseudo R-squared	0.08	0.0189	0.0362	0.029	0.069	0.107
F-statistic	1.244					
	(p=0.150)					

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown.

Table A.19: Regressions of the relationship between personality factors and sample size in the costly control task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Neuroticism	-0.095			0.000	-0.643*	0.501
	(0.987)			(5.516)	(0.313)	(0.898)
Extraversion	2.431*			0.000	0.187	1.420
	(1.003)			(3.868)	(0.295)	(0.958)
Agreeableness	-0.417			0.000	0.127	-0.267
	(1.075)			(0.489)	(0.363)	(1.087)
Openness to experience	-1.994			0.000	-0.442	-0.743
	(1.026)			(2.325)	(0.452)	(1.339)
Conscientiousness	-0.001			0.000	-0.353	1.685
	(0.864)			(3.694)	(0.392)	(1.063)
Risk aversion	0.200			0.000	0.078	0.609***
	(0.162)			(0.492)	(0.077)	(0.147)
Age	-0.057			0.000	-0.111	-0.275
	(0.247)			(0.287)	(0.061)	(0.182)
Female	0.135			0.000	-0.175	-0.303
	(0.781)			(1.626)	(0.280)	(0.841)
Education	0.342			0.000	0.291	-0.129
	(1.091)			(0.732)	(0.354)	(1.136)
Quantitative background dummy	0.328			0.000	0.245	0.957
	(0.877)			(0.967)	(0.342)	(0.830)
Treatment 2 dummy	5.101***			2.000	3.008***	5.765***
	(1.449)			(58.811)	(0.577)	(1.430)
Treatment 3	0.076			0.000	-0.011	-0.083

dummy					
	(0.698)		0.000	(0.309)	(0.850)
Treatment 4 dummy	1.543**		1.000	2.625***	3.216**
	(0.554)		(58.411)	(0.392)	(0.987)
Constant	2.576		1.000	7.127**	-0.745
	(8.761)		0.000	(2.409)	(8.805)
Observations	960		960	960	960
Adjusted/Pseudo R-squared	0.024		0.053	0.0583	0.0687
F-statistic	3.08				
	(p<0.001)				

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown. Quantile regressions without sufficient data are omitted.

Table A.20: Regressions of the relationship between personality facets and sample size in the costly control task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Anxiety (N1)	-0.041		0.136*	0.125	0.293	0.451
	(0.813)		(0.065)	(0.131)	(0.418)	(1.471)
Anger (N2)	-0.802*		0.077	0.155	-0.339	-1.526
	(0.399)		(0.051)	(0.102)	(0.326)	(1.147)
Depression (N3)	-1.936		-0.025	-0.054	0.052	0.221
	(1.160)		(0.071)	(0.143)	(0.456)	(1.604)
Self-consciousness (N4)	1.739		-0.043	0.016	0.314	0.749
	(1.148)		(0.066)	(0.132)	(0.422)	(1.484)
Immoderation (N5)	0.367		0.045	0.197	0.620	2.886*
	(0.754)		(0.057)	(0.114)	(0.364)	(1.281)
Vulnerability (N6)	1.759		-0.158*	-0.147	-0.407	0.640
	(1.141)		(0.076)	(0.154)	(0.492)	(1.730)
Friendliness (E1)	1.049		0.044	0.292	1.247*	2.234
	(0.907)		(0.081)	(0.163)	(0.522)	(1.836)
Gregariousness (E2)	0.812		-0.094	-0.230	-0.302	0.541
	(1.264)		(0.064)	(0.129)	(0.413)	(1.451)
Assertiveness (E3)	0.610		-0.093	-0.244*	-0.373	-1.329
	(0.933)		(0.061)	(0.122)	(0.391)	(1.374)
Activity Level (E4)	-0.207		0.058	0.120	-0.021	0.166
	(0.862)		(0.074)	(0.148)	(0.474)	(1.665)
Excitement Seeking (E5)	1.469*		0.143*	0.451**	1.095*	1.997

	(0.613)	(0.071)	(0.142)	(0.454)	(1.596)
Cheerfulness (E6)	0.384	-0.108	-0.315*	-0.541	-0.553
	(0.798)	(0.073)	(0.147)	(0.470)	(1.652)
Imagination (O1)	-1.101	-0.104	-0.368**	-0.545	-1.883
	(0.949)	(0.059)	(0.118)	(0.378)	(1.329)
Artistic Interests (O2)	0.464	0.098	0.163	0.589	0.847
	(0.507)	(0.052)	(0.104)	(0.332)	(1.166)
Emotionality (O3)	-0.899*	-0.009	-0.140	0.072	0.214
	(0.456)	(0.064)	(0.128)	(0.409)	(1.437)
Adventurousness (O4)	-1.686	0.062	0.007	-0.992*	-2.244
	(0.993)	(0.062)	(0.124)	(0.397)	(1.397)
Intellect (O5)	1.108	0.017	0.181	0.790*	1.330
	(0.745)	(0.058)	(0.117)	(0.372)	(1.309)
Liberalism (O6)	-0.511	-0.053	-0.092	-0.549	-1.632
	(0.647)	(0.059)	(0.119)	(0.379)	(1.334)
Trust (A1)	-0.605	0.029	0.190	0.260	-0.561
	(0.901)	(0.060)	(0.122)	(0.389)	(1.366)
Morality (A2)	0.087	0.059	0.197	0.689	2.072
	(1.281)	(0.072)	(0.145)	(0.463)	(1.629)
Altruism (A3)	-0.195	0.005	-0.034	-0.508	-1.462
	(0.641)	(0.087)	(0.176)	(0.562)	(1.977)
Cooperation (A4)	-1.521	-0.051	-0.074	0.188	0.242
	(0.871)	(0.070)	(0.140)	(0.447)	(1.573)
Modesty (A5)	1.994*	0.015	0.033	0.020	-0.276
	(0.926)	(0.058)	(0.118)	(0.376)	(1.322)
Sympathy (A6)	-1.168	-0.004	0.099	-0.765	-1.864
	(0.735)	(0.071)	(0.144)	(0.459)	(1.612)
Self-Efficacy (C1)	2.339*	0.060	0.230	0.616	3.685
	(1.078)	(0.086)	(0.174)	(0.555)	(1.953)
Orderliness (C2)	0.745*	0.013	0.106	0.390	0.917
	(0.338)	(0.043)	(0.087)	(0.279)	(0.982)
Dutifulness (C3)	-1.113	-0.059	-0.340*	-1.188*	-2.949
	(0.821)	(0.082)	(0.165)	(0.529)	(1.858)
Achievement-Striving (C4)	-1.052	-0.217**	-0.544***	-0.997*	-1.795
	(0.991)	(0.075)	(0.150)	(0.481)	(1.690)
Self-Discipline (C5)	0.383	0.173*	0.323*	0.221	1.836
	(0.692)	(0.079)	(0.159)	(0.507)	(1.783)
Cautiousness (C6)	-0.407	0.063	0.264**	0.102	-0.562
	(0.573)	(0.049)	(0.099)	(0.316)	(1.110)
Risk aversion	0.220	0.037	0.051	0.144	0.307
	(0.179)	(0.020)	(0.040)	(0.128)	(0.450)
Age	-0.029	-0.015	-0.072*	-0.082	-0.199
	(0.292)	(0.015)	(0.031)	(0.099)	(0.347)

Female	0.753	-0.062	-0.086	0.021	-0.373
	(0.853)	(0.080)	(0.160)	(0.512)	(1.801)
Education	0.291	0.041	0.376	0.285	0.607
	(1.296)	(0.101)	(0.203)	(0.649)	(2.281)
Quantitative background dummy	0.627	0.044	-0.007	0.771	1.171
	(1.149)	(0.083)	(0.168)	(0.536)	(1.885)
Treatment 2 dummy	4.667***	0.564***	1.438***	3.405***	7.862***
	(1.120)	(0.097)	(0.196)	(0.626)	(2.201)
Treatment 3 dummy	0.615	0.001	-0.056	0.727	1.047
	(0.743)	(0.110)	(0.221)	(0.706)	(2.481)
Treatment 4 dummy	1.487*	0.191	0.907***	2.742***	4.581*
	(0.749)	(0.101)	(0.203)	(0.649)	(2.280)
Constant	-5.413	0.923	0.678	2.334	-1.009
	(8.351)	(0.735)	(1.481)	(4.732)	(16.634)
Observations	960	960	960	960	960
Adjusted/Pseudo R-squared	0.037	0.000621	0.0759	0.0964	0.129
F-statistic	2.654				
	(p<0.001)				

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown. Quantile regressions without sufficient data are omitted.

A.4.2. Relationship Between Personality and Switch Ratios

Table A.21: Regressions of the relationship between personality factors and the switch ratio in the costly control task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Neuroticism	-0.022				0.000	-0.072
	(0.016)				(0.053)	(0.098)
Extraversion	-0.027				0.000	-0.116
	(0.017)				(0.057)	(0.097)
Agreeableness	-0.007				0.000	-0.008
	(0.021)				(0.051)	(0.091)
Openness to experience	-0.042*				0.000	-0.100
	(0.020)				(0.058)	(0.135)
Conscientiousness	-0.012				0.000	-0.014
	(0.020)				(0.054)	(0.096)
Risk aversion	0.005				0.000	-0.010
	(0.005)				(0.012)	(0.019)

Age	0.000				0.000	-0.020
	(0.004)				(0.010)	(0.016)
Female	0.007				0.000	-0.021
	(0.017)				(0.056)	(0.087)
Education	0.049*				0.000	0.311**
	(0.022)				(0.108)	(0.098)
Quantitative background dummy	-0.004				0.000	-0.025
	(0.016)				(0.048)	(0.076)
Treatment 2 dummy	0.048*				0.038	0.346**
	(0.022)				(0.200)	(0.119)
Treatment 3 dummy	0.037				0.000	0.312**
	(0.026)				(0.198)	(0.096)
Treatment 4 dummy	-0.040*				0.000	-0.050
	(0.019)				(0.141)	(0.093)
Constant	0.356*				0.000	1.321
	(0.150)				(0.542)	(0.939)
Observations	960				960	960
Adjusted/Pseudo R-squared	0.041				0.000836	0.157
F-statistic	3.738					
	(p<0.001)					

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown. Quantile regressions without sufficient data are omitted.

Table A.22: Regressions of the relationship between personality facets and the switch ratio in the costly control task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Anxiety (N1)	0.014				-0.002	0.021
	(0.016)				(0.038)	(0.066)
Anger (N2)	-0.015				-0.005	-0.038
	(0.010)				(0.029)	(0.052)
Depression (N3)	0.002				0.007	-0.031
	(0.018)				(0.041)	(0.072)
Self-consciousness (N4)	0.039*				0.012	0.166*
	(0.016)				(0.038)	(0.067)
Immoderation (N5)	0.009				0.010	0.040
	(0.013)				(0.033)	(0.058)

Vulnerability (N6)	-0.015	-0.012	-0.036
	(0.017)	(0.044)	(0.078)
Friendliness (E1)	0.040*	0.023	0.171*
	(0.019)	(0.047)	(0.083)
Gregariousness (E2)	-0.012	-0.006	-0.086
	(0.015)	(0.037)	(0.065)
Assertiveness (E3)	0.011	-0.002	0.077
	(0.015)	(0.035)	(0.062)
Activity Level (E4)	-0.008	-0.002	-0.025
	(0.016)	(0.043)	(0.075)
Excitement Seeking (E5)	-0.007	0.011	-0.144*
	(0.016)	(0.041)	(0.072)
Cheerfulness (E6)	-0.026	-0.002	-0.114
	(0.017)	(0.042)	(0.075)
Imagination (O1)	-0.002	-0.002	0.098
	(0.013)	(0.034)	(0.060)
Artistic Interests (O2)	-0.026*	-0.006	-0.077
	(0.013)	(0.030)	(0.053)
Emotionality (O3)	0.010	0.006	0.034
	(0.016)	(0.037)	(0.065)
Adventurousness (O4)	-0.017	-0.019	-0.055
	(0.013)	(0.036)	(0.063)
Intellect (O5)	0.031	0.009	0.108
	(0.016)	(0.034)	(0.059)
Liberalism (O6)	-0.012	-0.001	-0.086
	(0.014)	(0.034)	(0.060)
Trust (A1)	0.015	0.002	0.084
	(0.014)	(0.035)	(0.062)
Morality (A2)	0.043*	0.030	0.126
	(0.018)	(0.042)	(0.073)
Altruism (A3)	-0.019	-0.010	-0.027
	(0.019)	(0.051)	(0.089)
Cooperation (A4)	-0.031	-0.017	-0.058
	(0.018)	(0.040)	(0.071)
Modesty (A5)	0.004	-0.003	-0.005
	(0.014)	(0.034)	(0.060)
Sympathy (A6)	-0.035*	-0.010	-0.093
	(0.016)	(0.041)	(0.073)
Self-Efficacy (C1)	-0.020	-0.001	-0.018
	(0.020)	(0.050)	(0.088)
Orderliness (C2)	-0.008	0.001	-0.050
	(0.010)	(0.025)	(0.044)
Dutifulness (C3)	-0.048*	-0.026	-0.194*

	(0.020)				(0.048)	(0.084)
Achievement-Striving (C4)	-0.040*				-0.004	-0.201**
	(0.016)				(0.043)	(0.076)
Self-Discipline (C5)	0.070***				0.020	0.150
	(0.020)				(0.046)	(0.080)
Cautiousness (C6)	0.007				-0.001	0.038
	(0.010)				(0.029)	(0.050)
Risk aversion	0.005				0.003	0.015
	(0.005)				(0.012)	(0.020)
Age	0.000				-0.001	-0.001
	(0.004)				(0.009)	(0.016)
Female	0.012				0.002	0.071
	(0.018)				(0.046)	(0.081)
Education	0.054*				0.012	0.249*
	(0.024)				(0.059)	(0.103)
Quantitative background dummy	0.007				0.003	0.053
	(0.018)				(0.048)	(0.085)
Treatment 2 dummy	0.038				0.029	0.120
	(0.024)				(0.057)	(0.099)
Treatment 3 dummy	0.052				0.015	0.169
	(0.028)				(0.064)	(0.112)
Treatment 4 dummy	-0.036				0.008	-0.067
	(0.021)				(0.059)	(0.103)
Constant	0.198				0.018	0.742
	(0.179)				(0.427)	(0.750)
Observations	960				960	960
Adjusted/Pseudo R-squared	0.073				0.00549	0.266
F-statistic	2.548					
	(p<0.001)					

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown. Quantile regressions without sufficient data are omitted.

Table A.23: Regressions of the relationship between personality factors and the switch ratio in the costly sampling task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Neuroticism	-0.048		-0.023	-0.048		
	(0.033)		(0.026)	(0.115)		
Extraversion	-0.044		-0.021	-0.049		
	(0.033)		(0.025)	(0.112)		

Agreeableness	0.060	0.045	0.070
	(0.032)	(0.027)	(0.099)
Openness to experience	-0.139***	-0.037	-0.372**
	(0.038)	(0.029)	(0.128)
Conscientiousness	-0.029	-0.028	-0.102
	(0.036)	(0.029)	(0.110)
Risk aversion	0.007	0.013**	0.014
	(0.008)	(0.005)	(0.023)
Switch ratio (control task)	0.133*	0.085	0.213*
	(0.055)	(0.180)	(0.088)
Age	0.012*	0.009	0.017
	(0.006)	(0.008)	(0.012)
Female	-0.047	-0.081**	-0.098
	(0.031)	(0.030)	(0.093)
Education	-0.040	-0.043	-0.031
	(0.040)	(0.036)	(0.119)
Quantitative background dummy	0.025	0.071**	0.034
	(0.033)	(0.023)	(0.108)
Treatment 2 dummy	0.112**	0.141***	0.229
	(0.041)	(0.038)	(0.133)
Treatment 3 dummy	0.000	0.012	0.010
	(0.047)	(0.020)	(0.171)
Treatment 4 dummy	0.085*	0.140***	0.113
	(0.041)	(0.033)	(0.138)
Constant	0.894***	0.011	1.752*
	(0.256)	(0.187)	(0.856)
Observations	960	960	960
Adjusted/Pseudo R-squared	0.033	0.045	0.0603
F-statistic	3.903		
	(p<0.001)		

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown. Quantile regressions without sufficient data are omitted.

Table A.24: Regressions of the relationship between personality facets and the switch ratio in the costly sampling task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Anxiety (N1)	0.060*	0.030**	0.111***	0.083		
	(0.028)	(0.011)	(0.032)	(0.063)		
Anger (N2)	0.028	0.011	0.042	0.035		
	(0.022)	(0.009)	(0.025)	(0.049)		
Depression (N3)	-0.060*	0.000	-0.025	-0.068		
	(0.029)	(0.012)	(0.035)	(0.068)		
Self-consciousness (N4)	-0.039	-0.014	-0.037	-0.055		
	(0.028)	(0.011)	(0.032)	(0.063)		
Immoderation (N5)	-0.016	0.000	0.017	-0.108*		
	(0.024)	(0.010)	(0.028)	(0.055)		
Vulnerability (N6)	0.012	-0.025	-0.068	-0.010		
	(0.034)	(0.013)	(0.038)	(0.074)		
Friendliness (E1)	-0.039	-0.006	0.001	-0.090		
	(0.035)	(0.014)	(0.040)	(0.078)		
Gregariousness (E2)	-0.018	-0.001	-0.015	0.015		
	(0.027)	(0.011)	(0.031)	(0.062)		
Assertiveness (E3)	-0.032	0.001	-0.045	-0.106		
	(0.026)	(0.011)	(0.030)	(0.059)		
Activity Level (E4)	-0.015	-0.006	-0.045	-0.033		
	(0.031)	(0.013)	(0.036)	(0.071)		
Excitement Seeking (E5)	-0.011	0.012	0.075*	-0.089		
	(0.031)	(0.012)	(0.035)	(0.068)		
Cheerfulness (E6)	0.034	-0.006	0.010	0.094		
	(0.031)	(0.013)	(0.036)	(0.070)		
Imagination (O1)	-0.089***	-0.015	-0.052	-0.160**		
	(0.025)	(0.010)	(0.029)	(0.057)		
Artistic Interests (O2)	-0.068**	0.004	0.004	-0.146**		
	(0.022)	(0.009)	(0.025)	(0.050)		
Emotionality (O3)	-0.013	-0.004	-0.025	-0.051		
	(0.027)	(0.011)	(0.031)	(0.061)		
Adventurousness (O4)	0.090***	0.026*	0.050	0.194**		
	(0.026)	(0.011)	(0.030)	(0.060)		
Intellect (O5)	-0.032	-0.004	-0.009	-0.044		
	(0.025)	(0.010)	(0.028)	(0.056)		
Liberalism (O6)	0.005	-0.021*	-0.066*	0.002		
	(0.025)	(0.010)	(0.029)	(0.057)		
Trust (A1)	-0.005	-0.007	-0.012	0.021		
	(0.026)	(0.010)	(0.030)	(0.058)		

Morality (A2)	0.028	-0.004	0.022	0.063
	(0.030)	(0.013)	(0.035)	(0.070)
Altruism (A3)	0.004	0.019	0.012	-0.077
	(0.037)	(0.015)	(0.043)	(0.084)
Cooperation (A4)	0.027	0.007	0.010	0.080
	(0.030)	(0.012)	(0.034)	(0.067)
Modesty (A5)	0.006	0.007	0.026	0.002
	(0.025)	(0.010)	(0.029)	(0.056)
Sympathy (A6)	0.034	0.022	0.029	0.079
	(0.030)	(0.012)	(0.035)	(0.069)
Self-Efficacy (C1)	0.058	0.004	0.042	-0.008
	(0.036)	(0.015)	(0.042)	(0.083)
Orderliness (C2)	-0.024	-0.005	-0.025	-0.041
	(0.019)	(0.008)	(0.021)	(0.042)
Dutifulness (C3)	-0.028	0.006	-0.028	-0.050
	(0.035)	(0.014)	(0.040)	(0.079)
Achievement-Striving (C4)	-0.102**	-0.026*	-0.073*	-0.204**
	(0.032)	(0.013)	(0.037)	(0.072)
Self-Discipline (C5)	0.020	0.007	0.036	0.101
	(0.033)	(0.014)	(0.039)	(0.076)
Cautiousness (C6)	0.024	0.010	0.036	-0.055
	(0.021)	(0.009)	(0.024)	(0.047)
Risk aversion	0.008	0.006	0.015	-0.003
	(0.009)	(0.003)	(0.010)	(0.019)
Switch ratio (control task)	0.131*	0.042	0.047	0.170
	(0.056)	(0.024)	(0.068)	(0.133)
Age	0.011	0.002	-0.001	0.033*
	(0.006)	(0.003)	(0.008)	(0.015)
Female	-0.057	-0.032*	-0.084*	-0.058
	(0.034)	(0.014)	(0.039)	(0.077)
Education	-0.027	-0.005	0.008	-0.173
	(0.046)	(0.018)	(0.050)	(0.097)
Quantitative background dummy	-0.030	0.026	0.055	-0.001
	(0.036)	(0.014)	(0.041)	(0.080)
Treatment 2 dummy	0.087*	0.040*	0.174***	0.125
	(0.043)	(0.017)	(0.048)	(0.094)
Treatment 3 dummy	-0.059	0.002	-0.020	-0.127
	(0.051)	(0.019)	(0.054)	(0.106)
Treatment 4 dummy	0.067	0.050**	0.150**	-0.005
	(0.046)	(0.018)	(0.050)	(0.097)
Constant	0.862**	-0.147	-0.010	2.256**

	(0.317)	(0.128)	(0.361)	(0.709)
Observations	960	960	960	960
Adjusted/Pseudo R-squared	0.066	0.00767	0.0876	0.137
F-statistic	3.851			
	0			

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown. Quantile regressions without sufficient data are omitted.

Table A.25: Regressions of the relationship between personality factors and the switch ratio in the costly partial-feedback task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Neuroticism	0.051***	0.004	0.003	0.002	0.017	0.129***
	(0.015)	(0.005)	(0.004)	(0.004)	(0.016)	(0.030)
Extraversion	0.040**	-0.004	-0.006	-0.003	0.023	0.124***
	(0.015)	(0.005)	(0.004)	(0.005)	(0.016)	(0.032)
Agreeableness	0.002	0.004	0.003	0.007	0.009	-0.003
	(0.013)	(0.006)	(0.004)	(0.005)	(0.012)	(0.024)
Openness to experience	-0.037**	-0.008	-0.011*	-0.018**	-0.045***	-0.058
	(0.013)	(0.007)	(0.005)	(0.006)	(0.013)	(0.043)
Conscientiousness	-0.007	0.010	-0.002	-0.011	-0.019	0.024
	(0.014)	(0.005)	(0.004)	(0.006)	(0.014)	(0.033)
Risk aversion	-0.011**	0.002*	0.000	-0.002	-0.007*	-0.026**
	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)	(0.008)
Switch ratio (control task)	0.054*	0.012	0.010	0.024***	0.050*	0.029
	(0.023)	(0.013)	(0.008)	(0.006)	(0.020)	(0.056)
Age	-0.007***	-0.001	0.000	0.000	-0.003	-0.010
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.006)
Female	0.009	-0.005	0.002	0.001	-0.002	0.005
	(0.011)	(0.005)	(0.004)	(0.004)	(0.010)	(0.024)
Education	0.032*	0.002	-0.007	-0.004	0.015	0.077*
	(0.015)	(0.004)	(0.005)	(0.005)	(0.016)	(0.033)
Quantitative background dummy	-0.014	0.004	0.004	-0.003	-0.022*	-0.037
	(0.012)	(0.004)	(0.004)	(0.005)	(0.011)	(0.027)
Treatment 2 dummy	-0.008	0.003	0.009	0.004	0.016	0.037
	(0.020)	(0.007)	(0.006)	(0.012)	(0.032)	(0.086)
Treatment 3 dummy	-0.096***	-0.006	-0.002	-0.028***	-0.086***	-0.252***

	(0.015)	(0.005)	(0.006)	(0.007)	(0.023)	(0.046)
Treatment 4 dummy	-0.096***	-0.001	-0.002	-0.022**	-0.068**	-0.264***
	(0.015)	(0.005)	(0.005)	(0.007)	(0.024)	(0.042)
Constant	0.176	-0.010	0.074*	0.160***	0.323**	0.034
	(0.093)	(0.036)	(0.032)	(0.036)	(0.107)	(0.215)
Observations	960	960	960	960	960	960
Adjusted/Pseudo R-squared	0.118	0.0113	0.015	0.0166	0.0595	0.21
F-statistic	6.463					
	(p<0.001)					

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown.

Table A.26: Regressions of the relationship between personality facets and the switch ratio in the costly partial-feedback task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Anxiety (N1)	0.004	-0.006	-0.003	0.000	0.013	0.032
	(0.009)	(0.003)	(0.004)	(0.006)	(0.019)	(0.034)
Anger (N2)	0.008	0.001	0.005	0.002	0.026	-0.015
	(0.006)	(0.002)	(0.003)	(0.005)	(0.015)	(0.027)
Depression (N3)	0.043***	-0.001	0.007	0.021**	0.051*	0.067
	(0.011)	(0.003)	(0.004)	(0.007)	(0.020)	(0.037)
Self-consciousness (N4)	0.008	0.000	0.001	0.006	0.012	0.008
	(0.009)	(0.003)	(0.004)	(0.006)	(0.019)	(0.034)
Immoderation (N5)	0.004	-0.003	-0.003	-0.003	0.008	0.000
	(0.009)	(0.003)	(0.003)	(0.006)	(0.016)	(0.030)
Vulnerability (N6)	-0.021	0.003	0.000	-0.010	-0.056*	-0.084*
	(0.011)	(0.004)	(0.004)	(0.008)	(0.022)	(0.040)
Friendliness (E1)	-0.007	-0.003	-0.008	-0.003	-0.006	0.008
	(0.015)	(0.004)	(0.005)	(0.008)	(0.023)	(0.042)
Gregariousness (E2)	0.006	-0.002	0.004	0.003	0.003	0.021
	(0.009)	(0.003)	(0.004)	(0.006)	(0.018)	(0.034)
Assertiveness (E3)	-0.014	0.004	0.002	0.006	-0.023	-0.076*
	(0.012)	(0.003)	(0.003)	(0.006)	(0.017)	(0.032)
Activity Level (E4)	0.022	0.000	0.002	-0.002	0.003	0.060
	(0.013)	(0.004)	(0.004)	(0.007)	(0.021)	(0.038)
Excitement Seeking (E5)	0.025*	-0.005	-0.005	-0.001	0.015	0.038
	(0.011)	(0.003)	(0.004)	(0.007)	(0.020)	(0.037)
Cheerfulness (E6)	0.029	0.006	0.009*	0.015*	0.055**	0.034

	(0.015)	(0.004)	(0.004)	(0.007)	(0.021)	(0.038)
Imagination (O1)	-0.019	-0.004	-0.003	-0.004	-0.035*	-0.002
	(0.011)	(0.003)	(0.003)	(0.006)	(0.017)	(0.031)
Artistic Interests (O2)	0.055***	-0.006*	-0.003	0.003	0.058***	0.100***
	(0.010)	(0.003)	(0.003)	(0.005)	(0.015)	(0.027)
Emotionality (O3)	-0.006	-0.002	-0.002	-0.006	-0.012	0.013
	(0.009)	(0.003)	(0.004)	(0.006)	(0.018)	(0.033)
Adventurousness (O4)	-0.023*	0.000	0.000	-0.009	-0.046**	-0.095**
	(0.010)	(0.003)	(0.004)	(0.006)	(0.018)	(0.032)
Intellect (O5)	-0.020*	0.002	0.000	0.000	0.001	-0.037
	(0.010)	(0.003)	(0.003)	(0.006)	(0.017)	(0.030)
Liberalism (O6)	-0.001	0.008**	0.005	0.001	-0.010	-0.001
	(0.009)	(0.003)	(0.003)	(0.006)	(0.017)	(0.031)
Trust (A1)	0.022*	-0.001	0.004	0.008	0.029	0.061
	(0.011)	(0.003)	(0.003)	(0.006)	(0.017)	(0.032)
Morality (A2)	0.030*	0.007*	0.001	0.005	0.023	0.121**
	(0.015)	(0.004)	(0.004)	(0.007)	(0.021)	(0.038)
Altruism (A3)	-0.064***	0.003	-0.002	-0.018*	-0.102***	-0.175***
	(0.013)	(0.004)	(0.005)	(0.009)	(0.025)	(0.046)
Cooperation (A4)	-0.002	-0.008*	0.000	0.002	0.007	-0.025
	(0.012)	(0.003)	(0.004)	(0.007)	(0.020)	(0.036)
Modesty (A5)	-0.033***	0.002	0.001	-0.006	-0.035*	-0.094**
	(0.009)	(0.003)	(0.003)	(0.006)	(0.017)	(0.031)
Sympathy (A6)	0.015	0.004	0.000	0.008	0.042*	0.026
	(0.010)	(0.003)	(0.004)	(0.007)	(0.020)	(0.037)
Self-Efficacy (C1)	-0.003	0.002	-0.003	-0.015	-0.054*	-0.023
	(0.016)	(0.004)	(0.005)	(0.008)	(0.025)	(0.045)
Orderliness (C2)	0.004	0.000	-0.002	0.004	0.004	0.003
	(0.007)	(0.002)	(0.003)	(0.004)	(0.012)	(0.023)
Dutifulness (C3)	0.050**	0.002	0.008	0.019*	0.039	-0.009
	(0.015)	(0.004)	(0.005)	(0.008)	(0.024)	(0.043)
Achievement-Striving (C4)	-0.024*	-0.011**	-0.008	-0.017*	-0.012	0.026
	(0.010)	(0.004)	(0.004)	(0.007)	(0.021)	(0.039)
Self-Discipline (C5)	-0.012	0.001	0.003	0.007	0.001	-0.027
	(0.011)	(0.004)	(0.005)	(0.008)	(0.023)	(0.041)
Cautiousness (C6)	-0.002	0.001	0.003	-0.006	-0.021	0.010
	(0.006)	(0.002)	(0.003)	(0.005)	(0.014)	(0.026)
Risk aversion	-0.006*	0.002	0.001	-0.001	-0.010	-0.020
	(0.003)	(0.001)	(0.001)	(0.002)	(0.006)	(0.010)
Switch ratio (control task)	0.066**	0.000	0.013	0.019	0.054	0.116
	(0.025)	(0.007)	(0.008)	(0.014)	(0.039)	(0.072)
Age	-0.005*	0.000	0.001	0.000	-0.003	-0.019*

	(0.002)	(0.001)	(0.001)	(0.002)	(0.004)	(0.008)
Female	0.012	0.007	0.000	0.010	-0.006	-0.038
	(0.011)	(0.004)	(0.005)	(0.008)	(0.023)	(0.042)
Education	-0.012	-0.006	-0.012*	-0.009	0.002	0.087
	(0.017)	(0.005)	(0.006)	(0.010)	(0.029)	(0.053)
Quantitative background dummy	-0.009	0.007	0.001	0.003	-0.018	0.018
	(0.013)	(0.004)	(0.005)	(0.008)	(0.024)	(0.044)
Treatment 2 dummy	0.007	-0.001	0.001	-0.005	-0.005	0.092
	(0.017)	(0.005)	(0.006)	(0.010)	(0.028)	(0.051)
Treatment 3 dummy	-0.074***	-0.007	-0.005	-0.027*	-0.077*	-0.119*
	(0.014)	(0.005)	(0.006)	(0.011)	(0.031)	(0.057)
Treatment 4 dummy	-0.088***	-0.007	-0.009	-0.027**	-0.093**	-0.130*
	(0.014)	(0.005)	(0.006)	(0.010)	(0.029)	(0.053)
Constant	0.079	0.017	-0.015	0.064	0.448*	0.879*
	(0.112)	(0.036)	(0.042)	(0.072)	(0.211)	(0.385)
Observations	960	960	960	960	960	960
Adjusted/Pseudo R-squared	0.245	0.0398	0.0294	0.0394	0.133	0.339
F-statistic	4.038					
	(p<0.001)					

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown.

Table A.27: Regressions of the relationship between personality factors and the switch ratio in the costly full-feedback task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Neuroticism	-0.007		0.000	-0.002	-0.013	-0.060*
	(0.013)		(0.005)	(0.004)	(0.011)	(0.025)
Extraversion	0.004		0.000	0.008	0.011	0.014
	(0.010)		(0.005)	(0.004)	(0.011)	(0.027)
Agreeableness	-0.024*		0.000	0.003	-0.021*	-0.054*
	(0.010)		(0.005)	(0.005)	(0.010)	(0.023)
Openness to experience	-0.006		0.000	-0.012*	-0.030*	-0.048*
	(0.008)		(0.006)	(0.005)	(0.013)	(0.024)
Conscientiousness	-0.025**		0.000	-0.001	-0.026*	-0.063**
	(0.010)		(0.005)	(0.005)	(0.012)	(0.024)
Risk aversion	-0.008**		0.000	-0.002	-0.006*	-0.015**
	(0.003)		(0.001)	(0.001)	(0.003)	(0.005)
Switch ratio (control task)	0.010		0.000	0.000	0.030	0.099
	(0.018)		(0.013)	(0.009)	(0.031)	(0.057)

Age	0.001	0.000	0.000	0.002	-0.003
	(0.002)	(0.001)	(0.001)	(0.002)	(0.006)
Female	0.022*	0.000	-0.007	-0.003	0.042
	(0.010)	(0.005)	(0.004)	(0.010)	(0.026)
Education	0.000	0.000	0.002	-0.003	0.051
	(0.012)	(0.006)	(0.005)	(0.015)	(0.047)
Quantitative background dummy	0.001	0.000	0.000	-0.008	-0.024
	(0.010)	(0.004)	(0.006)	(0.010)	(0.023)
Treatment 2 dummy	-0.001	0.020***	0.012**	0.019	0.025
	(0.011)	(0.006)	(0.005)	(0.012)	(0.023)
Treatment 3 dummy	0.036**	0.020**	0.011*	0.062***	0.086
	(0.014)	(0.007)	(0.005)	(0.016)	(0.049)
Treatment 4 dummy	0.039**	0.020***	0.028***	0.051***	0.084***
	(0.014)	(0.006)	(0.006)	(0.011)	(0.025)
Constant	0.280***	0.000	0.049	0.351***	0.926***
	(0.082)	(0.037)	(0.034)	(0.103)	(0.216)
Observations	960	960	960	960	960
Adjusted/Pseudo R-squared	0.031	0.0049	0.00578	0.0356	0.0886
F-statistic	3.786				
	(p<0.001)				

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown. Quantile regressions without sufficient data are omitted.

Table A.28: Regressions of the relationship between personality facets and the switch ratio in the costly full-feedback task

Regressor	OLS	Quantile (0.10)	Quantile (0.25)	Quantile (0.50)	Quantile (0.75)	Quantile (0.90)
Anxiety (N1)	-0.004		-0.003	-0.008	-0.007	0.036
	(0.009)		(0.003)	(0.006)	(0.016)	(0.029)
Anger (N2)	0.013*		-0.002	0.000	0.002	0.046*
	(0.007)		(0.003)	(0.005)	(0.012)	(0.022)
Depression (N3)	0.038***		0.006	0.012	0.019	0.083**
	(0.010)		(0.004)	(0.006)	(0.017)	(0.031)
Self-consciousness (N4)	-0.043***		-0.007*	-0.016**	-0.017	-0.082**
	(0.009)		(0.003)	(0.006)	(0.016)	(0.029)
Immoderation (N5)	-0.010		0.004	0.001	-0.003	-0.016
	(0.006)		(0.003)	(0.005)	(0.014)	(0.025)

Vulnerability (N6)	-0.026**	0.000	-0.005	-0.010	-0.086*
	(0.009)	(0.004)	(0.007)	(0.019)	(0.034)
Friendliness (E1)	-0.026*	-0.002	-0.008	-0.022	-0.093**
	(0.013)	(0.004)	(0.007)	(0.020)	(0.036)
Gregariousness (E2)	-0.016*	-0.005	-0.006	-0.012	0.015
	(0.008)	(0.003)	(0.006)	(0.016)	(0.028)
Assertiveness (E3)	0.007	-0.001	0.000	-0.006	0.016
	(0.009)	(0.003)	(0.005)	(0.015)	(0.027)
Activity Level (E4)	0.006	-0.001	0.012	0.014	0.015
	(0.008)	(0.004)	(0.007)	(0.018)	(0.033)
Excitement Seeking (E5)	0.028***	0.004	0.004	0.000	0.068*
	(0.008)	(0.004)	(0.006)	(0.017)	(0.031)
Cheerfulness (E6)	0.043***	0.006	0.016*	0.060***	0.105**
	(0.011)	(0.004)	(0.007)	(0.018)	(0.032)
Imagination (O1)	-0.020**	-0.001	-0.001	-0.024	-0.051
	(0.008)	(0.003)	(0.005)	(0.014)	(0.026)
Artistic Interests (O2)	0.024**	-0.001	-0.003	-0.004	0.037
	(0.009)	(0.003)	(0.005)	(0.013)	(0.023)
Emotionality (O3)	0.012	0.005	0.009	0.025	0.030
	(0.008)	(0.003)	(0.006)	(0.016)	(0.028)
Adventurousness (O4)	-0.016*	0.000	-0.007	-0.001	0.024
	(0.007)	(0.003)	(0.006)	(0.015)	(0.027)
Intellect (O5)	0.017*	0.003	0.006	0.015	0.063*
	(0.007)	(0.003)	(0.005)	(0.014)	(0.026)
Liberalism (O6)	-0.029***	-0.002	-0.001	-0.016	-0.079**
	(0.007)	(0.003)	(0.005)	(0.015)	(0.026)
Trust (A1)	-0.018*	0.005	0.004	0.003	-0.026
	(0.008)	(0.003)	(0.005)	(0.015)	(0.027)
Morality (A2)	0.010	0.002	0.009	0.004	0.039
	(0.009)	(0.004)	(0.007)	(0.018)	(0.032)
Altruism (A3)	-0.032**	-0.007	-0.024**	-0.055*	-0.107**
	(0.012)	(0.004)	(0.008)	(0.022)	(0.039)
Cooperation (A4)	-0.004	-0.003	-0.011	-0.013	-0.002
	(0.008)	(0.004)	(0.006)	(0.017)	(0.031)
Modesty (A5)	-0.016*	-0.004	-0.005	-0.011	-0.002
	(0.007)	(0.003)	(0.005)	(0.014)	(0.026)
Sympathy (A6)	0.034**	0.005	0.012	0.017	0.068*
	(0.011)	(0.004)	(0.006)	(0.018)	(0.032)
Self-Efficacy (C1)	-0.053***	-0.011*	-0.017*	-0.055**	-0.107**
	(0.010)	(0.004)	(0.008)	(0.021)	(0.038)
Orderliness (C2)	-0.019***	0.001	-0.003	-0.003	-0.023
	(0.005)	(0.002)	(0.004)	(0.011)	(0.019)
Dutifulness (C3)	0.056***	0.008*	0.016*	0.033	0.064

	(0.011)	(0.004)	(0.007)	(0.020)	(0.036)
Achievement-Striving (C4)	-0.038***	-0.001	-0.006	-0.010	-0.077*
	(0.011)	(0.004)	(0.007)	(0.018)	(0.033)
Self-Discipline (C5)	0.021*	0.002	0.003	0.017	0.032
	(0.010)	(0.004)	(0.007)	(0.020)	(0.035)
Cautiousness (C6)	0.008	0.001	0.004	-0.003	0.039
	(0.007)	(0.002)	(0.004)	(0.012)	(0.022)
Risk aversion	-0.003	-0.001	-0.003	-0.006	-0.012
	(0.003)	(0.001)	(0.002)	(0.005)	(0.009)
Switch ratio (control task)	0.012	0.002	0.000	0.002	-0.020
	(0.016)	(0.007)	(0.012)	(0.034)	(0.061)
Age	0.000	0.000	0.000	0.000	-0.004
	(0.002)	(0.001)	(0.001)	(0.004)	(0.007)
Female	0.012	-0.005	-0.006	-0.013	0.006
	(0.010)	(0.004)	(0.007)	(0.020)	(0.035)
Education	-0.003	-0.003	0.002	0.000	0.040
	(0.014)	(0.005)	(0.009)	(0.025)	(0.045)
Quantitative background dummy	0.020	0.004	0.007	-0.004	0.012
	(0.011)	(0.004)	(0.008)	(0.021)	(0.037)
Treatment 2 dummy	-0.005	0.005	0.007	0.023	0.003
	(0.011)	(0.005)	(0.009)	(0.024)	(0.043)
Treatment 3 dummy	0.039**	0.004	0.019	0.051	0.068
	(0.013)	(0.006)	(0.010)	(0.027)	(0.049)
Treatment 4 dummy	0.037**	0.010*	0.020*	0.027	0.107*
	(0.014)	(0.005)	(0.009)	(0.025)	(0.045)
Constant	0.250**	0.014	0.094	0.354	0.276
	(0.086)	(0.037)	(0.066)	(0.181)	(0.325)
Observations	960	960	960	960	960
Adjusted/Pseudo R-squared	0.196	0.0262	0.0423	0.103	0.261
F-statistic	3.605				
	(p<0.001)				

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses. Ordinary least squares (OLS) regressions and quantile regressions at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles are shown. Quantile regressions without sufficient data are omitted.

A.4.3. Relationship Between Search Behaviours and Payoffs

Table A.29: Regressions of the relationship between sample size and expected payoffs earned in the experimental tasks with costly search

Regressor	Sampling task	Sampling task	Control task	Control task
Number of samples	-0.367***	-0.365***	-0.402***	-0.399***
	(0.021)	(0.022)	(0.028)	(0.029)
Neuroticism		0.022		-0.091
		(1.983)		(1.995)
Extraversion		-0.476		-0.345
		(2.008)		(2.019)
Agreeableness		0.144		-0.089
		(1.992)		(1.993)
Openness to experience		0.159		0.262
		(2.383)		(2.393)
Conscientiousness		-0.055		0.123
		(2.135)		(2.134)
Risk aversion		0.002		0.000
		(0.086)		(0.086)
Age		0.051		0.021
		(0.366)		(0.367)
Female		-0.052		0.081
		(1.861)		(1.871)
Education		-0.223		-0.272
		(2.276)		(2.276)
Quantitative background dummy		0.144		-0.051
		(1.895)		(1.903)
Treatment 2 dummy		0.582		-0.346
		(2.392)		(2.426)
Treatment 3 dummy		0.921		-0.203
		(2.554)		(2.555)
Treatment 4 dummy		0.197		-0.077
		(2.373)		(2.383)
Constant	1.546	0.831	2.376**	2.805
	(0.848)	(15.068)	(0.862)	(15.229)
Observations	960	960	960	960
Adjusted R-squared	0.222	0.212	0.04	0.027
F-statistic	309	20.79	210.5	15.54
	(p<0.001)	(p<0.001)	(p<0.001)	(p<0.001)

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses.

Table A.30: Regressions of the relationship between switch ratios and expected payoffs earned in the experimental tasks with costly search

Regressor	Sampling task	Sampling task	Control task	Control task	Partial-feedback task	Partial-feedback task	Full-feedback task	Full-feedback task
Switch ratio	-2.500	-3.138	-7.105*	-7.143*	-45.273***	-48.527***	-12.799*	-12.541*
	(2.223)	(2.141)	(3.254)	(3.381)	(5.205)	(5.489)	(5.338)	(5.458)
Neuroticism		-1.530		-0.191		1.668		-0.062
		(2.907)		(2.039)		(1.961)		(1.987)
Extraversion		-2.748		-1.494		1.118		-0.084
		(2.169)		(2.064)		(1.964)		(1.997)
Agreeableness		1.517		0.022		0.124		0.140
		(2.055)		(2.026)		(1.927)		(1.992)
Openness to experience		-0.721		0.810		-1.243		-0.001
		(2.414)		(2.423)		(2.322)		(2.383)
Conscientiousness		0.227		0.071		-0.078		0.151
		(2.149)		(2.162)		(2.085)		(2.135)
Risk aversion		0.051		-0.008		0.013		0.001
		(0.087)		(0.086)		(0.084)		(0.086)
Age		0.148		0.038		-0.195		0.003
		(0.391)		(0.391)		(0.360)		(0.364)
Female		-1.020		0.082		0.281		-0.145
		(1.917)		(1.888)		(1.818)		(1.869)
Education		-0.193		-0.049		0.922		-0.002
		(2.357)		(2.337)		(2.234)		(2.257)
Quantitative background dummy		-0.154		-0.181		-0.432		-0.014
		(2.043)		(1.933)		(1.857)		(1.890)
Treatment 2 dummy		4.065		-2.048		-0.431		0.113
		(3.061)		(2.463)		(2.343)		(2.388)
Treatment 3 dummy		3.930		0.014		-2.895		-0.245
		(3.037)		(2.591)		(2.534)		(2.548)
Treatment 4 dummy		0.987		-1.018		-2.923		-0.263
		(3.017)		(2.394)		(2.358)		(2.372)
Constant	0.022	4.224	1.306	4.100	5.638***	5.722	1.989*	1.472
	(1.709)	(16.499)	(0.897)	(15.811)	(0.986)	(14.973)	(0.923)	(15.132)
Observations	960	960	960	960	960	960	960	960
Adjusted R-squared	0	-0.006	0.003	-0.008	0.092	0.084	0.004	-0.009
F-statistic	1.265	0.641	4.767	0.448	75.64	5.676	5.75	0.409
	(p=0.261)	(p=0.831)	(p=0.0292)	(p=0.959)	(p<0.001)	(p<0.001)	(p<0.050)	(p=0.972)

Note. ***p<0.001, **p<0.01, *p<0.05. Robust standard errors and p-values are in parentheses.