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DISSERTAÇÃO

THE ROLE OF INFORMATION FORMAT IN FINANCIAL DECISION-MAKING: BRIDGING PSYCHOLOGY, NEUROSCIENCE AND ACCOUNTING RESEARCH

MADALENA STILWELL FERREIRA DA FONSECA

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ABSTRACT

The idea that not only *what* but also *how* financial accounting information is disclosed may impact financial evaluation and trading decisions has gained growing empirical support. Yet, despite its profound implications for accounting researchers and information users as well as policy regulators, we know little about the variables mediating these effects.

Crucial for both understanding these effects and efficiently designing financial reports is to understand the factors that influence the sampling, processing and use of financial information. Only then we will be able to shape policy and tailor organizational processes to promote efficient use of financial information.

A rich and biologically rooted understanding of how people make decisions and the factors that shape it will require integration of insights and tools from multiple disciplines including economics, psychology, computer science and neuroscience.

The aim of this paper is to review and bridge research from these different fields to address the importance of presentation variables in financial decision-making. More generally, the paper reviews and discusses the emerging field of 'neuroaccounting' and the potential as well as the challenges of this multidisciplinary approach to tackle behavioural accounting questions.

Keywords: Decision-making, Financial Reporting, Presentation Format, Psychology, Neuroscience, Accounting, Neuroaccounting

RESUMO

A ideia de que a avaliação e as decisões financeiras dependem não só do valor real das empresas espelhada na informação contida nos relatos financeiros, mas também da forma como a mesma é apresentada tem vindo a ser empiricamente demonstrada. Contudo, sabemos ainda muito pouco sobre os mecanismos subjacentes ao impacto que o formato tem nos processos de tomada de decisão.

Para compreender melhor o impacto da forma como a informação é apresentada e disponibilizada e para conseguir criar relatos financeiros mais eficientes ao nível da transmissão da informação desejada, é fundamental perceber os fatores que influenciam a aquisição, o processamento e utilização da informação financeira e contabilística.

O conhecimento dos processos psicológicos e neurais que culminam na tomada de decisões e dos fatores que os influenciam requer a integração de abordagens e ferramentas de várias disciplinas e áreas do conhecimento, designadamente da economia, da psicologia, das ciências computacionais e da neurociência.

O objetivo deste trabalho é rever e discutir a investigação mais recente nestes diferentes campos, em particular a relacionada com a importância da forma de apresentação da informação. Pretende-se ainda discutir a abordagem multidisciplinar que começa a emergir sob a designação de "neuroacounting", reconhecendo o seu potencial, mas também as suas limitações.

Palavras chave: Tomada de Decisão, Relato Financeiro, Formato de Informação, Psicologia, Neurociência, Contabilidade, Neuroaccounting

ABBREVIATIONS

ACC	-	Anterior cingulate cortex
AMG	-	Amygdala
BOLD	-	Blood-oxygen-level dependent
DA	-	Dopamine
dCS	-	Direct current stimulation
dPFC	-	Dorsal prefrontal cortex
EEG	-	Electroencephalogram
fMRI	-	Functional Magnetic Resonance Imaging
IGT	-	Iowa Gambling Task
NA	-	Nucleus Accumbens
OFC	-	Orbitofrontal cortex
PET	-	Positron Emission Tomography
PFC	-	Prefrontal Cortex
SCR	-	Skin Conductance Response
ST	-	Striatum
TMS	-	Transcranial Magnetic Stimulation
vmPFC	-	Ventromedial Prefrontal Cortex
VTA	-	Ventral tegmental area

CONTENTS

1. INTRODUCTION

Episodes like the financial crisis of 2008 show us that despite its profound social and economical implications, we are still far from having a complete understanding of market behaviour.

For a long time, financial theorizing revolved around the idea that behaviour, at the market level, is rational or, in the exact words of the most influential theory: efficient. According to the efficient market hypothesis (EMH), market prices always incorporate and reflect all the available information (Fama, 1970), and thus stock always trades at its fundamental value: the present value of its expected future cash flows (Fama, 1970, Barbaries & Thaler, 2003).

The EMH was widely accepted as an accurate model of financial markets, until, in the 1980s, empirical studies started questioning its descriptive validity. Today, there is a large body of literature showing instances where markets behave inefficiently: prices vary more than what EMH predicts, available information is sometimes not fully or only slowly reflected in prices and trading levels are much higher than expected (see Barbaries & Thaler, 2003 for a review).

Why and how these deviations occur is still not well understood. Efficiency models assume that individual "irrationality" reflects idiosyncratic behaviour and is thus irrelevant to aggregate market phenomena (Barbaries & Thaler, 2003). However, research from psychology has shown that these deviations are pervasive and appear to reflect regularities in how people process information and decide (Barbaries & Thaler, 2003; Garling et al., 2009).

Aware of the importance of psychological factors in understanding both individual and market level behaviour, many researchers started incorporating psychology findings into their research with the aim of building more accurate models. This led to the emergence of behavioural economics, behavioural finance and behavioural accounting, among others (Barbaries & Thaler, 2003, Garling et al., 2009). However, behavioural data alone, from the field or laboratory experiments, is often not enough to distinguish competing psychological theories. Furthermore, it offers a limited, only inferential, window into the actual processes behind choice (Frydman et al., 2014). Neuroscience offers an additional source of data that can prove invaluable in refining, as well as distinguishing, different psychological and behavioural theories (Frydman, 2012). Neurobiological measures can also provide additional predictive power over subjective reports, since much of the processing that goes on in the brain is not available to conscious awareness (Chua et al., 2011, Falk et al., 2011, Smith et al., 2014).

The potential of using neuroscientific data, in additional to choice data, to study economic and financial behaviour has been acknowledged by several researchers across the natural and social sciences, as shown by the emergence and fast growth of new fields such as neuroeconomics and neuromarketing (see e.g. Ariely & Berns, 2010; Frydman et al., 2014; Bossaerts et al., 2009; Camerer, 2013; Loewenstein et al., 2008).

More recently, behavioural accounting researchers have also started looking to apply this approach to accounting-related issues (Birnberg and Ganguly, 2012). Although some authors have already recognized and began to discuss the potential of neuroscience in accounting research, work bridging the two is still scarce and the little that exists has only touched on a few aspects of behavioural accounting e.g. the evolution of accounting principles. In particular, at least to our knowledge, there is no work to date applying this approach to the study of financial information disclosure format and its influence on decision-making.

The way information is presented or described has long been recognized in psychology as an important factor in decision-making, but it has only recently been considered in the field of financial accounting. The idea that not only *what* but *how* accounting information is disclosed may impact evaluation and trading decisions has gained growing empirical support. Yet, despite its profound implications for both accounting researchers and financial information users and regulators, we know little about the variables mediating these effects. Crucial for both understanding these effects and efficiently designing accounting reports is to understand the factors that influence the sampling, processing and use of financial information. Only then we will be able to shape policy and tailor organization process to promote efficient use of financial information. Reaching this understanding will require the integration of insights and tools from different levels of research. This paper aims to bridge research and approaches from behavioural accounting, economics, psychology and neuroscience, to explore this particular question. Rather than offering an answer, our aim is to bring together pertinent research from the different fields, discuss why it is important that this integration materializes and highlight possibilities for future multidisciplinary research.

This review is structured as follows: section 2 provides a brief introduction to the brain and neuroscience. Section 3 describes the different approaches taken by economics, psychology and neuroscience to the study of decision-making. Section 4 reviews and discusses the work at the intersection between these fields: the developments in neuroeconomics and the first steps in the emerging field of 'neuroaccounting'. Section 5 explores this multidisciplinary approach to address a specific financial accounting question: why and how is information format important for decision-making? We focus first on the processes and variables that are intrinsic to the information report itself (independent of a particular decision maker) (5.2.1-3) and then move on to explore those related to the internal state of the decision maker, i.e. emotional factors (5.2.4). For simplicity, we provide a summary and short discussion at the end of each part. In section 6, we expand on this discussion, by first providing an overall synthesis and then discussing more broadly the implications, future avenues and the possible challenges.

2. FUNDAMENTALS OF NEUROSCIENCE

2.1. Levels of analysis in neuroscience research

Neuroscience can be broadly defined as being interested in how nervous systems are organized and how they function to generate behaviour (Kandel, 2013). These questions can be explored at different levels of analysis using appropriate tools. According to the level of analysis, neuroscience is usually broadly divided into molecular (interested in the role of different molecules for neural function), cellular (cellular organization and function), systems (how different neural circuits process and represent information), behavioural (how neural systems interact to produce behaviour) and cognitive neuroscience (higher-level functions such as decision making and language) (Bears et al., 2007).

2.2. The nervous system

Neuroscientists have conventionally separated the vertebrate nervous systems anatomically into central and peripheral components. The central nervous system includes the brain and the spinal cord. The peripheral nervous system comprises the sensory and motor neurons that link the brain with the periphery.

The nervous system like the rest of the body is made up of cells, the fundamental unit of all living organisms. Nerve cells or neurons are specialized cells that are capable of electrical signalling over long distances and can communicate with other neurons via specialized sites called synapses. Glial cells offer structural and metabolic support to neurons. The human brain is estimated to contain around 86 billion neurons and approximately the same number of glial cells (Azevedo et al., 2009, Hilgetag & Barbas, 2009).

Neurons do not function in isolation, but are organized into networks or neural circuits that process specific types of information and provide the basis for sensation, perception and behaviour (Kandel, 2013). Neural systems can be broadly divided in one of three general functions. Sensory systems represent information about that state of the organism and the external environment. Motor systems respond to that information by generating behaviour. Finally, associational system include most of the cerebral surface of the brain and are broadly responsible for the complex processing that goes on between the arrival of input in sensory areas and the generation of behaviour in motor areas (Kandel, 2013).

The central nervous system is usually considered to have seven different parts: the spinal cord, medulla, pons, cerebellum, midbrain, diencephalon and cerebral hemispheres. In humans, the cerebral hemispheres are proportionally larger than in any other mammal and are usually divided into four lobes: occipital, temporal, parietal and frontal lobes (Kandel, 2013, see Appendix I). The remaining subdivisions of the forebrain lie beneath the cerebral hemispheres and include the basal ganglia, the hippocampus and the amygdala. Other important areas include the thalamus and the hypothalamus (Kandel, 2013)

2.3. Key relevant findings

One key finding from neuroscience research is that the brain is neither fully specialized nor integrated, but has different degrees of specialization. This means that no area can be said to be fully responsible for a given function or behaviour. Another key finding is that the brain is plastic, that is, it can change according to experience. Plasticity is most obvious in childhood but continues into adolescence and adulthood, with evidence that adults are also able to adapt to change and recover from injury (Camerer, 2007). Another important discovery is that contrary to traditional expectations, attention and conscious are actually rare (Camerer, Loewestein & Prelec, 2005), with much of the processing taking place outside awareness. This means that often we may have little introspective access to the underlying determinants of our behaviour. Finally, evolution conservation is the main reason why animal studies are so helpful in providing us information about human brain and behaviour. Humans share a significant amount of brain structure and function with non-human animals (Kalenscher & van Wingerden, 2011).

3. MULTIPLE APPROACHES TO DECISION-MAKING

Human decision-making has attracted attention from a variety of different fields including economics, psychology and neuroscience. Pursuing different goals, these areas have used different approaches that offer a unique, but complementary, perspective on decision-making.

3.1. Economics and Finance

The birth of neoclassical economics is often traced to 1930s, when a group of economist began to define a new, mathematically-rooted, approach to the study of choice behaviour (Glimcher & Fehr, 2014, Caplin & Glimcher, 2014).

At the core of the Revealed Preference Approach (Samuelson, 1938), as it became known, is the idea that economic models should be rooted not on psychological constructs, assumed a priori to predict choice, but on a set of simple mathematical principles, or axioms, that make clear behavioural predictions and can be rigorously tested (Glimcher & Fehr, 2014).

Thus, according to this view, economists should be concerned not with explaining how choices actually happen, but simply with whether they can be represented by a certain mathematical function. For instance, a decision maker's choices can be represented by the maximization of some utility function, if they obey a set of simple principles that can be mathematically shown to be necessary and sufficient for that representation to be valid. Such simple principles include the Weak Axiom of Revealed Preference (WARP; Samuelson, 1938) and the Generalized Axiom of Revealed Preference (GARP; Houthakker, 1950). The former states that individuals must have a stable rank order preference, that is, if a decision maker chooses A over B in one situations, then he should never choose B over A in another situations when both options are available. The later just means that individual choices must be transitive: if the subject prefers A over B and B over C, then when asked he must prefer A over C (Caplin & Glimcher, 2014).

In this framework, psychological "hidden" variables are irrelevant, as long as the decision-maker obeys these set of principles, he (she) can be assumed to behave "as if" they had an utility function and "as if" their choices sought to maximized it. In this way, his (her) choices can be modelled and predicted (Glimcher & Fehr, 2014; Caplin & Glimcher, 2014).

The revealed preference approach has been profoundly influential in economics and formed the basis of many subsequent models that, by adding additional axioms, extended the framework to various decision contexts including when outcomes are uncertain (standard and expected utility theories), delayed in time (discounted utility) or result from interactions between players (game theory) (Glimcher & Fehr, 2014). In all of them, decision-makers are assumed to maximize some utility function, what varies is the details of that function. It is important to note that although neoclassical economics continues to use words like preference or utility, which in earlier economic theorizing were connoted with abstract, psychological meaning, in this approach they are merely used as a mathematical tool, a convenient re-description of choice (Glimcher & Fehr, 2014).

Perhaps the most well known utility-based theory is the Expected Utility Theory (EUT, Von Neumann & Morgenstern, 1944, as cited in Glimcher & Fehr, 2014). According to EUT, decision makers when faced with a choice between options that have uncertain outcomes (and their probabilities are known) decide by computing the expected utility of each option - its utility multiplied by the probability of it actually occurring - and selecting the option with the highest value.

Utility-based theories and similar normative approaches have also been profoundly influential in financial theorizing. The traditional financial approach to market behaviour also relies on normative theories assuming that prices are set by normatively rational (Bayesian) agents that update their beliefs optimally given the available information and that, given those beliefs, make choices according to expected utility models (Barberies & Thaler, 2003).

Although the efficient market hypothesis (Fama, 1970) does not require that all market participants are rational, it assumes that rational agents are at least sufficiently well represented to guarantee that any inefficiencies caused by irrational trader activity are always fully and quickly eliminated and that prices always revert back to their fundamental value (Friedman, 1953, as cited in Barbaries & Thaler, 2003).

3.2. Psychology and Behavioural Economics

The axiomatic approach has been successful in modelling and predicting both consumer and market behaviour across a variety of contexts, however it has become increasingly clear that it is not sufficient to capture much of individual and market behaviour. In fact, a large body of empirical research has shown that decision-makers and markets often deviate from neoclassical assumptions (Libby et al. 2002, Barbaries & Thaler, 2003). For example, Kahneman & Tversky showed that contrary to what rational choice theory would predict, people are remarkably sensitive to the way information is described (Tversky & Kahneman, 1981). In a seminal experiment, they showed that depending on whether the options were framed to emphasise the gains or to emphasise the losses, people's preferences radically changed (Tversky & Kahneman, 1981). This effect became known as the "Framing effect" and has since been replicated across a variety of different contexts.

At the market level, several studies have reported market inefficiencies that came to challenge standard market theory. The excessive volume of trading observed in stock markets and the large variability ('volatility') in prices are only two examples (Libby et al., 2002, Barbaries & Thaler, 2003; see Fama et al., 1998 for a contrary perspective).

Why these deviations happen is still an open question and at the core of much of current research in the fields of behavioural economics and finance. One key finding of this line of research is that most of these deviations are not simply idiosyncratic behaviour but very systematic tendencies (Libby et al., 2002, Barbaries & Thaler, 2003). This suggests that they may reflect regularities in the way we acquire and process information and points research towards examining the psychological processes behind choice (Garling et al., 2009).

Key to this trend was the work of Herbert Simon on bounded rationality (Simon, 1955). Simon argued that the notion of maximization was simply not realistic given the findings from psychology research. In many situations, the computations that would be required to behave according to normative theories are simply not feasible. Thus, rather than maximizers, decision-makers, he said, are better described as boundedly rational, that is, as seeking to achieve a good enough solution given the various constraints they face (Simon, 1955). Simon's work highlighted the importance of studying the underlying psychological processes to understand how and why decision makers decide the way they do, laying the foundation for much of subsequent behavioural economic research (Glimcher & Fehr, 2014).

One way that researchers have used to study psychological processes behind choice is by, indirectly, inferring them from choice. Much like cognitive psychologists infer visual processes from optical illusions, the heuristics approach aims to examine the "errors" (deviation from normative predictions) that decision-makers make across a wide range of decision problems to then infer the underlying processes or strategies that generated it (Glimcher and Fehr, 2014). For instance, people have been shown to make systematic errors when judging event probabilities. Based on these deviations, Tversky and Kahneman suggested that people use the "availability heuristics", that is, they judge the probability of an event based on how easily they can recall instances of that event (Tversky and Kahneman, 1973).

These simple decision rules are thought to be useful but imperfect strategies that allow rapid, although sometimes incorrect, decisions in situation that may be impossible or too costly to solve normatively. In this case, the problem arises from the fact that "easiness of retrieval" depends not only of the frequency of event occurring but also on other "irrelevant" factors such as their saliency and recency (Tversky and Kahneman, 1973, 1974). Tversky and Kahneman, and many others since, have described a variety of other systematic "errors" and proposed a number of different heuristics to explain them (e.g. Tversky and Kahneman, 1974).

This approach has been crucial in highlighting the descriptive inadequacy of many normative theories and in providing some insight into *how* decisions are actually made. However, they do not explain *why* people use them, and exactly *when* people choose one heuristics over the other or why people are sometimes able to correct their answers. More generally, inferring psychological processes from behavioural data alone may be difficult since different psychological theories often have similar behavioural predictions (Frydman et al., 2014).

Neural data may offer an additional source of data that can prove invaluable in distinguishing psychological theories and in getting closer to the actual determinants of behaviour (Frydman et al., 2014, Smith et al., 2014). For this reason, many behavioural researchers have become increasingly interested in incorporating neuroscientific techniques and findings in their research (Birnberg and Ganguly, 2012).

3.3. Neuroscience

In its study of decision-making, neuroscience aims to understand the neural mechanisms underlying simple and complex decision. It aims not only to map cognitive and behavioural functions to brain circuits but to clarify the general principles of how circuits are organized, what computations they perform and how they give rise to function.

Neuroscientists have used a variety of approaches in both humans and other animals to study decision-making. These include assessing deficits after a lesion or brain damage, monitoring or manipulating neural activity while subjects perform a decision-making task and using computational models to link behavioural and neural data (Glimcher & Fehr, 2014).

Brain lesions are a crude but useful way to establish a first link between a specific deficit and a brain region. For instance, patients with brain damage to the orbitofrontal cortex (see Appendix II, also called the ventromedial prefrontal cortex) often display problems with decision-making in real-life situations. In particular, they appear to overlook the long-term consequences of their actions, a phenomenon often referred to as "myopia for the future" (Damásio, 1994).

A common approach involves correlating direct measurements of brain activity, i.e. electrical activity of single neurons, with behavioural events in simple tasks, where inputs (i.e. the information the subject receives) can be carefully controlled. For example, monkeys can be trained to evaluate an ambiguous visual signal (e.g. moving dots on a screen) that indicates which of two responses will lead to reward. By recording activity from neurons in a motion-sensitive part of the visual cortex, Newsome and colleagues showed for the first time that the firing rates of single neurons could be used to reliably predict the monkeys' choices (Newsome et al, 1989; Glimcher and Fehr, 2014).

This line of work has been very fruitful not only in advancing our understanding of the neuro-correlates of decision-making but also in demonstrating that nonhuman animals, i.e.

monkeys and rodents, can perform complex tasks including those involving integration of evidence (Shadlen & Newsome, 2001, Hanks et al., 2015), probabilistic reasoning (Kiani & Shadlen, 2009), numerical reasoning (Nieder et al. 2002), decision confidence judgements (Kepecs et al. 2008), context-dependent decision (Mante et al., 2012), among others (Gomez-Marin & Mainen, 2016).

Recent developments in non-invasive recording methods, such as electroencephalogram (EEG), positron emission tomography (PET) and functional magnetic resonance imaging (fMRI), have opened the possibility of also measuring brain activity (albeit more crudely) in humans while they perform cognitive tasks. EEG is the oldest method and measures rapid changes in electrical activity using electrodes attached to the scalp (Camerer, Loewenstein & Prelec, 2005). PET measures changes in blood flow or glucose metabolism in the brain based on the movement of injected radioactive material (Huettel, Song & McCarthy, 2009). Finally, fMRI measures changes in blood oxygenation over time; because blood oxygenation levels change following activity of neurons, it is used as a proxy for neural activity, allowing researchers to map activity across the brain (Huettel, Song & McCarthy, 2009, Logothetis, 2008). Each of these methods has its relative strengths and weaknesses. EEG provides high temporal resolution (millisecond scale) and contrary to fMRI and PET, it provides a direct measure of neural activity. Another major advantage is its portability and relatively low expense. However, EEG has poor spatial resolution and it can only measure activity in superficial parts of the brain. PET has better spatial resolution, however it requires the use of radioactive tracers, which limits significantly its applicability. fMRI does not require the use tracers and can thus be used as many times as needed by the same individual. It has the highest spatial resolution out of the three (milimiter scale) and offers intermediate temporal resolution (order of seconds). These advantages have made fMRI incresingly popular among researchers (Camerer, Loewenstein & Prelec, 2005, Huettel, Song & McCarthy, 2009).

It is important to note that the currently available non-invasive techniques offer only a crude measure of brain activity. Neural events occur in a milisecond scale and in less than 0.1 milimeters space, yet the spatial and temporal resolution of a typical fMRI scanner is several mms (thousands of neurons) and several seconds. Another aspect to keep in mind is that studies using these techniques usually require a comparison between two conditions or tasks performed by the same subject. By subtracting the two (an experimental and a control condition), the researcher can get a measure of the regions of the brain that are differentially activated by the experimental task. Importantly, an obvious implication of this kind of design is that a meaningful interpretation of the results crucially depends on an appropriate selection of the control condition, which may not be trivial. Despite these limitations, fMRI has reached a high level of sophistications that combined with careful experimental designs and analysis methods can still provided rich information on the neural correlates of behaviour (Braeutigam, 2012).

Other, non-neural, physiological measurements, such as heart rate, skin conductance response (SCR) and pupil dilation, are also commonly used (e.g. as indicators of emotional arousal), either in isolation or in combination with other techniques. These are perhaps the simpler to use and the most portable. The disadvantages are their non-specificity, for example, several different emotional states can lead to similar physiological responses. Eye movements can also be measured using eye-tracking technology, which is becoming increasingly cheaper and more portable.

Beyond correlational methods (all above except brain lesions), causal links between neural activity and behaviour can be tested using manipulation techniques. In animals, researchers can use invasive techniques such as electrical or optical activation of different groups of neurons or manipulations with pharmacological agents (some also possible in humans). Non-invasive tools for manipulating neural activity are also becoming increasingly popular. Transcranial magnetic stimulation (TMS) is one example that can be used to temporarily modulate activity in certain brain regions (Fehr & Rangel, 2011, Huettel, Song & McCarthy, 2009).

It is important to emphasize that neural and behavioural understanding evolve hand-in-hand. On one hand, understanding neural mechanisms of decision-making, or indeed any behaviour, crucially depends on having appropriate behavioural paradigms, that 1) capture the cognitive process of interest and 2) are adequate to the constraints, e.g. temporal, of the technique being used (LeDoux, 2015, Milner & White, 1987). On the other hand, insights from neural data can help better understand the behavioural itself. So one must go back and forward between the psychological and neural level: using biology to constraint psychological models and psychological theory to guide neural search and interpretation.

3.4. Bringing together economics, psychology and neuroscience

Having a biologically based theory of how humans make decision that is useful for both natural and social sciences will require the integration of findings and approaches from several different disciplines including economics, psychology and neuroscience (Rangel, Camerer & Montague, 2008). Economics offers a rich variety of choice paradigms and mathematical models of the variables that the brain needs to compute to make decisions. Psychology offers a large body of behavioural data on how people and other animals choose under different conditions and theories about those processes. Neuroscience offers the knowledge of the brain and the tools to study the neural events underlying decision-making processes. A forth discipline whose contribution is becoming widely recognized and that is key to bridging these different levels of description is computer sciences. Computational models can help identify the signals that are required by different decision problems and thus offer a crucial bridge between behavioural and neural data (Rangel et al. 2008).

4. INTERSECTIONS: NEUROECONOMICS AND NEUROACCOUNTING

4.1. Neuroscience in the study of economic choice

To explore the potential of interdisciplinary research in tackling behavioural accounting questions, it is informative to look at how neuroscience findings and tools have been applied in other fields such as economics, and how these fields have evolved.

Neuroeconomics is a relatively recent field that aims to relate formal theories of choice to neural measures, to produce a detailed computational and neurobiological account of decision-making processes (Fehr and Rangel, 2011). It combines methods and theories from neuroscience, psychology, economics and computer science to investigate the variables computed by the brain when making different types of judgements and choices (Rangel et al., 2008).

As Glimcher & Fehr (2014) describe it, the field of Neuroeconomics can be divided into partially overlapping communities. One that is mostly focused on using fMRI as a tool to test and develop alternatives to neoclassical theories, and a second that uses economic theory as a tool to test and develop models of the brain mechanisms underlying choice (Glimcher & Fehr, 2014).

Most of the initial work focused on mapping brain areas that are active when a subject is performing a particular cognitive task (Glimcher & Fehr, 2014). However, many of these studies relied on reverse inference, a form of resoning that is not deductively valid and that Poldrack (2016, p. 59) nicely puts as follows: "(1) In the present study, when task comparison A was presented, brain area Z was active. (2) In other studies, when cognitive process X was putatively engaged, then brain area Z was active. (3) Thus, the activity of area Z in the present study demonstrates engagement of cognitive process X by task comparison A." This logic would only be valid if we knew that brain area Z was active if, and only if, cognitive process X was engaged. However this seems to be rarely the case (Poldrack, 2006, 2011, Birnberg & Ganguly, 2012). The use of reverse inference can be useful as a starting point and provide some information, however it should be used with great care, especially when the selectivity of the brain region is not established or is known to be weak (Poldrack et al, 2006). Novel statistical analyses have since emerged allowing research to make more useful and careful use of this type of inference. For example, bayesian approaches can be used to estimate the likelihood of a cognitive process from a pattern of brain activity taking into account not only the number of previous studies that reported that activity pattern when using a particular task, but also those that reported the same pattern when *not* employing that type of task (Poldrack et al., 2011).

Beyond trying to map specific brain areas to cognitive task, the tendency in both neuroscience and neuroeconomics has been to develop sophisticated computational approaches that careful model the behaviour to then identify areas or networks of areas that, across tasks, correlate consistently with the same putative computational process (Braeutigam, 2012, Glimcher & Fehr, 2014).

Recent years have also seen an increase in the number of studies addressing causality, using non-invasive techniques such as transcranial magnetic stimulation (TMS) or direct current stimulation (dCS), that allow manipulation of neural activity in specific parts of the brain (Fehr & Rangel, 2011).

Numerous, partly overlapping reviews have appeared describing and discussing this rapidly growing field and the more recently emerging subfields of neurofinance and neuromarketing (e.g. Ariely & Berns, 2010, Camerer et al., 2005, Frydman et al., 2014; Bossaerts et al., 2009; Camerer, 2013; Loewenstein et al., 2008). Among the benefits discussed, they highlight the potential of neural data to help tease apart psychological theories with similar behavioural predictions; the potential of revealing and defining neurobiological constraints that can refine behavioural theories (Camerer, Loewenstein & Prelec, 2005), the potential of using observations from neural activity patterns to formulate novel behavioural hypotheses and predictions (e.g. if distinct brain activity patterns are observed, despite similar behaviour, then it becomes interesting to know what factors may be involved). Furthermore, neuroscience can offer objective and independent measures that provide a way to validate introspective reports, and of revealing what cannot be accessed introspectively (Chua et al., 2011, Falk et al., 2011, Smith et al., 2014). Finally, neuroscience, and more specifically, comparative studies of brain and behaviour, can help provide insight into the evolutionary roots of economic behaviour (Kalenscher & van Wingerden, 2011).

It has also received critics. Some neurobiologists are skeptic that neuroimaging techniques can provide significant insight into complex behaviours such as decision-making (Birnberg & Ganguly, 2012). From the economists side, some have argued that algorithmic level studies of decision making just provide finer grain and are unlikely to improve the predictive power of the revealed preference approach (Birnberg & Ganguly, 2012, Glimcher & Fehr, 2014).

Although no approach is free of limitations and indeed progress will dependent on having converging data from different techniques and experimental conditions from both animals and humans, there seems to be a general recognition of the potential of incorporating neuroscience into the study of human decision-making. There have been an exponentially increasing number of publications in neuroeconomics as well as growing interest from other areas such as finance, marketing and accounting (Braeutigam, 2012).

4.2. The emergence of neuroaccounting

Behavioural accounting researchers have also started showing interest in applying neuroscience findings and related tools to their research, with a few reviews and research papers emerging since 2009 (see Birnberg & Ganguly, 2012), that I will briefly review and discuss in this section.

4.2.1. The potential of neuroscience in accounting

Accounting has been typically defined as the process of collecting, summarizing and analysing past transactions as well as reporting financial information to potential users

Behavioural accounting in particular is interested in studying both individual and aggregate behaviour while they carry one or more of these functions (Birnberg & Ganguly, 2012).

Some authors have started discussing the potential of incorporating neuroscience into accounting research (Birnberg & Ganguly, 2012, Dickhaut et al., 2010). There seems to be a general recognition that neuroscience can contribute to accounting research by helping to understand how people process information and stimuli, how they react to different types of information and events including favourable and unfavourable ones, how their behaviour is shaped by others and how current accounting practices may have emerged and evolved (Birnberg & Ganguly, 2012, Dickhaut et al., 2010).

4.2.2. First steps in neuroaccounting

One of the first to show an interest in incorporating neuroscience into accounting research was Dickhaut and colleagues, who hypothesized that the origin and evolution of recordkeeping – the most basic of accounting functions – is a consequence of the organization and limitations of our brain (Dickhaut et al., 2010). At the core of their hypothesis is the idea that as societies became more complex, with a growing number of possible exchange partners, increased diversity of food and ability to store it, the brain's ability to remember all the relevant information was challenged, and thus societies turned towards external recordkeeping, as a memory aid (Dickhaut et al., 2010, Birnberg & Ganguly, 2012).

In a series of papers (Dickhaut et al. 2009a, 2009b, 2010), Dickhaut and colleagues review neuroscience findings, which, they argue, support their recordkeeping hypothesis and more generally, the idea that many culturally evolved accounting principles are consistent with, and linked to, the brain's evolution. In their review, they discuss a series of findings concerning the types of variables that the brain computes and draw parallels between those computations and specific accounting procedures including revenue realization and conservatism.

Most of the findings that Dickhaut and colleagues present are, as Birnberg and Ganguly note, fairly generic (Birnberg & Ganguly, 2012) and would need to be tested in a financial context. More worrying however, for addressing their question of interest, is the serious difficulty in distinguishing culturally and genetically determinants of brain activity and behaviour. This is a crucial issue that they do not explicitly discuss. Looking at the brain nowadays will indeed help us understand the brain computations underlying these accounting procedures but can do little in clarifying whether these computations were already present before or after societies started using those same accounting principles. For one, there is the problem of correlation of recording techniques, preventing drawing conclusions of whether the activity observed is causally related to the behaviour observed. But even if we established the causality between "present brain activity" and "present behaviour", which new techniques allow, we are still left with the serious issue of establishing the direction of the causal relationship in evolutionary terms: whether the way the human brain works nowadays is the origin or the consequence of the cultural accounting procedures. Accounting principles may have evolved because of how the brain worked, as Dickhaut et al. suggest, but it is also possible, given the large body of neuroscience research showing that our brain can change even in adulthood (e.g. Maguire et al., 2000), that our brain has adapted to efficiently deal with culturally imposed accounting principles.

This is a general issue that is often ignored in evolutionary psychology arguments. Biological basis should not be confused with genetically determined basis. Since both genetics and culture shape brain function, it is not enough to look at present-day adult human brain activity to distinguish whether certain function is hardwired, culturally determined or results from an interaction of the two. Thus, to address evolutionary hypothesis, one must rely on comparative studies looking across different related species (Kalenscher & van Wingerden, 2011). Although, Dickhaut and colleagues do present some non-human primate research, they do not explicitly discuss their importance for addressing their questions. Future work in this area should focus on comparing across species that are evolutionary close to humans but have not experienced the same cultural forces.

In the same year that Dickhaut and colleagues began to present their work, the term "neuroaccounting" also appeared in a conference in Brazil (Cesar et al., 2009). In this work, which was subsequently published (Cesar et al. 2012a), Cesar and colleagues incorporated findings from neuroscience into a theoretical model of decision-making, including variables that have been traditionally ignored in economic models i.e. emotions. They focused on management decision-making. More specifically, in budget targeting decisions.

They based themselves on two important findings from psychology and neuroscience research (reviewed in Camerer et al., 2005). First, that much of the processing that goes on in the brain occurs automatically, and without conscious deliberation (Scheiner & Shiffrin 1977, Shiffrin & Scheiner 1977). Second, that our judgements and decisions are critically dependent on, and strongly influenced by, emotional factors. The importance of emotions to "rational" decision-making is clear from the dramatic decision-making impairments seen in patients with disrupted emotional processing (Damásio, 1994). Importantly, and as Camerer et al. (2005) emphasize, the growing literature suggests that the two axis (affective/cognitive and automatic/controlled processing) are orthogonal. Contrary to the frequent assumption that emotional processing is always automatic, and that cognitive processing is always deliberate; several studies show instances of automatic cognitive processing (e.g. pattern recognition in visual perception or language processing) and of controlled emotional processing (e.g. cognitive emotional regulation) (Camerer et al., 2005).

Based on this, Cesar et al. (2012a) developed a theoretical framework to more realistically model budget targeting decisions that incorporates both the mode (controlled or automatic) and information processed (cognitive or affective). With this model, the authors hope to promote the development of accounting support systems within organizations that can anticipate the influence of each of these factors and help optimize decisions. Not by trying to suppress them but by exploiting them in the best possible way. They discuss that, for instance, automatic processing can be very advantageous to investors in some situations, allowing them to identify, through experience, the patterns of information that best predict positive outcomes. However, because of its inflexible nature, the automatic (or habitual) behaviour may become maladaptive, preventing the investor to detect or rapidly adapt to changes in contingencies (when the old pattern of information is no longer predictive).

Since the proposal of the model, Cesar's group has gone to considerable lengths to test and apply it. First in interviewed-based qualitative study with a sample of managers (Cesar et al. 2009) and later in several questionnaire-based quantitative studies in organizations from different sectors including transport, cosmetics and steel industry (Cesar et al 2010, Cesar et al. 2011, Valero et al 2012).

Although, an increasingly number of neuroscience researchers is proposing to move beyond binary-based classifications (e.g. affective vs. cognitive; automatic vs. deliberate) arguing that this cannot capture the complexity of these interactions (e.g. Phelps, Lempert & Sokol-Hessner, 2014), these models are still a useful starting point and as Cesar and colleagues have shown, can be very useful in translating academic research findings into organizational contexts.

Cesar's group has also started using neuroscientific tools to empirically test more specific questions about automatic processing in the context of accounting decision making (Cesar et al., 2012b). They combined behavioural analysis and electrocephalogram (EEG) recordings to examine the influence of automatic processes, namely implicit learning, on accounting-based decisions. As discussed in previous sections, it is a fairly crude measure sampling activity over large areas of the brain, but it is a relatively cheap method and has high temporal resolution, which makes it useful to look at temporal correlations between behavioural and neural events. They adapted the probability classification, or "weather prediction", task commonly used in psychology and cognitive neuroscience (Knowlton et al., 1994, 1996), to study non-declarative (implicit) learning and memory. In this task, participants are asked to predict the weather (if it will rain or shine) based on a combination of visual cues. The cues are probabilistically related to the outcome, but subjects are not told what that relationship is.

Studies on these probabilistic learning tasks have shown that after some exposure, individual become very good at these tasks, despite being apparently unaware of how they are solving them. The dissociation between explicit and implicit learning becomes even more evident when examining two different groups of patients. Patients that became amnesic after damage to the medial temporal areas show intact performance in this (implicit) task, despite being profoundly impaired in explicit memory tests. Whereas Parkinson and Huntington's patients, that have dysfunctional basal ganglia circuits, show the opposite pattern (Knowlton et al., 1996), suggesting that these two types of learning are not only dissociable at the psychological but also, at least partially, at the neural level.

Cesar et al. build on these findings to study automatic learning in the context of investment decisions (Cesar et al., 2012b). In their task, participants were asked to forecast this year's investment level for 200 offices of the same company, based on graphically presented information. They were shown 4 different panels each with one indicator, i.e. profit projections or cash earnings. What participants did not know was that only two of these indicators were relevant for solving the task and that their different combinations predicted the correct level of investment. To assess whether investors were paying attention to all or just a subset of the information, Cesar et al. added a twist. They combined 4 graphical indicators to reflect either realist (congruent) or impossible (incongruent) scenarios. The prediction was that if participants were processing the information as a whole, they would be sensitive to the manipulation. What they found was that in line with the results from the weather prediction task, participants became progressively better at solving the task, even though when later asked, most of them could not identify the "hidden rule". Interestingly, the authors showed that the congruency of the information only affected choice in the beginning of the session but not later on, consistent with the idea that the reliance on the information subset is learned over the session. Despite not affecting performance later on, congruency did affect how long subjects took to respond (they were slower in incongruent trials) and it modulated EEG signals. This pattern of results suggests that although they learned to only rely on a subset, participants still continued to process, at least to some extent, the entire set. Cesar et al.'s study is a good example of how tools and paradigms from neuroscience may be adapted and applied to examine behavioural accounting questions.

Another recent study employing EEG to measure brain activity while auditors and accountants assessed information to make judgements about "going concern" probability (Carvalho, 2012). What the author found was that although both groups behaved similarly, including being more sensitive to blocks with negative evidence, they had different EEG patterns, which may suggest the use of different strategies. The authors go further by trying to suggest how each group is deciding, claiming that accountants show "more cognitive effort" and existence of "conflict" (Carvalho 2012, e.g. p. 120-121). Unfortunately, the authors claim this not by directly testing their hypothesis but by inferring them from the differences in brain patterns, an example of reverse inference (see Section 4.1) that, in this particular case, is aggravated by other weakly supported assumptions. The author says that activity in the anterior cingulate cortex (ACC, see Appendix II) indicates the existence of "conflict" because previous studies have correlated activity in this area with conflict (e.g. Botvinick et al, 2004 for a review). This conclusion is in itself arguable, since ACC activity has also been correlated with other cognitive functions (Yarkoni et al., 2011), but more worrying is assuming activation of ACC based on data from an electrode located in the front of the brain that is capturing activity from numerous different brain areas. Despite the perhaps overly ambitious interpretation, Carvalho's study does show an interesting example of dissociations between behavioural outcome and underlying neural activity.

More recently, two different groups started applying functional magnetic resonance imaging (fMRI) technology to investigate accounting issues. Barton et al. (2014) used fMRI to explore how the brain processes earnings news. Their hypothesis was that announcements convey information to investors akin to reward and punishments (where reward is traditionally defined as an appetitive stimuli that reinforces behaviour and punishment defined as a negative, aversive stimuli that diminishes it).

Based on previous neuroscience studies showing that ventral striatal activity correlates with predictions errors (e.g. McClure, Berns & Montague, 2003), the authors hypothesised that earnings news would lead to ventral striatum activation. Specifically, they predicted that positive earnings (like reward prediction errors) would lead to increased activity in ventral striatum (see Appendix II) and negative would decrease it.

To test this hypothesis, they showed investors earnings per share disclosed by 60 publicly traded companies. Before imaging, subjects were asked to forecast each companies earnings (based on the historical earnings per share and on a forecast made by financial analysts). They were also asked to choose between a short and long equity position in its stock to then finally view the actual earnings of each company. Only in this final stage they were imaged. The authors showed that indeed earnings surprise led to changes in ventral striatum activity (the only region analysed), with an asymmetric effect for negative and positive surprise. In addition they showed that other variables such as investor personality traits, and firms earnings predictability modulated this response. They went further to analyse how ventral striatal activity related to market-level phenomena, showing a correlation between the magnitude of ventral striatal response and market-level measures such as stock returns and trading levels.

Farrel et al. (2014) also used fMRI and behavioural analysis but to explore a different question: how compensation plan design influences investment choices. Based on dual processing theories that classify processing into automatic (system 1) and deliberate (system 2), they aimed to examine the influence of contracts (performance-based incentive or fixed wage) on choice and brain activity in emotionally charged scenarios. More specifically, they wanted to investigate the influence of these factors (contract and emotion) on (putative) “system 1” and “system 2” processing.

To test this, they manipulated affect and contract type in a task that presented subjects with a series of investment decisions. Participants had to choose between two investment projects recommended by two different proposers: a familiar (previously associated with negative, positive or neutral descriptions) or unfamiliar. Importantly the experiment was designed in such a way that decisions based on affective reactions (positive or negative) would lead to less profitable decisions. From the behavioural data, they showed that the percentage of non-optimal choices was lower in the performance-based contract relative to fixed contract condition. They then looked for areas that were more active in the affective versus neutral context in each type of contract. They saw areas, previously suggested to be associated with “system 1” processing, active in both contract types, and some areas, putatively associated with "system 2", only in the performance-based contract. Based on this they claim that, first, affect induced "system 1 processing" and second, that in performance-based contracts, system 2 is additionally engaged to "at least partially override" system 1 (Farrel et al., 2014).

Besides the lack of explicit statistical comparison between the two contracts that would be needed to claim differences between those conditions, the interpretation is problematic. As the authors acknowledge briefly in the discussion, the mapping between System 1 and 2 modes of processing and different brain networks is premature: "(…) we use a System 1-System 2 framework as a way to connect dual process theories and neuroscience research. However, neuroscience is far from definitively establishing the functions of individual brain regions and how regions interact when performing particular tasks. As such, our use of the System 1–System 2 framework and our identification of relevant brain regions within them is an early step in bringing this work to accounting." (Farrel et al., 2014, p. 2005). Indeed, although dual-system theories may be a useful heuristics to think about different modes of processing, there is little evidence for a clear separation between the two, even less for dissociable neural substrates (Lempert & Phelps, 2014, Phelps et al., 2014). Thus, interpretations based on these weak mappings should be cautiously considered.

Indeed, even if we did accept that there were dissociable neural correlates for the two types of processing, we would still be left with the difficult task of inferring cognitive processes (type 1 or 2 processing) from brain activity – another example of reverse inference. For example, the authors use the fact that previous studies have shown that "the left inferior insula (…) is associated with negative emotions such as anger and disgust (…)" (Farrel et al., 2014, p. 1994), as evidence that participants (who show insula activation) are engaging in System 1 processing. Yet, this is not a valid conclusion since one third of all fMRI studies (including studies using different cognitive tasks) detect insula activation (Yarkoni et al., 2011).

4.2.3. Summary

Recent years have seen the appearance of a number of studies starting to incorporate neuroscience findings and its tools in the study of behavioural accounting issues. The field is still at a very early stage, and the initial studies, although important first steps, need to be carefully and critically considered, e.g. conclusions drawn from the use of reverse inference. Much more needs to be done until this type of work has real impact in accounting research. Nonetheless, as already discussed by several researchers (e.g. Birnberg and Ganguly, 2012) and hinted by this initial stream of studies, the interaction between neuroscience, psychology and behavioural accounting holds promisse in advancing our understand of these and other behavioural accounting questions

5. THE ROLE OF PRESENTATION FORMAT IN DECISION-MAKING

Previous sections reviewed the different approaches and the possibilities for interaction between neuroscience, psychology, economics and behavioural accounting. This section will review research from these fields pertinent to the study of the impact of format variables on the processing and use of financial accounting information. The focus here is in understanding the regularities of how humans acquire, process and weight information to make judgements and choices, irrespective of whether they translate into choice behaviours that are in line or deviate from what normative theories predict. Rather than a comprehensive list, we review those areas of research that seemed more relevant for this particular question.

Most of the research that will be presented is not directly addressing financial decision making or financial information itself, but is in line with the belief that by understanding the simple (e.g. decision-making in perceptual tasks), we will be better prepared to conceptualize and tackle the more complex (e.g. decisions based on financial accounting information). Furthermore, it highlights methodological approaches that can be adapted to financial accounting research.

5.1. Do the format and presentation of information matter?

5.1.1. Individual and market evidence

Standard economic theory assumes that "incidental" variables, that is, factors irrelevant to the decision outcomes, should have no influence on choice. Yet, a wealth of data suggests that humans are often influenced by such seemingly irrelevant factors making choices that are inconsistent or intransitive and that fail to maximise reward (Tversky and Kahneman, 1974, 1981).

A classic example is the framing effect in which small variations in how information is presented, or "framed", lead to dramatic differences in choice (Tversky and Kahneman, 1981). In their experiment, the authors asked subjects to choose between alternative disease-prevention strategies: in one scenario the options (a certain and a risky option) were presented in terms of live saved, in the other the same outcomes were presented in terms of lives lost. Despite the fact that the scenarios had equivalent outcomes, subjects overwhelmingly preferred the certain option in the "lives saved" (positive) frame and the risky option in the "lives lost" (negative) frame. This effect has since been shown to hold across a variety of different conditions.

These and similar results have clearly shown that even small differences in how information is presented, including changes in the order in which information is presented (Hogarth & Einhorff, 1992), the way in which it is described (Framing) or how it is organized ("chunking", e.g. Miller, 1956) can systematically influence judgement and choices.

These finding have important implications for financial accounting as they suggest that *how* accounting information is disclosed may have an impact on evaluations and trading decisions at an individual level and potentially even influence market outcomes.

Indeed, evidence has begun to emerge in behavioural finance suggesting that subtle differences in disclosure format can affect investors' evaluation and trading decisions (Koonce &

Mercer, 2005). For example, Cotter and Zimmer (2003) find that investors are more likely to positively value information about a firm's asset revaluation if the information is recognized in the main body of the financial statement rather than in footnotes (Cotter & Zimmer, 2003). Others have shown that whether the same information is placed in the income statement or statement of change in equity can have a systematic influence on analysts' forecasts (Hirst & Hopkins, 1998).

The order in which information is disclosed has also been found to systematically influence investors' judgements. For example, Tuttle, Cotter and Burton (1997) find that investors show a recency effect, a well described effect in psychology: people are more likely to recall and weight information that was displayed at end of a document or more recently presented (Hogarth & Einhorn, 1992).

Clearly understanding the underlying psychological and neural processes engaged in processing information and the factors that shape it can shed light into the underlying structure behind these behavioural effects. But is this of any use for understanding market level phenomena?

Proponents of the Efficient Market Hypothesis do not claim that individual decision makers cannot be biased, but rather that at the market level, these individual processing bias will be eliminated. Either by the action of sophisticated, rational traders who, by exploiting the inefficiencies created, will ensure that prices always revert back to their fundamental value - a phenomenon known as arbitrage (Friedman, 1953, as cited in Barbaris & Thaler, 2003), or because (random) inefficiencies will cancel out.

However, this has been called into question. First, emerging evidence suggests that real world arbitrate may in fact be limited (eg. Shleifer & Vishny, 1997; Barbaris & Thaler, 2003). Secondly, the fact that equivalent are observed in non-human animals (Chen et al., 2006, Kalenscher & van Wingerden, 2011) suggest that these biases may in fact reflect, at least in part, regularities in the processes and neural substrates that are strongly conserved across phylogeny.
Indeed, research in behavioural finance and accounting suggests that even experts are susceptible to judgement biases (e.g. Hirst & Hopkins, 1998, DeBondt and Thaler, 1985), and that biases seen at the individual level, including disclosure-related ones, can extend to market (e.g. Tuttle et al., 1997).

5.1.2. Summary and implications for financial reporting

There is growing evidence to suggest that small differences in information format can influence judgement and choice. This has strong implication for the design and regulation of financial accounting reports as it suggests that not only *what* but *how* information is disclosed can influence evaluation and trading decision. Further understanding these effects and optimally designing financial accounting reports will depend on clarifying both the psychological and neural processes behind them. The following sections attempt to review and discuss pertinent existent literature and highlight venues for future research.

5.2. How and why format affects processing and decision making?

We know from psychology and behavioural finance research that contrary to what standard economic theory suggests judgement and choices are not "description-invariant" (e.g. Kahneman & Tversky, 1981). Incidental variables such as the way a decision problem is described, the number of alternatives to be considered, among others, can profoundly affect choice. But this only tells us that decision makers do not meet normative assumptions, not how or why. To understand which variables drive these effects, we need to understand the underlying processes involved.

This section reviews what we know about the psychological and neural processes that support decision-making, and how they are influenced by variables related to the presentation of the information, including its visual presentation and computational requirements.

5.2.1. We don't see it all – the need for selection and its determinants

5.2.1.1. Selective attention – what is it and why we need it

Perception and cognition are capacity limited and thus we are, at any moment, limited in how much information we can acquire, process and use (Marois & Ivanoff, 2005). This limited processing capacity dictates a need for selection. Attention refers to the collection of processes by which the brain prioritizes and selects information according to their behavioural relevance (Marois & Ivanoff, 2005, Chun, Golomb & Turk-Browne, 2001). The primary goal of attention research is to understand which information is selected; how it is selected and what happens to both selected and unselected streams of information.

Multiple stimuli or options compete for selection and the goal of attention is to bias competition in favour of a target stimuli or event (see Desimone & Duncan, 1995 for a recent model). For example, in a cocktail party we may want to focus on a conversation with a friend and not on all other conversations and competing sounds. Selection has however a cost: unattended information may be missed, whether it is an important announcement in the cocktail party, a traffic light while driving and talking on the phone (Strayer & Johnson, 2001) or a gorilla passing right in front of our eyes while we focus on a challenging task (Simons & Chabris, 1999). Interestingly, this research has also shown that we are largely unaware of these costs, thinking that we "see" all that is around us when in fact we miss a large part of it (Simon & Chabris 1999).

Attention is not a unitary process (Chun et al., 2001) and one way researchers have used to classify it is based on the type of information over which it operates: whether a spatial location, an object or a feature. Spatial attention concerns how to prioritize spatial locations in the environment, it is central to vision and often compared to a "spotlight" that moves in the visual field (Cave and Bichot, 1999). It can be overt (linked to eye movements), or covert, where location is attended without being fixated (Juan et al., 2004).

Attention can also be directed to features or objects. Features are points in modality-specific dimensions such as colour, saltiness and temperature (Chun et al., 2001). The saliency of features, which is typically defined as the unusual or extreme values, e.g. a red flower in a green field, is, as we will see, a primary determinant in attention selection. Finally, attention can also be directed towards whole objects that may include several distinct features (O'Craven et al., 1999).

At the neural level, a number of neurophysiological and neuroimaging studies have shown that attention is reflected in an enhancement in the neural representation of task-relevant information. This occurs at the expense of competing and irrelevant stimuli, which are suppressed (Vuilleumier, 2005). For example, attention to specific features (e.g. colour) directly modulates and enhances the processing within feature-selective (e.g. color-related) brain areas (Reynolds & Chelazzi, 2004).

5.2.1.2. Attention control – How is attention allocated?

There are two modes of attention control that determine which aspects of the available information gets prioritized: a goal-directed, by which attention is voluntarily driven by knowledge, expectations and current goals (eg. searching for the car key), and a stimulus-driven mode, in which attention is automatically captured by salient features or events in the environment (e.g. orienting to a sudden noise) (Chun et al., 2001).

Both modes of attention are pervasive in our everyday life and it is the interaction between them that determines, at any given moment, where, how and what we attend to. Each mode has its benefits and costs: voluntary attentional control is goal specific but relatively slower to implement. By contrast, involuntary attentional capture can be very rapid and adaptive in many situations i.e. rapid orienting towards threatening stimuli, but can also lead to distraction and maladaptive behaviour (Chun et al., 2001).

These two control modes can be studied in the lab using different paradigms. To capture attention in a stimulus-driven way, one can use a cue such as a flashing light, at the same location of a target. This cue will draw attention to that location, facilitating the detection of targets presented in that position and slowing down detection of targets at other locations.

To study goal-directed attention, researchers usually use a symbolic cue such as an arrow or a left/right word, that is presented at the centre of the screen and that informs, in advance, the participants about where the target will most probably appear. Cueing in this manner typically facilitates the subsequent detection of the target (Chun et al., 2001).

5.2.1.3. What features of the input capture attention?

The fact that attention can be stimulus-driven, that is, controlled by features of the visual display, independent of our say, means that salient items even if task-irrelevant will be prioritized over, and divert processing capacity from, less salient potentially important items. One key question is what determines the ability of a stimulus, event or information, to automatically attract or bias attention.

5.2.1.3.1. Perceptual saliency

The primary determinant is perceptual saliency, that is, unexpected or extreme values. For example, we will automatically and effortlessly detect a red flower in a green field – a phenomenon referred to as “pop out” (Treisman & Gelade, 1980)

5.2.1.3.2. Emotional ‘saliency’ of the stimuli

Emotional stimuli are also effective attractors of attention, capturing it often in a reflexive and involuntary manner (Vuillumier, 2005). A famous example is the easiness with which we detect our name, even if it comes up in a conversation we were not attending to.

Evidence for the importance of emotional saliency comes from visuals search paradigms, in which emotion-laded stimuli such as an angry or happy face (e.g. Fox, 2002) or a snake among flowers (e.g. Ohman et al., 2001) are found to be more rapidly detected than a neutral stimulus. In spatial orienting task, targets are detected faster if they appear on the same side as an emotional cue, e.g. threat word or a shape previously associated with a fearful stimulus (Vuilleumier, 2005).

Emotions can even influence sampling and detection without our awareness. Evidence for this comes from variety of subliminal paradigms such as the visual background masking, in which briefly presented targets can be made invisible if immediately followed by a second masking stimulus. If what is “hidden” is an emotional stimulus, subjects will show changes in physiological measures such as skin conductance response, even if the target is not consciously detected (Dolan, 2002).

We are now beginning to understand some of the neural mechanisms involved in this phenomenon. Electrophysiological studies show rapid and widespread neuronal responses to emotional stimulus that precedes responses associated with actual stimulus identification (Dolan, 2002). The amygdala – a small, almond shaped nucleus in the medial temporal lobe (see Appendix II) - seems to be an important mediator of emotional influences on perception. This area is known to be crucial for fear processing and learning but also for a wider range of functions related to the affective significant of stimulus and reflexive emotional reactions. Visual information is thought to reach the amygdala in two ways: through a slow, cortical, route that sends fully processed information (the standard visual pathway) and a fast, subcortical, route that sends very coarse, but rapid, visual inputs to allow for early detection prior to full perceptual processing (Romanski & LeDoux, 1992, Phelps, 2006). For example, a stick that looks like a snake would trigger a rapid “flight or fight” response through the fast route. Once the stimulus was recognized as a harmless wood stick by the slow route, the response would be terminated.

Consistent with amygdala playing an important role, a study using fMRI and visual backwards masking found amygdala responses that can discriminate between unseen emotional and unseen non-emotional targets (Morris et al., 1998).

The power of emotional stimuli can be adaptive in many circumstances (e.g. detecting danger) but can also be maladaptive when task-irrelevant, biasing attention away from current goals.

5.2.1.3.3. Learned value

Simuli can capture attention by their intrinsic physical properties or intrinsic (possibly innate) value, but also through their acquired importance. Previously neutral, irrelevant stimuli can, through association with biologically relevant outcomes such as reward and punishment, become powerful attractors of attention. These associations are learned and can automatically bias attention, even when they are irrelevant to the current goal.

This value-based mechanisms of attention capture may be useful for rapidly detecting potential rewards in complex natural scenes but can also introduce suboptimal biases by prioritizing desirable over accurate information (Gottlieb et al., 2014). Such learned effects have been suggested to underlie the "optimistic bias" observed in risky decision making, leading to underestimation of unpleasant information (Sharot, 2011). A brain area called anterior cingulate cortex, located in the most frontal and medial part of the brain, appears to play an important role in this phenomenon (Sharot, 2011).

5.2.1.4. What determines the amount of processing of attended and non-attended information?

5.2.1.4.1. Perceptual load

For years, psychologist debated whether the "bottleneck" of attention was at earlier perceptual levels or later in processing, with empirical data to support each of the views. Recently, based on findings from an attention task in which a visual stimulus (the target) needs to be detected from among other stimulus (distractors), Lavie et al. (2004) have proposed a theory that reconciles the two views. The basic idea is that the amount of processing that unattended stimuli receive depends on how difficult it is to process the attended target. If detecting the target is easy, e.g. it is very different from the distractors, then there will be attentional resources left to process unattended stimuli and they will impact behavioural performance (Lavie, 2005). If the detection is very difficult, e.g. there are many distractors, then all resources will be devoted to the target, and the unattended items will be filtered out early in processing. This is seen in the brain as an attenuation of neural responses in the brain areas that process the distractors and an enhancement of target-related neural activity (e.g. Chen et al., 2008).

Other stimulus manipulations, collectively referred to as perceptual load manipulations, include decreasing the quality of the stimulus, increasing the number of distractions, increasing the similarity between targets and distractions or define the target as conjunctions (e.g. red square) instead of a single features (e.g. a red shape) (Lavie et al., 2004, Lavie, 2005).

5.2.1.4.2. Cognitive load

The amount of information processing does not only depend on the perceptual load but also on the amount of cognitive resources available for processing (referred as "cognitive load"). For instance, if the subject is required to hold in memory or carry a calculation while simultaneously performing the detection task, he will become slower at detecting the target (Lavie, 2005).

This happens because attention allocation depends on certain cognitive processes to actively maintain stimulus-processing priorities throughout performance of the task. Any manipulation that loads these control processes (e.g. loading working memory) will results in a “loss of control” over the focus of attention, leading to increased task-irrelevant processing (Chun et al., 2011).

The cognitive control processes can be seen as just another attentional process that rather than selecting externally-originated input, selects and coordinates processing among different internal representations including representations from working memory or long term memory, task rules, decisions and responses (Chun et al., 2011, Miller & Cohen, 2001).

Perceptual or ‘external’ attention and cognitive control or ‘internal attention’ share partially overlapping fronto-parietal networks but with some differences (Chen et al., 2011, Nobre et al, 2004). Esterman and colleagues compared brain activity associated with switching spatial attention (external), switching task set (internal) and switching along memory representation (internal). They found that a region of superior parietal cortex was involve in all types of switching, but that they could train multivariate classifiers to differentiate between the patterns evoked by spatial attention versus cognitive control (Esterman et al., 2009).

Cognitive load manipulations include increasing the number of items that must be maintained in working memory or performing other executive functions such as task switching (Lavie et al., 2004).

Working memory is at the interface between ‘external’ attention and cognitive control. It enables the maintenance and manipulation of information in the absence of sensory support (D’Esposito et al., 1995) and is thus required for short-term memory and for manipulation of both thought and memory. Working memory is an essential to most daily activities from holding in mind a phone number to complex mental arithmetic.

Research on working memory has been trying to quantify its limits. For visual material, we appear to hold, on average, only 4 items (Luck & Vogel, 1997, Buschman et al., 2011). For verbal material, we have capacity of about seven ’chunks’ (Miller, 1956) and its effectiveness depends on the phonetic characteristics of the acoustic input (e.g. words) being rehearsed (Baddeley, 1992). When performed simultaneously, working memory tasks can disrupt simple spatial orienting (Dell’Acqua et al., 2006) and visual search (Han & Kim, 2004). The interaction is bidirectional: working memory contents can influence “external” attention but “external” attention can also influence what gets maintained in working memory (Chun et al., 2011). The most common way to manipulate working memory specifically is to increase the number of items that needs to be maintained “online” in memory.

At the brain level, working memory maintenance appears to rely on signals from the prefrontal cortex that modulate processing in relevant sensory cortex and suppresses irrelevant information (Miller & Cohen, 2001), although there is still debate.

5.2.1.5. Summary and implications for financial reporting

The findings reviewed highlight the importance of considering the level and type of load involved in any task. Simply instructing people to focus attention on a certain aspect of information is not sufficient to guarantee processing (Lavie, 2005).

Applied to financial reports, these findings suggest that efficient processing of goal-relevant information will depend on the characteristics of the report itself (e.g. how much information is present, how salient it appears, if information is explicitly signalled as important, whether calculations are required), but also on whether cognitive resources are being "taken up" by concurrent processing (e.g. sampling information while simultaneously manipulating information in working memory). Future research should directly test these ideas, adapting these simple paradigms for stimuli more close to financial information. In these conditions loading cognitive resources, i.e. loading working memory, should result in less efficient information sampling, potentially making decision makers more prone to "incidental", task-irrelevant factors.

5.2.2. Computational costs as a determinant of decision strategy

Standard economic theories see the agent as maximizing some utility function. Some models consider factors such as the delay or the uncertainty of the outcomes, but always under the assumption that the agent is capable of and wants to perform all the computational steps required for these estimations.

Behavioural research has shown repeatedly that humans deviate from the predictions of these normative theories, and based on this data, many researchers have suggested a number of non-normative "heuristic" rules that decision makers may be using. However, so far it has not been clear what are the factors that determine whether a certain decision rule is used over the other. If a certain optimal strategy is simply not computationally possible given our brains, it is easy to see why we would not use it, but even then, how do we choose between the possible alternatives? In many situations it is not even clear whether people are not capable of solving a problem optimally or whether they simply chose not to (e.g. in situations where people are able to later correct their answers). One possibility is that agents are trading off different costs and benefits, but many of which are not considered in classical economical models i.e. emotional factors and cognitive, or mental, effort.

5.2.2.1. Cognitive effort discounting

Cognitive load does not only influence what information gets sampled and processed, but it can also affect how a decision problem is approached. The amount of cognitive effort required to solve a particular problem appears to be experienced as subjectively costly, and discounted in the selection of the decision rule or strategies.

An influential idea has been that decision makers select a decision strategy by trading off the effort costs and the accuracy benefits of different computational demanding strategies (e.g. Payne, Bettman, & Johnson, 1988, Shah & Oppenheimer, 2008, Kool et al, 2010).

In certain circumstances, optimal strategies may be computationally intractable, and thus not feasible, as Simon (Simon, 1955) pointed out when proposing the concept of Bounded rationality. Even when multiple strategies are available, decision makers do not necessarily employ the "normative" one, but rather compare the various options using a cost-benefit analysis, in which cognitive demands are incorporated as a cost (Kool et al. 2010, Botvinick & Braver, 2015).

The idea of cognitive or mental effort as a "cost", that is avoided or minimized in the context of decision-making, is long lived in psychology. A wide range of observations in psychology, behavioural economics and consumer research have been discussed in terms of effort-avoidance (eg. Tversky & Kahneman, 1974, Payne et al., 1988, Monsel, 2003). A number of processing models have also explicitly incorporated a principle of "least effort", referring to the demands of automatic versus controlled information processing (Gray, 2000). Yet until recently, it had not been directly tested.

Kool and colleagues were one of the first to do it (Kool et al., 2010). They conducted a series of experiments in which participants could select between strategies that differed in the amount of cognitive demand. Across a variety of tasks, they found that decisions makers have a systematic bias towards the less demanding strategy and that this result cannot be explained by a desire to simply minimize the time spent on the task or increase the reward rate received. One of the experiments they performed is particularly interesting for the present discussion. Building on previous evidence that "carrying" digits increases computational complexity of a mathematic problem, and that it places demands specifically on working memory control processes (e.g. "hold on" the digit, manipulate the information, etc.), the authors designed a task where participants could choose to solve one of two possible 2-digit mathematical problems. One that required carrying a digit and other that did not. Consistent with the idea of cognitive demands avoidance, they found that people systematically avoided the strategy that involved carrying a digit, in favour of a less demanding option (Kool et al., 2010).

A number of studies have begun to uncover the neural basis of how such control costs are registered and to identify which decision processes are sensitive to them. The anterior cingulate cortex (ACC) is thought to be a central area for physical effort-based decision-making. Rats with ACC lesions show decreased willingness to engage in physical work to earn reward (Walton et al. 2006). In addition some neurons in this area have been shown to code physical effort during an effort-based decision-making. Projections of the dopaminergic system, a chemical messenger in the brain, to an area called the ventral striatum and to the ACC also appear to be involved, with dopamine blockage leading to reduced willingness to engage in effort based decisions.

Initial studies on cognitive effort have shown that its underlying circuitry partially overlaps with that of physical effort, but with some distinctions (Botvinick & Braver, 2015). Botvinick, Huffstetler and McGuire (2009) performed one of the first studies focusing on the neural signals that reflect cognitive control costs. In their experiment, participants performed various cognitive tasks to earn money. They found increasing ventral striatum activity at the time of reward delivery.

Critically, the response strength was modulated by the degree of cognitive effort that was required to obtain the reward. Specifically, reward responses were reduced when a high degree of mental effort was required by the task, consistent with the idea of cognitive effort discounting, in which the subject value of rewards are decremented by the cost in effort required to attain it (Botvinick et al., 2009).

Consistent with this, Kool et al. (2013) showed that ventral striatal reward responses correlated negatively with the degree of activity in both the ACC and the dorsal prefrontal cortex during performance on a foregoing cognitive task, in which participants can choose between completing a currently presented task or forgo it and advance to the next trial (where they will be presented with a different task). Botvinick and colleagues have also shown that a manipulation of task switching demand influences activity in the nucleus accumbens (part of the ventral striatum) in response to reward (Botvinick et al., 2009). Specifically, rewards appeared to be discounted by the associated cognitive effort with responses in the nucleus accumbens being lower for higher levels of cognitive demands.

Other studies have linked ACC and dPFC activity in driving cognitive effort avoidance. Magno et al. (2006) presented subjects with a series of search arrays that were attention demanding: for each array, participants could choice between identifying the presence or absence of a target OR to skip (forgo) that trial. Activity in both areas, measured with fMRI, was higher on trials in which subjects chose to forgo. Interestingly, the degree to which performance of a cognitively demanding task engaged these regions, was shown to predict the extent to which the task would be later avoided (McGuire & Botvinick, 2010).

Finally, it has been shown that participants show elevated skin conductance responses just before selecting a high demand alternative (Botvinick & Rosen, 2009). This may reflect anticipatory avoidance mechanisms in response to effort requirements.

An open question is the origin of these cognitive costs. One possibility is that it may arise from the consumption of resources throughout the brain, for example, from the use of a resource pool (Reichle et al, 2000). Alternatively, costs may be specifically related to the engagement of control processes (Miller & Cohen, 2001). According to this view, costs should originate in brain regions that are consistently engaged in situations where control is required. Two main regions identified in such situations are the PFC and the ACC (Duncan & Owen, 2000).

5.2.2.2. Summary and implications for financial reporting

Contrarily to what was traditionally assumed in economic theories, computational demands are an important factor is how the decision makers will solve a decision problem. In the context of financial reporting this suggests that different financial accounting reporters may encourage the use of different decision-making strategies. Until recently, the literature presented a somewhat binary view as either do it "optimally" or "non-optimally", but there is continuous spectrum of decision strategies that can be used and understanding the factors that impact their selection is crucial if we want to have a handle on how different forms of input (e.g. formats of financial information) impact decision processes and its output (e.g. judgements or choices).

The research reviewed in this section shows that cognitive effort is one of these factors influencing which decision strategy is used. This suggests that to encourage the use of a particular strategy (more or less close to what is considered optimal) and/or a consistent strategy across different situations (e.g. evaluating reports from different companies), then we ought to pay attention to the cognitive demands that our format imposes (e.g. whether it requires "carrying" a digit, holding information "online"). Unfortunately our knowledge of the specific features of a task or report that make it more or less demanding is still scares. More research is needed to identify the features of the input or tasks translate into cognitive (i.e. memory, attention, representation) demands.

5.2.3. Context dependent coding as a possible mechanism for presentation effects

We have been discussing how display or presentation variables may influence decision processes and ultimately judgements and choice. These are all examples of "incidental" variables that according to traditional economic theories should have no influence on decisions. Yet, research shows that they clearly play an important role. The most well studied example of these presentation or, more generally, context dependencies is the framing effect. In this section, we review research on the neurobiological mechanisms and computations that may underlie these effects. This is aimed not by any means as an explanation of all the presentation effects presented so far, but rather as an example of how behavioural, computational and neuroscientific disciplines can work together to better understand behavioural phenomena that would appear puzzling and inexplicable in the eyes of traditional economic models.

Changing simple presentation variables such as the description of prospects can robustly affect choice. Prospect theory (Tversky & Kahneman, 1979) explained these and other pattern of results by introducing a reference point, whereby decision makers view gains and losses in relative manner (against normative model assumption that the value of options are evaluated in an absolute manner, independent of other alternatives). Although it has some explanatory power, the nature of the reference point is still under dispute (Louie & DeMartino, 2014). On-going research is beginning to outline the different brain regions that mediate these shifts and is starting to clarify neurobiological mechanisms that may underlie it.

De Martino et al. (2006) examined the neural computations associated with the framing effect, using a subtle framing manipulation. Participants were told at the beginning of each trial that they had been given a certain amount of money ("You received 50 pounds") and asked to choose between a safe option, e.g. a certain 20 pounds, or a gamble matched in expected value, e.g. 40% probability of receiving 50 pounds and 60% of receiving zero). The critical manipulation was in the wording of the safe option: in half of the trials the safe option was presented in a gain frame by using the word "keep 20 pounds", while in the other trials it was presented in a "loss" frame using the word lose (“lose 30pounds”). This simple manipulation elicited a robust framing effect with participants consistently preferring the safe option in the gain frame (57.1% trials) but not the loss frame (38.4%). Using fMRI, they found that the asymmetric choice pattern was associated with changes in amygdala activity: increasing when subjects chose the safe option in the positive context, but decreasing in the negative frame.

One possibility that has been suggested for this pattern of results is that the amygdala updates the value of the safe option under the different contexts (Morrison et al., 2010). More specifically it may code an ’innate’ reflexive approach-avoidance signal depending on the frame, biasing subjects choice. Consistent with this idea, Guitart-Masip et al. (2010) showed that using aversive and appetitive conditioned stimuli could induce similar behavioural and neural patterns. Interestingly, subjects showed significant inter-subject variability in how susceptible they were to framing and this variability was correlated with activity in the medial orbitofrontal cortex (OFC), suggesting that perhaps OFC exerts control over the magnitude of framing, allowing individuals to make more consistent and less contextual dependent choices (De Martino et al., 2006) perhaps by modulation of the amygdala (Louie & De Martino, 2014).

5.2.3.1. What is the origin of these contextual dependencies?

A growing body of neuroscience evidence points to a possible mechanism that could be at the source of these behavioural effects.

Unlike behaviourally inferred quantities such as utility, neural activity is constrained in both their minimal and maximal levels. To ensure efficient coding across a wide range of stimulus parameters, neural system use compensatory algorithms such as divisive normalization by which the response of neurons are divided by the summed activity of a pool of its neighbours. This ensures that neurons adjust their dynamic range to continue to efficiently code the input despite scale changes. These transformations produce an intrinsic relative, context dependent coding. These neurobiological constraints may be at the source of many cases of context-dependency in valuation.

It is widely believed that neuronal firing rate (average activity) is a primary information carrier in neural activity. The relation between the input variable and the resulting spiking activity can be represented as an input-output function (Louie & De Martino, 2014). Importantly, there are two fundamental limitations in this response function. First, firing rates are non-negative and thus cannot represent parameters below a certain level, and second, neurons are functionally constrained to a maximum rate of firing. This is because neurons need to recover for a minimum period of time before another electrical pulse can be transmitted (the refractory period). These constraints impose limitations on the dynamic range over which neurons can represent the inputs that they receive.

One way to optimize their processing capacity is to adjust the dynamic range to match the distribution of inputs. According to the Efficient Coding hypothesis, sensory systems adjust their response to the regularities of their inputs (Barlow, 1961, as cited in Louie & De Martino, 2014), so that if the input changes, the input-output function of the coding neuron adapts. These adjustments in neural code, referred as gain control mechanisms, are widely implemented in the sensory system and have important consequences for perception and behaviour. One everyday example is our ability to see constant relative brightness even when faced with widely different levels of ambient illuminations (Louie & De Martino, 2014).

Recent studies have shown that these gain control mechanisms are not limited to sensory systems but extend to higher order brain areas such as motor, parietal and orbitofrontal areas that have been implicated in decision-making (Louie & Glimcher, 2012). For example, in the parietal cortex, the activity of neurons associated with a particular action is strongly influences by its value (e.g. Sugrue et al. 2004). More importantly, this value representation is not absolute but relative: the activity of the neuron increase with increases in value of the represented action but decrease with the increase in value of alternative actions (e.g. Louie et al. 2011, Louie & Glimcher, 2012 for a review). By making the neural representation of the value of one option dependent on the value of the other options, this normalization introduces an intrinsic context dependency.

The question is then whether this mechanism is causal in affecting behaviour. One recent study points in this direction. Louie et al (2013) developed a choice model derived directly from neurophysiological data of value normalization that predicted significant context-dependent effects in stimulations, driven either by the value or number of alternative options. They then tested human and monkey behaviour under conditions in which the model specifically predicted context-driven distortions of choice and found reliable results in both species, consistent with normalization.

5.2.3.2 Summary and implications for financial reporting

Understanding the neural mechanism that generate reference, context dependent choice will not only tell us more about the behavioural phenomena, but also allows us to link possible disparate behavioural phenomena that arise from a single underlying neural mechanism and distinguish separate ones that appear similar at the behavioural level but originate from different computational processes (Louie & De Martino, 2014).

This is only one example, focused on reference dependence in decision-making, which is relevant to content framing in financial accounting reporting, but more generally, it serves as a model approach of how similar questions can be tackled. It touches several important ideas: first, that by understanding the constraints and computational principles at the level of neural coding (e.g. maximal and non-negative firing rates, adaptations to maintain useful dynamic ranges, among others) one can help refine psychological level theories to be more biologically plausible. Second, that understanding the neural computations behind behavioural effects can help us arrive at a more meaningful classification of behavioural phenomena based on its origins (i.e. whether they share the same computational processes or not), and third, insight into mechanism can helps us better predict how different manipulations at the level of the input will impact the output behaviour.

5.2.4. Beyond the information per se – the importance of emotional factors

So far the focus has been on the presentation of information itself, but information is not in a vacuum. It is acquired by a decision-maker in a particular internal state. Some emotional influences on attentional process were already reviewed in previous sections. In this section, the focus is not on emotion-laden information, but on emotional states of the decision-maker himself that may also influence how information is processed and used.

The hope is that by understanding how various affective variables impact processing, we can both better explain and predict decisions outcomes in financial contexts, but also devise strategies that will help people process information as efficiently as possible. Researchers still lack a single, widely accepted, definition of emotion, but most would agree that it is not a unitary construct and that it compromises various different components including autonomic responses (e.g. changed in heart rate), behavioural changes (e.g. tendency to approach or avoid) and cognitive changes (e.g. cognitive interpretation of these changes, subjective feeling) (Lempert & Phelps, 2014). In its more strict definition, emotion is used to describe a set of discrete reaction to an internal or external event, in contrast to the terms mood or stress that may be relatively longlasting and may not be tied to particular events. But while mood is mainly defined by subjective feelings, stress is characterized by specific physiological and neuro-hormonal changes (Lempert & Phelps, 2014). Usually the term "affect" is used as an umbrella term for these various processes (Lempert & Phelps, 2014).

Affective research has distinguished two main ways in which affect can impact decision making, depending on whether those emotions are related (elicited by the choice options themselves) or unrelated to choice (a more general affective state).

5.2.4.1. Incidental affect

Incidental affect refers to a baseline affective state that is unrelated to the decision at hand but can nevertheless affect choice (Lempert & Phelps, 2014). Perhaps the most well studied example is stress. A growing body of research shows that stress can have a profound impact on decision-making. Most psychology research in this area has focused on inducing stress using a variety of laboratory stressors, e.g. immersion of arm in icy water or social competition, and assessing its impact on judgement and choice. One of the first of such studies (Porcelli & Delgado, 2009) examined the impact of stress on the reflection bias: people's tendency to show risk seeking in the loss domain and risk aversion in the gain domain (Kahneman and Tversky, 1979). They showed that exposure to a physical stressor exaggerated this tendency, demonstrating that stress can impact choice even when the stressor is unrelated to the problem at hand.

Neuroscience research has focused on how stress may influence brain structure and function. Stress typically results in a "stress response" that includes physiological arousal (e.g.

increased heart rate), glucocorticoid release and rating of negative affect (Phelps et al., 2014). These changes have been shown to functionally impact a number of brain systems, including the prefrontal cortex, the amygdala and dopaminergic (dopamine is a brain chemical messenger) transmission in the striatum (Phelps et al., 2014).

Porcelli & Delgado's results and other similar findings (Starcke & Brand, 2012) have been interpreted as reflecting an increase in more automatic or habitual decision-making (as opposed to more deliberate, goal-directed), possibly by affecting "top-down" control by areas such as the prefrontal cortex (PFC). However, there is no direct evidence of diminished PFC involvement in any of the human behavioural tasks reviewed. There is one relevant study examining the impact of stress on goal-directed action in rodents that indeed found evidence for stress-induced changes in both PFC and striatum (Dias Ferreira et al., 2009). Dias Ferreira et al. (2009) examined how chronic stress influenced expression of goal directed vs. habitual actions in a task where the value of the outcome was manipulated. These so called "devaluations tasks" are a commonly used measure to distinguish habitual responses, which are not sensitive to value changes, from goal-directed ones, which will change depending on the value of the outcome. Rats that were not stressed modified their response rate after the devaluation manipulation to reflect the devaluated reward outcome. By contrast, chronically stressed rats failed to adjust their responses in light of the devaluation, consistent with responses being habitual. Stressed rats also showed neuronal atrophy of the medial PFC and associative (dorsal medial) striatum coupled with hypertrophy of sensorimotor (dorsal lateral) striatum. These results suggest that stress may influence decision making by both impairing PFC function and enhancing habit related circuits.

In summary, stress, even if unrelated to the decision, can impact decision-making. Based on the evidence reviewed, stress appears to bias decision-making towards more habitual responding over goal-directed, perhaps through its influence over prefrontal cortex, striatum and/or the dopaminergic system. However, the evidence in human is still scares, and further research will be needed to confirm this.

5.2.4.2. Decision-related affect

Beyond incidental factors, choice options themselves may elicit emotional reactions, which in turn may influence decision processes (Lempert & Phelps, 2014). One way that this has been studied in the laboratory is by correlating emotional physiological changes (e.g. skin conductance response, SCR) and choices. The SCR is an objective, transient indicatior of autonomic nervous system arousal in response to a stimulus and it is a common measure of emotional arousal.

One of the first studies to measure SCR during decision-making was Bechara and colleagues (1997, 1999) using a risky decision-making paradigm called Iowa gambling task (IGT). In this task, participants are presented with four decks of cards: two that give small gains and losses (safe decks) and two that give larger gains but occasionally large losses (risky decks). They are then asked to select cards sequentially from the different decks to win as much money possible. Over time, healthy participants began to show anticipatory SCR before selecting from the risky deck and shortly after they began to preferentially choose the safe over the risky deck. By contrast, patients with OFC damaged, neither generated these anticipatory responses nor did they avoid the risky deck. Based on these findings, Bechara, Damásio and colleagues put forward the somatic marker hypothesis (Damasio, 1994) suggesting that the anticipatory arousal response is a bodily signal of the value of the choice and that this signal serves to guide participants away from risky choices. Since OFC patients cannot generate these emotional responses, Bechara hypothesized that they also could not change their choices.

Over the years several studies have challenged some of the assumptions in this hypothesis (Maia & McClelland, 2004, Fellows & Farah, 2005). Nevertheless, this study remains one of the first to link emotional response and brain systems to behavioural choice patters and has been crucial in pushing forward the study of emotions in the context of decision-making.

Other studies have looked at how emotional arousal to losses and gains is linked to choice. Sokol-Hessner et al. (2009) tested participants in a gambling task in which they had to choose between a certain outcome and a gamble with 50/50 changes of winning or losing money. With this design, they were able to quantify loss aversion and risk sensitivity independently for each subject. They found that higher SCRs to losses versus gains were linked to greater loss aversion, but did not find a relationship between arousal and risk. Follow up studies showed that greater amygdala response to monetary losses (relative to gains) also correlated with loss aversion. These results are consistent with another study that demonstrated that patient with amygdala damage were less loss-averse overall compared to healthy controls (DeMartino et al. 2010). This series of studies offer strong evidence that the amygdala is important in mediating aversion to losses but is not linked to risk tendencies, showing that neural mechanisms can help dissociate different psychological constructs. Using other decision tasks, e.g. pay-to-play games similar to slot machines, other studies have shown that emotional responses, including pleasantness ratings, SCR and cardiovascular measures, to wins and near misses are good predictors of gambling propensity (Lole et al., 2011, Clark et al., 2012).

In summary, these studies show that autonomic measures of arousal correlate with different components of decision tasks and that different brain regions linked to arousal (ventromedial PFC, insula, amygdala) may mediate this relationship.

5.2.4.3. Emotion regulation strategies

Our emotional reactions are determined in part by how we interpret a particular situation or event (Scherer, 2005, Phelps et al., 2014). The ability of shifting emotions by actively changing one’s interpretation of an event is known as reappraisal and can be taught. In a typical reappraisal experiment, the participant is asked to think about the stimulus in a different way in order to reduce its negative emotional consequences (Phelps et al., 2014).

Research on cognitive regulation has shown that reappraisal can alter both arousal measures and choices. In Sokol-Hessner et al. (2009) participants were instructed to reappraise the significance of the choice they were considering by thinking of it as only one in many or to "think like a trader" building a portfolio. The use of this strategy led to a reduction in skin conductance response and this reduction correlated with diminished loss aversion. Interestingly, it had no effect on risk sensitivity (Sokol-Hessner et al., 2009). In a different study, involving intertemporal choice, reframing the interpretation of a future reward resulted in more patience (Benoit et al., 2011).

Cognitive regulation techniques are powerful tools that can be quickly acquired, but they require active effort and practice. With further practice, these may become more automatic and less deliberate. As suggested by Phelps et al. (2014), this may be why novice stock traders have been reported to show more physiological arousal to volatility in the stock market, a result attributed to loss aversion, when compared to more senior traders, who show less arousal and better choices (Lo & Repin, 2002).

The studies described above provides not only a strategy for shaping choice but also strong evidence for the role of emotions in decision-making, demonstranting that by changing emotions, one can also change choice.

5.2.4.4. Summary and implications for financial reporting

Decision-making arises from a collection of complex processes that are influenced by a variety of factors including emotional ones. The research reviewed in this section adds to a large stream of evidence suggesting that contrary to the traditional idea that emotions and reason are competing forces (e.g. Cohen, 2005), emotions are an intrinsic part of adaptive decision-making. As we have just seen, emotion can influence cognition (e.g. value estimations); and cognition (e.g. reappraisal) in turn can influence emotional reactions. Furthermore, contrary to a dual-system view (emotion vs. cognition), there is no evidence for a clear separation of brain areas involved in cognition versus emotion and no evidence for a unitary "emotional" system (Lempert & Phelps, 2014, Phelps et al., 2014). Based on this, various neuroscientists have proposed the replacement of the dual-system view with a more complex, but more realistic, framework in which emotions modulate, rather than compete with, cognitive function, through multiple neural circuits.

Financial decision-making involves among other things, balancing a variety of emotional aspects, estimating risk and computing value signals (Bossaerts, 2009). In previous section, we explored the role of emotional cues in shaping attention and information sampling. The research reviewed in this section shows that emotional reactions elicited by choice options themselves, as well as incidental states such as stress, can directly influence choice. Thus highlighting the importance of considering emotional factors when studying financial decision-making. Furthermore, to the extent that emotions affect choice, we should be able to change choice by changing emotion. Research on emotional regulation has shown the efficacy of techniques such as reappraisal to shape choice. Future work should expand this research to financial accounting contexts. This will provide not only better understanding and predictive power in financial accounting settings, but also help researchers and regulators devise strategies that help people process information as efficiently as possible.

6. SYNTHESIS AND CONCLUSIONS

Economics has traditionally studied decision making by asking what people “ought to do”. While this has been a fruitful approach, research has now robustly shown that decision makers systematically deviate from these normative standards. A rich and complete understanding of humans actually decide will require the integration of insights and tools from multiple disciplines including economics, psychology, computer science and neuroscience.

6.1. Towards a multidisciplinary approach

Behavioural accounting researchers have begun to show interest in applying a multidisciplinary approach to the study of accounting problems. From that interest a new subfield has emerged, called neuroaccounting. Although there is work emerging, this is still a very young field. Having good quality data and interpretation will require further cross talk between fields. Although integration is the goal, the fast advances in both ideas and methodology in the different fields require specialization, thus high quality multidisciplinary work will depend on bringing different researchers with specialized or integrative training together in the pursuit of the same question. Physical proximity can ease this integration. The “Institute for the Interdisciplinary Study of Decision Making” at New York University has been a pioneer and successful case of this belief. It will also depend on making information available between the fields, attracting interest from the different researchers and funding agencies and building a common lexicon that can support an efficient interaction. Interdisciplinary reviews such as this one, meetings and other encounters can help on this.

In this paper, besides reviewing the various approaches and techniques that have been used to study decision making and look at work emerging in the young field of neuroaccounting, we aimed to encourage the application of this interdisciplinary approach focusing on a particular question of interest: the importance of presentation variables in financial accounting reporting. We believe that attracting interest from the various parts including funding will depend on spelling out how the different parts can contribute to answering specific problems, what can be achieving and importantly, also what currently cannot. The gaps between fields and lack of interaction can also lead to unrealistic expectation and over interpretation of what, for example, certain neuroscientific tools alone can give us, i.e. over interpreting functional MRI data, that in the long run will lead to disappointment rather than fruitful work and will repel rather than attract future researchers. Exploiting the potential of this interdisciplinary will depend on a clear understanding of the advantages and disadvantages of the techniques used to guarantee appropriate experimental designs and justified conclusions. Importantly, no technique is enough on its own, knowledge will come from the convergence of evidence from different techniques and different paradigms.

6.2. The role of information format – current findings and future directions

As reviewed in section 5 there is mounting evidence for a role of presentation both from the field of psychology and more recently from behavioural accounting itself. This research shows that variables such as the order in which information is presented, where it is located, among other factors can have a profound impact on evaluation and choice. One of the reasons that has led to resistance in taking up this idea is the belief by some, and following efficient market theories, that individual biases reflect idiosyncratic behaviour and are thus not relevant for market level phenomena. However, research in the behavioural subfields of economics, finance and accounting has accumulated evidence that many of these deviations from normative standards are not random but systematic and seem to reflect regularities in the way we process information and decide.

In this review, we aimed to bring together findings and methodologies from behavioural, different disciplines that may be pertinent to answer this question and foster future collaborative work. From this research review, emerge the following ideas:

- Contrarily to our common belief, at any moment, we can pay attention to only a small part of what is in our visual field;
- What aspects of the display get our attention will be determine by a variety of factors, many of which are automatic and beyond our goal-directed control. This automatic capture of attention may be adaptive in many situations (e.g. quickly detect threat) but can also bias our attention away from goals (e.g. prioritizing preferred over accurate information);
- The effect of attention can be studied by measuring how long people take to search for or orient toward a target stimulus after having been cued in diferent ways to a locations;
- The power of emotional influence can also be studied using subliminal paradigms, i.e. visual background masking, and measure speed of response or psychophysiological measures i.e. skin conductance, upon subsequent stimuli;
- How much processing attended and non-attended inputs will get will depend on factors such as how difficult is to process the target information, how many distractors are present and whether the subject is performing concurrent cognitive demanding tasks;
- These findings highlight the important of considering the level and type of load involved in any financial report. It means that efficient processing and prioritization of relevant information will depend on the characteristics of the report including how much information is presented, its order, etc. Unfortunately we still know relatively little on exactly what these variables are. Future work will need to further characterize the relevant features of the information and extend this to financial accounting contexts;
- Computational requirements are an important factor in how decision makers approach a problem. This has strong implications for financial reporting suggesting that reports should

keep computational demands as low as possible or at least at a similar level between companies that are being compared. More research is needed to clarify what other factors increase computational requirements;

- Moving from saying that people are "irrational" to actually understand their choices will require understanding how the brain breaks down problems, represents different variables and selects courses of action. Research into neural coding of decision variables i.e. value has been fruitful and shown that many behavioural effects, i.e. reference dependent valuation, that according to economic theory are abnormal, make sense if we look at how neurons actually represent these variables and the biological constraints they face;
- Accounting information is not processed in a vacuum. Understanding decision-making as well as better predicting its outcomes will depend on understanding the different variables that modulate decision processes. Both the emotional reactions elicited by the decision problem (e.g. losses) and other emotional states unrelated to the decision at hand (e.g. stress) can have powerful influences on decision-making. However, they are not all beyond our control – emotional regulations techniques are effective in modulating at least part of these influences.
- Rather than viewing the relationship between "emotion" and "cognition" as two competing forces, affective neuroscientists suggest a modulatory view, whereby emotions modulate in different ways, and via different circuitry, cognitive functions.

6.3. From simple tasks to financial relevant contexts

We are still far from fully understanding how people sample, process and use financial information, but the evidence from more simple stimuli and tasks can provide a foundation for hypothesis to be tests and methods to be used in more complex, financial relevant, contexts.

In moving from simpler to complex, especially when trying to understand neural mechanisms, it is important to emphasize that although indeed neural data will help refine our behavioural theories, it is also true that understanding neural mechanisms of decision making, or indeed any behaviour, will crucially depend on having appropriate behavioural paradigms, that on one hand capture the cognitive process of interest and on the other, are adequate to the constraints, e.g. temporal, of the technique being used (LeDoux, 2015, Milner & White, 1987).

Without an understanding of the kind of processes and computations engaged in a particular task or decision problem, it is hard to interpret the neural data or the effects of our manipulations. We are left with a crude conclusion (e.g. area x is necessary for task y, which "I am not sure what entails") and difficulty in generalizing to other decision contexts. Here is where psychological theory and computational models are instrumental. Computational models can help identify the kinds of signals and signals dynamics that are required by different decision problems (Rangel et al., 2008). Rather than merely reporting the activation of a brain regions in a given experimental condition, researchers now try to identify regions that implement a specific computational process, that is, which across different tasks and contexts, show response profiles consistent with a particular computation. This approach allows a more convincing form of inference than in traditional fMRI studies.

One final concern is the validity of laboratory tasks compared to real-world scenarios, not only in the physical context but also in the population of study (e.g. the use of university students instead of experts). With advances in technology, some of the tools including EEG, psychophysical measurements, eye-tracking technology, amount other, are becoming increasingly more affordable and portable. And advances in computing are allowing ever more complex behavioural tasks. But ultimately, these are limitations of any laboratory–based approach and the findings will always complement rather than replace field data.

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APPENDIX

Appendix I - Brain regions mentioned in the text

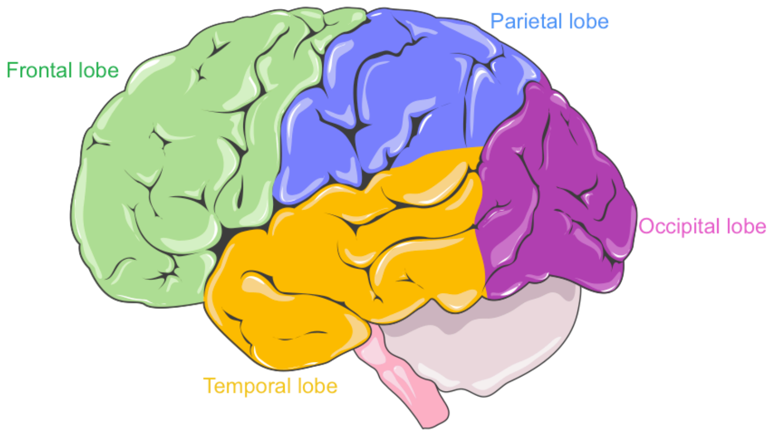

Fig. 1. Main division of the human brain. Image retrieved from *Nervous System*, Servier Medical Art by Servier under a Creative Commons Atrribution 3.0 Unported License.

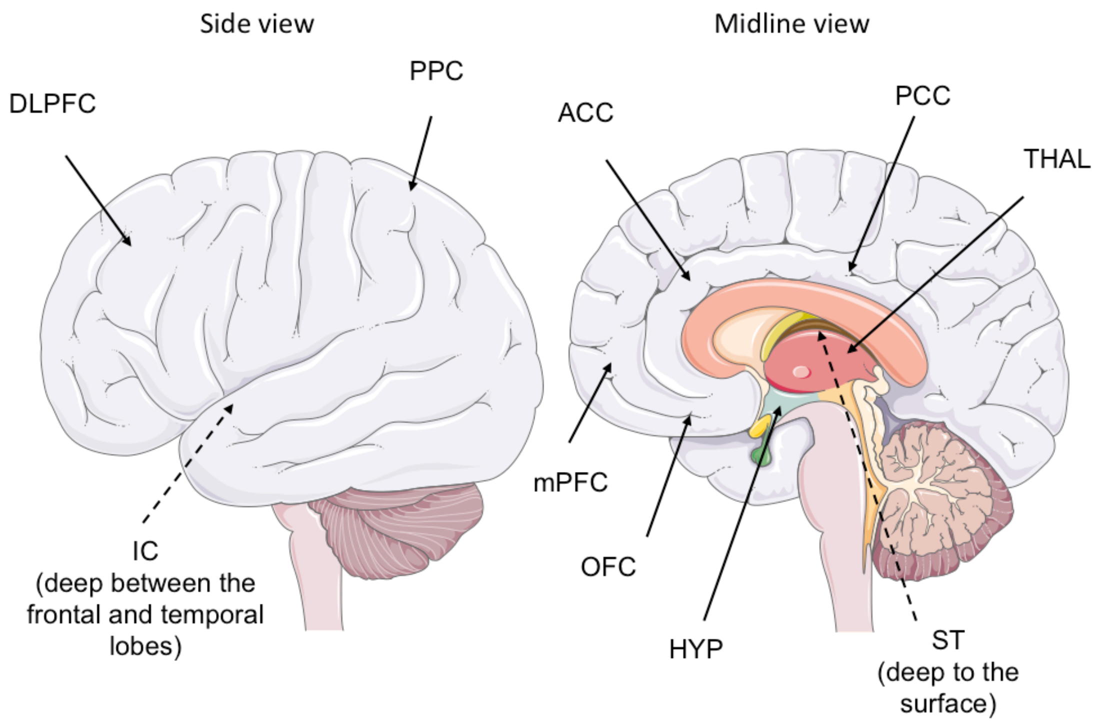

Fig. 2. Main brain areas referred in the main text. The side view shows the location of the dorsolateral prefrontal cortex (DLPFC), the posterior pariental cortex (PPC) and the insular cortex (IC). The midline view, or sagittal section, shows the location of the anterior cingulate cortex (ACC), the posterior cingulate cortex (PCC), the medial prefrontal cortex (mPFC), the orbitrofrontal cortex (OFC), the thalamus (THAL), the hypothalamus (HYP) and the striatum (ST). Dotted lines = deeper in the brain, out of view. Images adapted from *Nervous System*, Servier Medical Art by Servier under a Creative Commons Atrribution 3.0 Unported License.

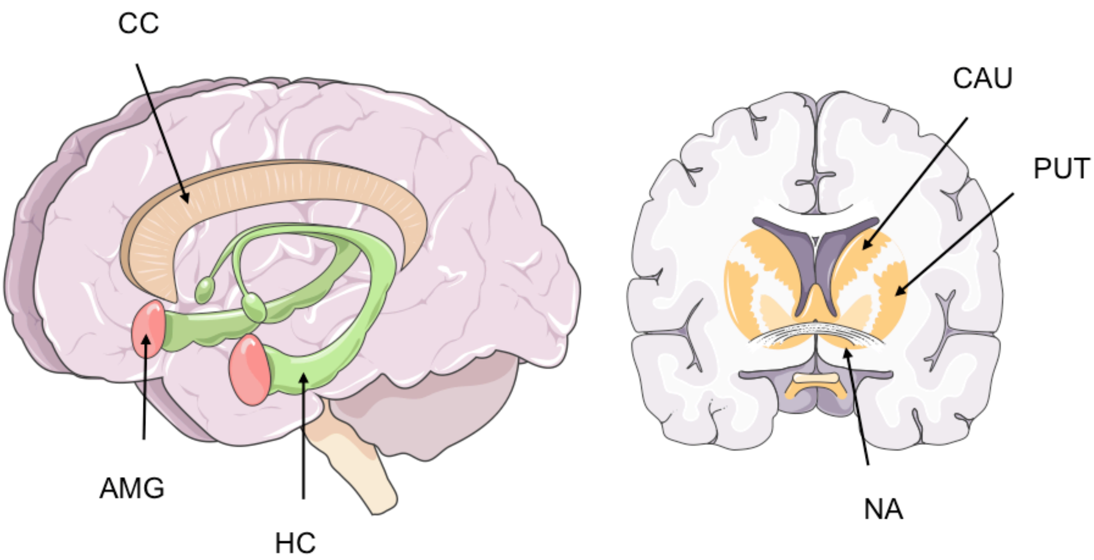

Fig. 3. Sagital and coronal views of the human brain showing amygdala and striatal areas refered in the main text. Left panel: Localization of the amygdala (AMG), hippocampus (HC) and cingulate cortex (CC). Right panel: Subcomponents of the striatum. A coronal section illustrating the location of the caudate nucleus (CAU), putamen (PUT), that together make the dorsal striatum, and nulcues accumbens (NA) which is part of the ventral striatum. Images adapted from *Nervous System*, Servier Medical Art by Servier under a Creative Commons Atrribution 3.0 Unported License.