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A Multidisciplinary Approach of the Decision-Making Process

Sébastien Massoni

► **To cite this version:**

Sébastien Massoni. A Multidisciplinary Approach of the Decision-Making Process. Economics and Finance. Université de Lorraine, 2021. tel-03108559

HAL Id: tel-03108559

<https://hal.univ-lorraine.fr/tel-03108559>

Submitted on 13 Jan 2021

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BETA
Bureau
d'économie
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A Multidisciplinary Approach of the Decision-Making Process

THÈSE

présentée et soutenue publiquement le 7 janvier 2021

pour l'obtention d'une

Habilitation de l'Université de Lorraine

(en Sciences Économiques)

par

Sébastien Massoni

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L'Université de Lorraine n'entend donner aucune approbation ni improbation aux opinions émises dans cette thèse. Elles doivent être considérées comme étant propres à l'auteur.

Remerciements

Je remercie en premier lieu Mohammed Abdellaoui d'avoir accepté d'être le garant de cette HDR et d'avoir pu me guider dans son écriture. Ton accord pour ce parrainage scientifique représente beaucoup.

Je remercie également tous les membres du jury, Aurélien Baillon, Nicolas Jacquemet, Meglena Jeleva, Eve-Angéline Lambert, Mathias Pessiglione et Ferdinand Vieider pour le temps et le travail qu'ils ont consacré à la lecture de ce manuscrit et particulièrement aux rapporteurs pour l'investissement nécessaire.

Bien que ce travail soit une synthèse individuelle, il est principalement le fruit d'un travail collaboratif. Je remercie vivement l'ensemble de mes co-auteurs qui m'ont énormément appris et permis de m'épanouir scientifiquement et humainement. En particulier je tiens à remercier : Olivier Chanel, Steve Fleming, Thibault Gajdos, Madalina Olteanu, Lionel Page, Nicolas Roux, Jean-Christophe Vergnaud et Marie Claire Villeval. Je remercie aussi tous ceux avec qui je suis en train de collaborer et qui ne tarderont pas à rejoindre cette liste.

Je remercie mes doctorants, Ambroise Descamps, Gevorg Ordyan, mes étudiants, en particulier Charlotte Ossom, Olga Rouaud, Enzo Santese, et les doctorants du QuBE, Azahr Potia en premier lieu, pour m'avoir permis de développer mon intérêt pour l'encadrement. Je remercie grandement mon doctorant Thomas Garcia de m'avoir fait confiance et de m'avoir permis de découvrir et de m'épanouir dans ce rôle de directeur de thèse. J'ai beaucoup appris grâce à vous tous!

Je remercie mes collègues rencontrés dans mes différents laboratoires d'accueil. Sans cette émulation scientifique notre métier, comme nous le montre la période actuelle, serait bien moins agréable. Merci pour ces échanges que ce soit au CES, à QUT ou au BETA. Merci à mes

nouveaux collègues du BETA, en particulier Mehdi Ayouni, Yannick Gabuthy, Eve-Angéline Lambert et Thomas Lanzi, pour votre accueil et pour avoir rendu ce retour en France un peu moins compliqué.

Merci également à l'équipe de direction du BETA, en particulier Agnès Gramain, et de l'IUT de m'offrir d'excellentes conditions de travail. Merci aussi à l'équipe administrative du BETA (et de mes précédents laboratoires) de me faciliter la tâche au quotidien.

Je remercie mes parents qui m'ont toujours encouragé.

Enfin je tiens à remercier Chloé et Enzo pour le bonheur qu'ils m'apportent au quotidien et évidemment Vanessa pour son soutien inconditionnel et sans laquelle tout ceci n'aurait pas pu être.

À Chloé, Enzo et Vanessa.

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Abstract

How to make a decision under uncertainty? Since the beginning of my PhD, my research interests have been mainly focused on answering this question. To understand the cognitive processes of decision-making I rely on a multi-disciplinary approach. My questions come from decision theory, my tools from experimental economics and my models from cognitive sciences. Using these different fields allows me to go beyond outcome-based results and to search for the decision process itself. My studies showed that such decision implies multiple cognitive mechanisms. One of them is at the core of my past and ongoing research: the abilities to form adequate subjective beliefs about our choices. I show how this metacognition is central to study, explain and predict behaviors in different domains. Complementary to this, I recently extend this approach to the question of social preferences. My future research will continue to tackle these questions, still with a particular focus on the cognitive processes themselves.

Keywords: Decision process ; subjective beliefs ; confidence ; metacognition ; uncertainty ; social preferences ; applied public economics

Résumé

Comment prendre une décision en univers incertain? Depuis le début de mon doctorat, mes recherches se sont principalement intéressées à cette question. Pour comprendre les processus cognitifs d'une prise de décision j'utilise une approche multidisciplinaire. Mes questionnements viennent de la théorie de la décision, mes outils de l'économie expérimentale et mes modèles des sciences cognitives. Utiliser ces différents champs me permet d'aller au-delà de la seule étude des comportements observés et de chercher à comprendre le processus de décision en lui-même. Mes travaux ont montré que de telles décisions impliquaient de multiples processus. L'un d'entre eux est au cœur de mes recherches passées et futures : les capacités à former des croyances subjectives adéquates à nos choix. Je montre comment cette capacité métacognitive est centrale pour étudier, expliquer et prédire les comportements dans de multiples contextes. De manière complémentaire, j'ai récemment étendu cette approche à la question des préférences sociales. Mes recherches futures continueront à essayer de cerner ces différentes questions, toujours en portant un intérêt particulier aux processus cognitifs eux même.

Mots-clés: Procéssus de décision ; croyances subjectives ; confiance ; métacognition ; incertain ; préférences sociales ; économie publique appliquée

Scientific Agenda

How do people make decision in an uncertain environment? How do they form subjective beliefs about these uncertain events and the consequences of their acts? Understanding the way human behave under uncertainty has been the core of my research agenda. But contrary to standard economic decision theory I am not only studying the decision as an outcome but I want to understand the whole process of this decision. To make sense of behaviors under uncertainty we need to invoke some unobservable mental states in addition to the observed choice. Subjective beliefs are one of them. This concept has been central in decision theory from its beginning. Yet we do not know many things about them. Standard economics does not say anything on how individuals form them, how they use them and how these beliefs can dramatically shape behaviors. Thanks to revealed preferences approach, decision theory reasons *as if* individuals have such beliefs in mind to make their decision and then finds the compatible values with the observed behaviors. My aim is to study these subjective beliefs as they really are i.e. real mental phenomenon form by individuals to make decision. My research paradigm implies to move from an *as if* perspective to an *as is* perspective. Doing that requires to extend my analytical framework. Based on decision theory questions I use tools from experimental and behavioral economics but also from cognitive psychology. In particular, computational models of decision give me some insights on how the decision is processed. At first, having an interest in the processes involved and not only in the outcome of the decision was synonym of not doing economics for a part of my colleagues. However, since the start of my PhD in 2009, I have observed a change in the mentalities and a growing openness to non-standard approaches of

economics. It is now well (or just better?) accepted that studying the cognitive process of the decision is worthy of interest and leads to better models of decision-making. I will first present the methodological debate on what is the purpose of an economic theory and show how multiple sources of scientific knowledge benefit the understanding of the decision. Then I will explain what I aim to understand on the specific questions of subjective beliefs and how it shapes my past and future research.

Following the revealed preferences approach, economists should focus only on the observation of the choices made by individuals. Decisions are made under a black box and thus decision processes are outside of the research scope. In a less restrictive approach, an interest can be turned on the processes but still by using exclusively the output of the decision. One might wonder why economists restrict their possibilities in such a way. This question has to be linked to a broader debate on the nature of an economic model. A model of decision-making searches to explain the behavior of an individual. Under some rationality assumptions, it can explain and predict the observed behaviors on the basis of mental constructs such as preferences and subjective beliefs. To do that two different scientific (and philosophical) methods can be used. The behaviorism approach restricts the psychological states and processes to descriptive constructs useful only to make sense of the observed behaviors. The mentalism approach sees them as a representation of real phenomena that gain to be studied. Behaviorism and revealed preferences have been the dominant paradigm in economics since Samuelson's works on consumption theory. They have proved their utility and offered a powerful framework for decision theory. Following Gul and Pesendorfer (2008)'s defense of "mindless" economics, an economic theory should be based on the following points. Its content deals only with choice implications. Choices are modelled through representation forms coming from the maximization of objective functions. Data needed to identify the parameters of these forms are the observed choices only and any non-choice data are irrelevant. This approach allows economists to develop formal and abstract models of decision and to identify the relevant mental states of a model to predict behaviors. Facing this

paradigm, one should ask whether adding psychological states and processes in the model can be helpful? Does a knowledge of the decision processes can *in fine* improve the model and its predictive power? Does such a paradigm still fit within economics? The mentalism approach answers positively all these answers (Dietrich and List, 2016; Clarke, 2020). It argues that a lot of behaviors can hardly be explained without an interest to the underlying cognitive mechanisms.¹ Two main points have to be raised against behaviorism. First restricting data to observed (or intended) choices makes no more sense now that we have different direct measurements of the mental states themselves (e.g. by introspective, physiological, neuro-imaging data). Then a better understanding of the decision process can only lead to better choice modelling and *in fine* better behaviors predictions (see the point between paramorphic and homeomorphic models of decision by Wakker, 2010).²

Overall, I argue in favor of a scientific (and economic) approach of decision-making through the whole decision-process itself using choice and non-choice data with analytical and experimental tools issued from different disciplines.³ I will apply this scientific paradigm mostly to the study of subjective beliefs. My past and future research aims to get a better understanding of the processes involved and thus a better knowledge of the decision. To do that I sometimes left the economic choices framework to study simple sensorial decision. This allows me to gain information, for example, on the way subjective beliefs, and in particular confidence in own

1. Note that the debate between behaviorism and mentalism approaches happened in psychological science. Noam Chomsky and then Jerry Fodor critics of behaviorism led to its complete replacement by mentalism approaches.

2. The issues with the revealed preferences approach can be illustrated by the question of risk preferences measurements. Different methods to infer risk attitudes from observed behaviors in the lab have been used. But estimations between methods are first inconsistent (Pedroni et al., 2017; Holzmeister and Stefan, 2020) and even worst are unable to explain risky behaviors in the field (Friedman et al., 2014; Charness et al., 2020). On the contrary, simple survey-based stated preferences outperform these revealed preferences methods in explaining real-world behaviors (see Mata et al., 2018; Arslan et al., 2020).

3. As I did not use neuroscience data in my previous research and do not have a precise plan to do so in a near future, I did not review here the methodological advances of neuroeconomics. But I see it as a part of the mentalism approach and advocate against the "hard" neuroeconomics that aims to replace high-order processes of choices and their mental states by only low-level mechanisms of brain activation. See Camerer (2013) for the neuroeconomics goals, Harrison (2008) for a critical point of view, and on the contrary Bossaerts and Murawski (2015) for a pure biological approach of decision.

performance, are formed and used. The objective being at the end to integrate this knowledge in economic-related decisions.

Beyond these methodological debates, my research is primarily focused on the questions of how individuals form a subjective belief facing an uncertain decision. More precisely, I mainly study the subjective judgments they have on the quality of this decision through confidence estimation. In this literature two main open debates will lead my future works and interests: the knowledge of the nature of confidence and the understanding of the roles of confidence in the decision processes. I will briefly give an overview on these two questions and show how my scientific agenda is related.

The question of the nature of confidence is still open. It even refers to two different questions: whether confidence is a Bayesian process or something else (heuristics, partial Bayesian, etc.)? And what types of evidence are used for its estimates. To overcome the aforementioned difficulty of the subjective aspect of confidence, a statistical framework has to be used. Confidence is seen as the Bayesian posterior probabilities of being correct given the level of evidence received (Meyniel, Sigman and Mainen, 2015; Pouget, Drugowitsch and Kepecs, 2016). This Bayesian confidence has become the standard way of representing confidence and is offering some clear predictions about what confidence should be i.e. its statistical signature (Kepecs and Mainen, 2012; Drugowitsch, 2016; Hangya, Sanders and Kepecs, 2016; Sanders, Hangya and Kepecs, 2016). It has been reinforced by neural and behavioral evidence favoring this representation (Kiani and Shalden, 2009; Kepecs et al., 2008). However, this Bayesian nature of confidence and its statistical pattern of predictions have been discussed recently and evidence for partial or non-Bayesian confidence emerge (Aitchison et al., 2015; Navajas et al., 2017a; Adler and Ma, 2018a,b). The second related question is to know on which type of evidence is based this Bayesian confidence. The simplest model assumes that confidence is based on the same evidence than decision. This first-order model thus infers confidence as the Bayesian posterior

probabilities of the event conditional to the decision and its evidence. In a more interesting way, post-decisional model assumes that evidence used for confidence contains additional information than those for decision.⁴ While a link between evidence used for decision and confidence has been empirically documented (De Martino et al., 2013; Gherman and Philiastides, 2015) the large amount of literature on the dissociation between task performance and confidence favors a weak relationship. Indeed, studies found evidence in favor of an additional processing of decision evidence (Yu, Pleskac and Zeigenfuse, 2015), an accumulation of new evidence (Kvam et al., 2015), an inaccessibility of decision evidence to confidence (see blindsight - Persaud, McLeod and Cowey, 2007) and an inaccessibility of confidence evidence to decision (see error detection - Del Cul et al., 2009). These results open the debate about the way evidence for confidence are proceeded: by a serial architecture (Maniscalco and Lau, 2016) or in parallel systems (Charles, King and Dehaene, 2014)? Questions are also about the way we should model confidence formation. Computational models of confidence have been based on *signal detection theory* which links decision and confidence in a static environment and *sequential analysis* which adds a time component to this confidence choice. While signal detection confidence is still a powerful tool, the deliberation time of confidence can hardly be ignored and argues in favor of these dynamic approaches (Fetsch, Kiani and Shadlen, 2014). My previous research has been based on these signal detection-based confidence models but I aim to investigate into these dynamic approaches of confidence (Ratcliff and Starns, 2009; Pleskac and Busemeyer, 2010) in my future works. More broadly the question of response time and decisions will be one of my future research interests and it has become an interesting framework for economic decisions (Fehr and Rangel, 2011; Krajbich, Oud and Fehr, 2014).

The question of the roles of confidence in decision-making is also under investigation. The functions of confidence in decision making has been documented in different studies. Confidence

4. See Fleming and Daw (2017) for a detailed presentation of the models and their expected effects on confidence in multiple settings. They also proposed a more general second-order model where confidence comes from a coupled but distinct decision system.

is a valuable indicator of likely success: among multiple tasks individuals will choose the ones in which they expressed higher level of confidence (Carlebach and Yeung, 2020). Confidence will also predict information seeking: individuals sample additional information before giving a response when they express low confidence and even for similar levels of accuracy (Desender, Boldt and Yeung, 2018). Likewise, choices made with low confidence are less likely to be repeated (Folke et al., 2016) and have less influence on change of strategy (Purcell and Kiani, 2016). Lastly confidence is important to make predictions, learn from mistakes, and plan future actions (Yeung and Summerfield, 2012; Meyniel, Sigman and Mainen, 2015). Still a lot has still to be discovered on its roles and the processes involved. An extension of this question will be to see how confidence matters in different types of task and whether what is known in perceptual decisions can extend to more complex (economic) decisions. This line of research aims to contribute to the ongoing debate on the metacognitive abilities across domains (Rouault et al., 2018): Is metacognition a global domain-general process? Or is it domain-specific with independent processes according to the type of decision? By doing confidence studies on simple decision (perceptual) and complex ones (economic, judicial), with different forms of self-performance estimates (confidence reports, subjective probabilities, bets, insurance levels) and within different settings (individual or group decisions, with or without social impacts), I will get some new insights on this question of a "global" metacognition existence. It will also contribute to the link between perceptual (sensorial) and economic (value-based) decisions (see Summerfield and Tsetsos, 2012).

My HDR thesis is outlined as follows. I will first detail my academic resume. Then I will present my research summary with past works on subjective beliefs, social preferences and public policy. My research program will be then developed through four different main projects: subjective beliefs, risk and ambiguity, social preferences and judicial decisions. Different work projects within each topic will be presented with more or less details depending of the temporal horizon of their realization.

Curriculum vitae

1 Academic Positions

Assistant Professor (Maître de Conférences), Since 2019
University of Lorraine & IUT - Nancy Charlemagne,
Bureau for Economic Theory and Applications (BETA - CNRS, INRA, AgroParisTech,
Université de Lorraine, Université de Strasbourg)

Postdoctoral Research Fellow, 2013–2019
Queensland University of Technology, Brisbane, Australia
QuBE - School of Economics and Finance,
Australian Centre for Entrepreneurship Research

2 Education

Ph.D. in Economics, Paris School of Economics - University of Paris 1 2013
Dissertation: *“Essays on Subjective Probabilities and Metacognition”*
Advisor: J.-C. Vergnaud; Committee: P.-Y. Geoffard (PSE); O. L’Haridon
(CREM-GREHEC); G. Rees (UCL); J. Sackur (ENS Ulm); J.-M. Tallon (PSE)

M.A. in Economics, Paris School of Economics - University of Paris 1 2009

B.A. in Economics, Paris School of Economics - University of Paris 1 2007

B.A. in Economics and Sociology, University of Paris X Nanterre 2006

3 Publications

- [15] Garcia, T., Massoni, S., & Villeval, M.C. (2020). Ambiguity and Excuse-Driven Behavior in Charitable Giving, *European Economic Review*, 124.
- [14] Rahnev, D. et al. (2020). The Confidence Database, *Nature Human Behaviour*, 4:317-325.
- [13] Massoni, S. & Roux, N. (2017). Optimal Group Decision: A Matter of Confidence Calibration, *Journal of Mathematical Psychology*, 79:121-130.
- [12] Hollard, G., Massoni, S., & Vergnaud, J.-C. (2016). In Search of Good Probability Assessors: An Experimental Comparison of Elicitation Rules for Confidence Judgments. *Theory and Decision*, 80(3): 363-387.
- [11] Fleming, S.M.*, Massoni, S.*, Gajdos, T., & Vergnaud, J.-C. (2016). Metacognition About the Past and Future: Quantifying Common and Distinct Influences on Prospective and Retrospective Judgments on Self-Performance. *Neuroscience of Consciousness*, 2016(1).
- [10] Chanel, O., Chichilnisky, G., Massoni, S., & Vergnaud, J.-C. (2016). Exploring the Role of Emotions in Decision Involving Catastrophic Risk: Lessons from a Double Investigation. in *The Economics of Global Environment - Catastrophic Risks in Theory and Policy*, G. Chichilnisky, A. Rezai (Eds.), Springer. *Studies in Economic Theory*, 29:553-575.
- [9] Massoni, S. (2016). Confiance, métacognition et perception. *L'Actualité Economique. Special Issue on Experimental / Behavioral Economics*, N. Jacquemet & O. L'Haridon (Eds.), 90(1-2): 459-485.
- [8] Massoni, S., Gajdos, T., & Vergnaud, J.-C. (2014). Confidence Measurement in the Light of Signal Detection Theory. *Frontiers in Psychology*, 5:1455.
- [7] Massoni, S. (2014). Emotion as a Boost to Metacognition: How Worry Enhances the Quality of Confidence. *Consciousness and Cognition*, 29:189-198.
- [6] Egozcue, M., Massoni, S., Wong, W.-K., & Zitikis, R. (2014). Integration-Segregation Decisions under General Value Functions: "Create your own Bundle - Choose 1, 2, or all 3!". *IMA Journal of Management Mathematics*, 25(1):57-72.

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- [5] Massoni, S., Olteanu, M., & Villa-Vialaneix, N. (2013). Which Dissimilarity is to be used when Extracting Typologies in Sequence Analysis? A Comparative Study. in *Advances in Computational Intelligence: IWANN 2013*, I. Rojas, G. Joya, J. Cabestany (Eds.), Lecture Notes in Computer Science 7902, Springer Berlin / Heidelberg, 69-79.
- [4] Massoni, S. & Vergnaud, J.-C. (2012). How to Improve Pupils' Literacy? A Cost-Effectiveness Analysis of a French Educational Project. *Economics of Education Review*, 31(1):84-91.
- [3] Chanel, O., Luchini, S., Massoni, S., & Vergnaud, J.-C. (2011). Impact of Information on Intentions to Vaccinate in a Potential Epidemic: Swine-origin Influenza A(H1N1). *Social Science & Medicine*, 72(2):142-148.
- [2] Hainaut, M. Massoni, S., & Vergnaud, J.-C. (2010). Apprendre à bien lire: une étude coût-efficacité des Actions Lecture. *Revue d'Economie Politique*, 120(5):823-843.
- [1] Massoni, S., Olteanu, M., & Rousset, P. (2009). Career-Path Analysis Using Optimal Matching and Self-Organizing Maps. in *Advances in Self-Organizing Maps: WSOM 2009*, J. Principe, R. Miikkulainen (Eds.), Lecture Notes in Computer Science 5629, Springer Berlin / Heidelberg, 154-162.

4 Working Papers

- [10] Aiming to Choose Correctly or to Choose Wisely? The Optimality-Accuracy Trade-off in Decisions Under Uncertainty, with T. Garcia. (*submitted*)
- [9] Optimal Hesitation, an Experiment, with A. Descamps and L. Page (R&R *Experimental Economics*)
- [8] Testing a Boost Policy to Enhance Mutualized Health Insurance, with T. Gajdos, H. Huber, J.-C. Vergnaud (*submitted*)
- [7] Gift versus Conditional Incentives for Commitment and Achievement: Evidence from a Laboratory Experiment, with U. Dulleck, A. Potia, B. Torgler (*submitted*)
- [6] Insurance Behaviors of Buyers and Sellers Facing Risky, Imprecise or Conflictual Informa-

tion, with T. Dupont-Courtade (Reject & Resubmit *Theory and Decision*).

[5] Manipulating Payoff Processing Order in Perceptual Decision-Making, with T. Garcia, I. Rafai. (R&R *Experimental Psychology*)

[4] Do Stated Preferences Favour Plutocratic Choices?, with O. Chanel, J.-C. Vergnaud (*submitted*)

[3] Subjective Beliefs Formation and Elicitation Rules: Experimental Evidence, with G. Hollard, J.-C. Vergnaud (2010). *Working paper divided into Massoni et al. (2014, Front. Psychol.) and Hollard et al. (2016, Theory Decis)*

[2] Career-Path Analysis Using Drifting Markov Models and Self-Organizing Maps, with M. Olteanu, P. Rousset, *Proceedings of MASHS'10* (2009).

[1] A Direct Revelation Mechanism for Eliciting Confidence in Perceptual and Cognitive Tasks: An Experimental Study (2009).

5 Works in Progress

A global test of message framing on behavioural intentions, policy support, information seeking, and experienced anxiety during the COVID-19 pandemic, with C. Dorison et al. and Psychological Science Accelerator Team (*Data collected*).

A global test of brief reappraisal interventions on emotions during the COVID-19 pandemic, with K. Wang et al. and Psychological Science Accelerator Team (*Registered Report at Nature Human Behaviour*) (*Data collected*).

Anticipation and PTSD in a Natural Disaster Framework: A Field Experiment on Flood Risk in South of France, with O. Chanel, J.-C. Vergnaud (*Data collected*).

Beyond Overconfidence: Metacognition and Excess Market Entry (*Data collected*).

Confidence and Errors Monitoring: Distinct Accumulation Processes (*Data collected*).

Effect of communication styles on motivation to follow versus defy social-distancing guidelines

during the COVID-19 pandemic, with N. Urry et al. and Psychological Science Accelerator Team (*Data collected*).

From Perception to Economic Decision-Making: A Global Framework of Subjective Beliefs, with J.-C. Vergnaud (*Data collected*).

Peers-Effect on Risky Decision: Does Social Preferences Matter? (*Pilot data collected*).

Social Contagion of Memory: Trust and False-Memory, with O. Rouaud (*Pilot data collected*).

Social Risk Preferences: Rank and Range Matter, with G. Ordyan (*Data collected*).

Social Status and Dishonest Behaviors, with C. Ossom (*Pilot data collected*).

Status and Choice Shift in Risky Group Decision, with G. Ordyan (*Data collected*).

Status-Inconsistency and Bargaining Power, with G. Ordyan, L. Page (*Data collected*).

Testing the Bayesian Nature of Confidence Formation, with N. Roux (*Data collected*).

Worry's Effects on Insurance Behaviors and Subjective Probabilities, with J.-C. Vergnaud (*Data collected*).

6 Technical Reports

An exploratory analysis of how to increase the Early Start Kindergarten (ESK) grant take-up rate, with U. Dulleck, D. Sarkar, and J. Silva Goncalves, Report for Department of Education and Training - Victoria State Government (2015). 53p.

Economic evaluation of the Action Lecture program in Paris' primary schools. (in French), with J.-C. Vergnaud, M. Hainault, F. Rousseau, Report for French Ministry of Education and Académie de Paris (2008). 95p.

7 Teaching

Université de Lorraine since 2020

- Experimental Economics (PhD), 2020–2021

Sciences Po since 2020

- Microeconomics: Information, Designs and Institutions (B.A.), 2020–2021

Institut Universitaire de Technologie - Nancy Charlemagne since 2019

- *Economics 1* (A.D.), 2019–2021 (*in French*)

- *Economics 2* (A.D.), 2019–2021 (*in French*)

Queensland University of Technology 2014–2019

- *Policy Economics and Evaluation* (Honours, PhD), 2014–2015

- *Applied Behavioural Economics* (B.A.), 2015

- *Economics and Data Analysis* (M.A.), 2016–2019

Teaching Assistant, University of Paris 1 2009–2013

Microeconomics (B.S.), Probability (B.A.), Statistics (B.A.), Linear Algebra (B.A.)

8 Supervision

PhD: Thomas Garcia (GATE - QUT) *A behavioral approach of decision making under risk and uncertainty* (2015-2019, co-direction with M.C. Villeval; Economist at Banque de France);

Ambroise Descamps (QUT) *Essays on information and beliefs in dynamic choices* (2015-2017, co-direction with L. Page; QUT Outstanding Doctoral Thesis Award; Analyst at Oxera Consulting Brussels);

Gevorg Ordyan (QUT) *Social status and economic behavior* (2014-2017, co-direction with L. Page, Market analyst at Lonergan Sydney)

Master Thesis: T. Garcia (2015, ENSAE - PSE); C. Ossom (2018, 2019, Paris 1 & 5); E. Santese (2018, 2019, Paris 1 & 5); O. Rouaud (2019, 2021, Paris 1 & 5); G. Tzedakis (2019, Paris 1 & 5); M. Ulrich (2021, Paris 1 & 5); I. Sadok (2021, Paris 1 & 5)

Internship: H. Mihoub (2012, Paris 1); T. Garcia (2014, ENSAE - QUT); K. Montalibet (2015, ENSAE - QUT), T. Frizzo (2020, Univ Lorraine)

PhD Committee: Azhar Potia (QUT, 2019) - chair, supervisor: Uwe Dulleck; Zhixin Xie (QUT, 2017) - chair, supervisor: Lionel Page.

9 Administration

Seminar organization,

BETA Economic Seminar,	since 2020
Queensland University of Technology Economics and Finance Seminar,	2014–2016
Queensland Behavioural Economics Seminar,	2014–2018

Conference organization

<i>FUR 2020 - Foundations of Utility and Risk Conference</i>	Sydney, 2021
<i>GLEA 2020 - German Law and Economics Association</i>	Nancy, 2021
<i>APESA 2018 - Asia Pacific Economic Science Association</i>	Brisbane, 2018
<i>Economics and Biology of Contests Conference 2016</i>	Brisbane, 2016

Lab Manager, Queensland University of Technology QUT Business School Experiments Laboratory	2015–2018
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Research Ethics Advisor, Queensland University of Technology	2015–2018
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10 Referee

Journals: *L'Actualité Economique, Adaptive Behavior, Brain Sciences, Consciousness and Cognition, Economic Analysis and Policy, Educational Research, Games and Economic Behavior, International Journal for Quality in Health Care, PLOS ONE, Quarterly Journal of Experimental Psychology, Revue d'Economie Politique, Theory and Decision.*

Grants: *Polish National Science Centre.*

11 Awards and Grants

Future Leader, <i>Experimental Approach of Judicial Decision-Making,</i> Lorraine University of Excellence (€75,000).	2020–2021
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Tokohu UL (P.I. J. Dinet & R. Nouchi), 2020
A Robotics Virtual Coach for Promoting Motor Activity, Cognitive function, and Quality of Life for Elderly People,
Tohoku University-Université de Lorraine Joint Research Fund (€30,000).

S2C3 ECOPSY (P.I. T. Gajdos), 2016
From Economics to Psychology: The Contextual Effects On the Decision-Making Processes,
CNRS - French Ministry of Research (€20,000).

Research award, Vice-Chancellor's Performance Award 2014 - Research from Queensland University of Technology (AUD5,000)

DEECD (P.I. U. Dulleck), 2014–2015
Behavioural Analysis of Early Start Kindergarten Participation,
Department of Education and Training - Victoria State Government (AUD25,000).

Thesis awards, The Solemn Prize of the Chancellery of Paris Universities (Louis Forest Prize, 2014, €10,000) and The Honoric Prize of the Chancellery of Paris Universities (Richelieu Prize, 2015).

APO CREMCO (P.I. T. Gajdos), 2012–2014
Beliefs, Emotions and Behaviors,
Région Provence Alpes Côte d'Azur (€40,000).

Small Research Grants,
QuBE Research Fund (AUD5,000), 2016.
PSE Research Fund (€4,000), 2013.
PSE Research Fund (€4,000), 2012.

ANR RISKEMOTION (P.I. O. Chanel), 2009–2012
Decision under Risk and Emotion for Natural Disasters,
ANR - French Ministry of Research (€88,000).

ATER Fellowship Teaching and Research Assistant, 2012–2013
University of Paris 1 and French Ministry of Research.

Doctoral Fellowship, 2009–2012
University of Paris 1 and French Ministry of Research.

ANR CONTROL (P.I. J.-M. Tallon), 2007–2010
The Feeling of Control: A Multi-Disciplinary Approach,
ANR - French Ministry of Research (€200,000).

12 Presentations

2019: UCD Seminar (Dublin), BETA Seminar (Univ. de Lorraine)

2018: APESA 2018 (Brisbane), University of Queensland Seminar (Brisbane), Monash University Seminar (Melbourne), Behavioural and Experimental Economics and Finance Workshop (Sydney)

2017: AMPC 2017 (Brisbane), University of Sydney Seminar (Sydney), ANU Seminar (Canberra), Young Researchers Workshop - Department of Social Services - Australian Government (Canberra)

2016: AMSE Seminar (Marseille), GATE Seminar (Lyon)

2015: ACE 2015 (Brisbane), ESA 2015 (Sydney), ANZWEE 2015 (Hobart), Queensland University of Technology seminar (Brisbane)

2014: ICON 2014 (Brisbane), ASSC 18 (Brisbane), ESA 2014 (Honolulu), ESAM/ACE 2014 (Hobart), Asian Pacific ESA 2014 (Auckland), Systems Neuroscience Group seminar (QIMR Berghofer), ICM Confidence Seminar (Brain and Spine Institute), GATE Seminar (Univ. Lyon), BETA Seminar (Univ. de Lorraine)

2013: Annual Conference of the Neuroeconomics Society (Lausanne), 8th AEW (Roma), 8th ANZWEE (Brisbane), SIMA Seminar (Univ. Paris 1), 2013 Interdisciplinary Symposium on Decision Neuroscience (Philadelphia), 8th RES PhD Meeting (London), ADRES Doctoral Conference (Strasbourg)

2012: EMPG 2012 (Pamplona), ESA 2012 (New-York), AFOSR Workshop on Catastrophic Risk (Stanford), CREM Seminar (Univ. Rennes 1), Econometric Society at ASSA Meeting

(Chicago)

2011: Dauphine Workshop on Economic Theory (Paris), NordicExpe'11 (Lund), Trajectories'11 Workshop (Paris), SIMA Seminar (Univ. Paris 1), 9th IWOR (La Habana), EMPG 2011 (Paris), ESA 2011 (Chicago), ASFEE 2011 (Schoelcher)

2010: NeuroComp'10 (Lyon), SABE 2010 (San Diego), ESA 2010 (Copenhagen), FUR XIV (Newcastle), 9th ICOR (La Habana), VII LabSi Workshop (Siena), 5th EBIM Workshop (Paris)

2009: ESE Conference (Rotterdam), MASHS'09 (Toulouse), SAMOS Seminar (Univ. Paris 1) Modèles et Apprentissages en Sciences Humaines et Sociales

13 Impact

Citations	415
h-index	10
i10-index	10

TABLE 1 – Google Scholar citations - 15/11/2020

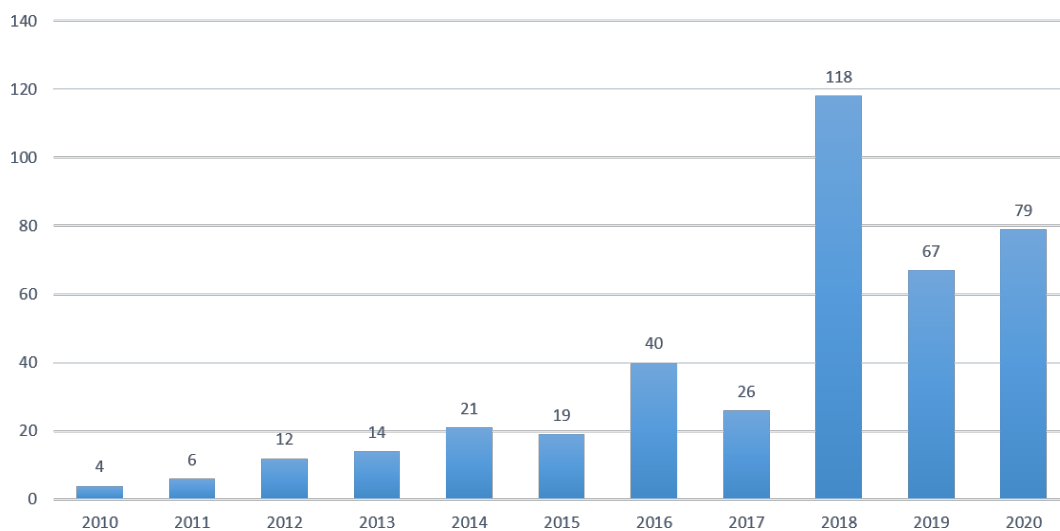


FIGURE 1 – Annual Google Scholar citations - 15/11/2020

Mathematical folklore: my Erdős number is 3 (see <https://oakland.edu/enp/>).

Research Summary

My primary research interest deals with the formation of subjective beliefs in decision under uncertainty and the quality of these beliefs. My PhD was focused on this topic and it is still the main framework of a large part of my current research. During my postdoc I developed a complementary research field with studies on social preferences. Finally, I have always been interested by doing some applied works on public economics at different points of my career. I will thus summarize my past research according to these three different topics with an emphasis on the question of subjective beliefs that stays my most important field of interest.

1 Subjective Beliefs and Metacognition

Subjective beliefs have been at the core of decision theory since the seminal works from Ramsey (1931), de Finetti (1937) and Savage (1954). Decisions under uncertainty share the idea that events are weighted by the corresponding subjective probabilities. But, even if they are central in almost all theories, not so much is known about their nature. My works try to give some insights about the way subjective beliefs (and in particular confidence in own performance) are formed and used by individuals. To do that I had to extend my analytical toolbox and to search beyond economics. Indeed, cognitive sciences have been also interested in the metacognitive process and how individuals reflect on their own cognition (Fleming and Frith, 2014).⁵ But contrary to economists they are more interested in the process of decision itself rather

5. If the term metacognition was first introduced by Flavell (1979), it is related to the question of consciousness which has a long history in psychology and philosophy.

than just the outcome.⁶ I tried to combine these different approaches in my studies to have an overview on the formation, the use and the quality of subjective beliefs. By doing so the idea is to inform both economics and psychology and to contribute to the ongoing bridge between these fields.

In this section I will present my previous works on subjective beliefs and metacognition. After a short presentation of the methodological framework used I will explain how I tried to answer different questions. How to reveal subjects' beliefs in the lab? What is the nature of these beliefs? What are their roles in the decision processes?

1.1 Methodological Framework

From a methodological point of view my works are based on a multi-disciplinary perspective. My interest for the study of subjective beliefs and their importance in decision-making under uncertainty finds its roots in decision theory. My approach in the lab with the search of incentivized mechanisms of behaviors comes from experimental economics. But most of my analytical tools as well as the tasks used in the lab are to be found in computational models from cognitive sciences. In particular I rely a lot on Signal Detection Theory (SDT) to understand the formation of confidence and the role of the linked metacognitive abilities. I will therefore present the basics of SDT for decision (type I) and confidence (type II).

Signal Detection Theory

SDT is an analytical framework used to understand the decision-making process under uncertainty (Green and Swets, 1966). It starts with the idea that decisions are taken under uncertainty: the information available is insufficient or too noisy to be sure about the accuracy of the answer. The distribution of the resulting mistakes will depend of both the uncertainty of

6. To illustrate the dynamism of this field in cognitive science, we can cite the *Confidence database* (<https://osf.io/s46pr/>) that Rahnev and 82 co-authors (included myself) recently shared. It contains 145 datasets with data from more than 8700 participants and almost 4 million trials including (at least) choice and confidence (Rahnev et al., 2020).

the event and the decision processes used. SDT allows us to disentangle and to identify both sources. The most natural setting to apply SDT is perceptual decisions. Yet all decisions based on the identification of a signal in a noisy environment can be modelled.⁷ Examples are multiple: a physicist searching evidence of a tumor on an fMRI scan; a judge reviewing evidence on a defendant's case; a financial trader trying to identify a trend in noisy market fluctuations; etc. The idea is for the individual to decide if he is facing only some noise or a signal in a noisy environment. As the signal is too weak and/or the noise too strong, his decision is made under uncertainty. SDT can be used in three different ways (Wickens, 2002): an analytical tool to describe observed behaviors; a measure of treatments effects by playing on the decision parameters; a normative model of how actual decision should be made. I will briefly present SDT for choice (type I SDT) and confidence (type II SDT). An extensive presentation of SDT can be found in Green and Swets (1966) and Wickens (2002). I explained in details SDT for confidence in Massoni (2013).

An individual has to determine if he is facing a signal or a noise. Depending of his answer ("report signal" or "report noise") and the true state of the world ("signal" or "noise"), four types of answers can be observed: two correct and two incorrect.

	Signal	Noise
Report Signal	Hit	False Alarm
Report Noise	Miss	Correct Rejection

A first way to describe behaviors is to compute two relevant probabilities: the hit rate (number of correct detection relative to the number of signal trials) and the false alarm rate (number of false alarm relative to the number of signal trials). This characterization offers some basic information about the way individuals decide.

7. I define a perceptual decision as a choice facing a task of detection, discrimination, or categorization of sensory information. By contrast economic decisions refer to the way to choose between different options according to the preferences. See Summerfield and Tsetsos (2012) for a review on the links between them.

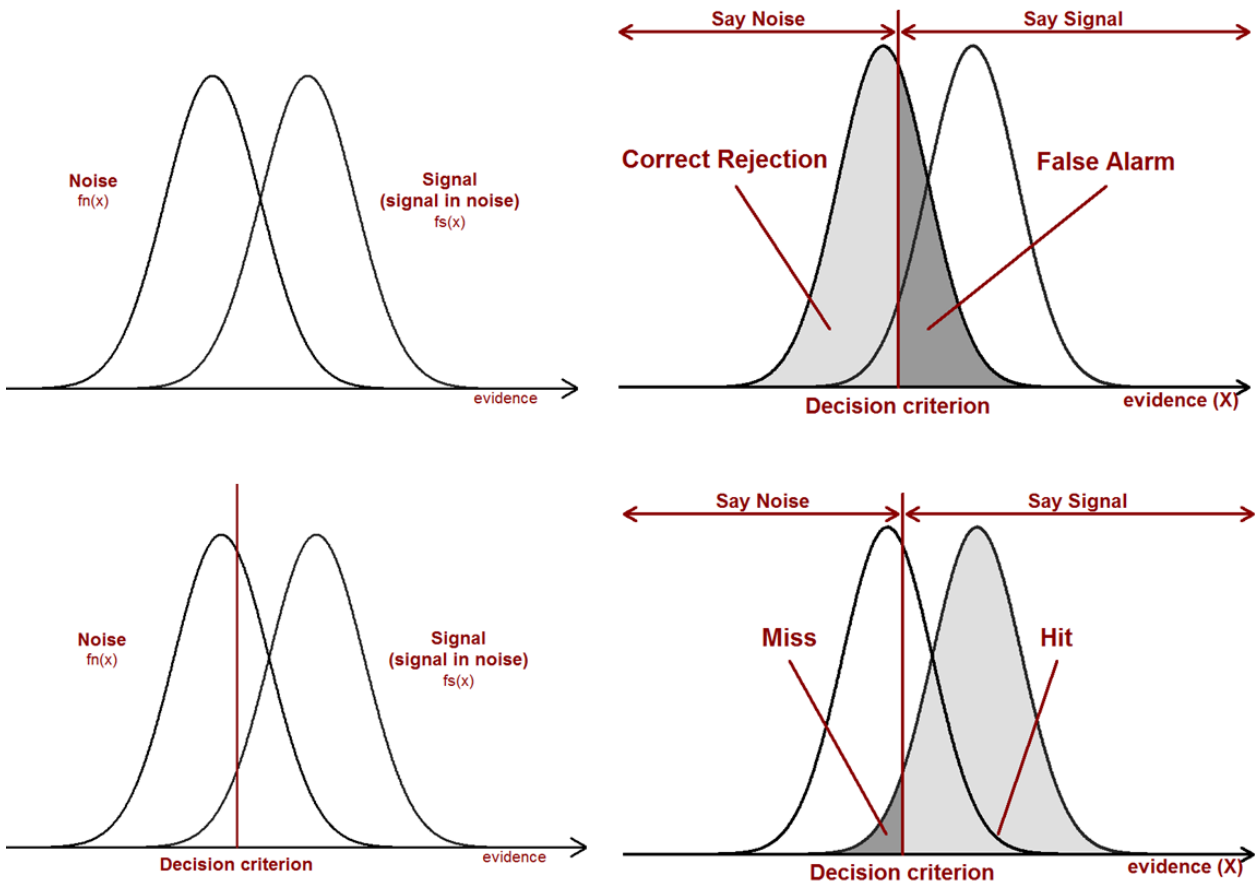


FIGURE 1 – Signal Detection Theory. (*top left panel*) Density functions of noise and signal in noise as a function of the level of evidence received. (*bottom left panel*) Decision criterion. A criterion on the left indicates a cautious strategy; on the right a risky one. (*top right panel*) Correct Rejection and False Alarm rates according to the criterion placement in a noise trial. (*bottom right panel*) Miss and Hit rates according to the criterion placement in a signal trial.

SDT goes beyond and describes the ability to discriminate the signal from the noise as well as the decision criterion used. It needs three assumptions: individuals accumulate evidence X in favor of the signal and its value is unique; this evidence follows a random process; the decision is taken by applying a criterion based on the level of evidence received. We can thus represent the probability distribution of observing the signal and the noise or the noise only according to the level of evidence received: $X_N \sim N(a, \sigma_{a,i}^2)$ and $X_S \sim N(b, \sigma_{b,i}^2)$ with $a \geq b$ and σ_i the individual visual ability (Figure 1 top left panel). Then the answer depends whether this level of evidence is below or above a decision criterion β (Figure 1 bottom left panel). The difficulty to discriminate the signal (d') depends of the distance between the modes of the two distributions (Figure 2). The false alarm and hit rates depend of the criterion placement (Figure 1 right panels). Thus, this criterion characterizes the decision process with more or less risky or conservative decision strategies.

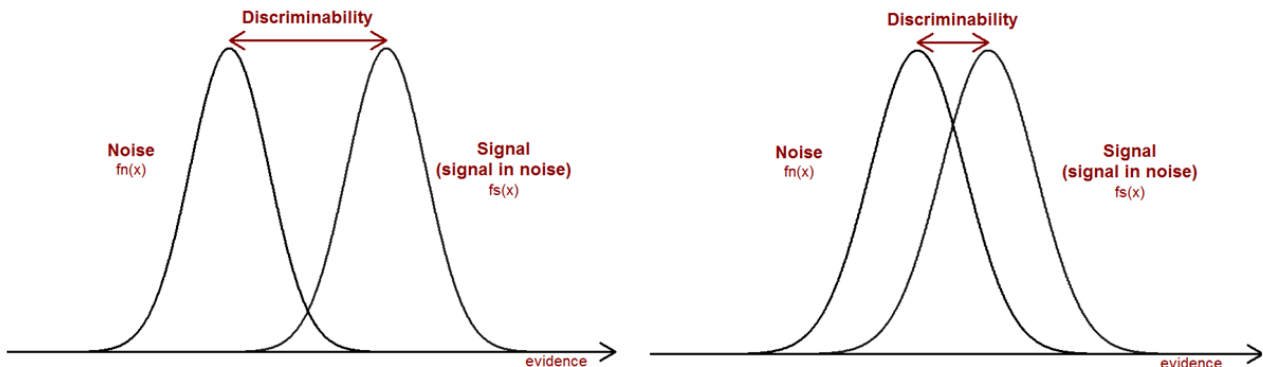


FIGURE 2 – Discrimination. (*left panel*) show a high intensity of the signal and thus an easy decision with a high d' . (*right panel*) shows a difficult decision with a large crossover between curves and thus a small d' .

How these two rates vary according to the criterion placement is summarized by the *Receiver Operating Characteristics* (ROC) curve. The area under the curve gives the probability of being correct and thus measures the sensitivity. An area of 0.50 means random choices and of 1.00 a perfect classification (Figure 3).

Type II SDT aims to apply the same methodology to the confidence decision. After his type

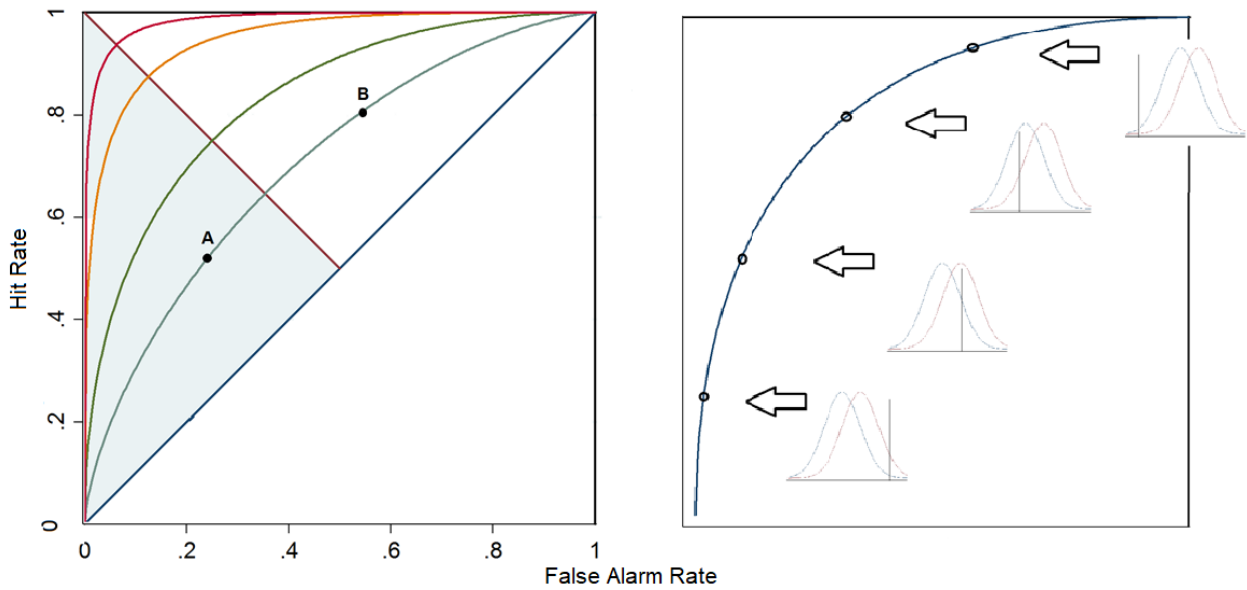


FIGURE 3 – ROC curves. (*left panel*) ROC curves for different d' . The grey area represents criterion below 1. A and B are two different strategies (respectively cautious and risky) for a same d' . (*right panel*) ROC curve for a given d' with different criterion placements.

I decision, the individual will estimate his confidence on this answer's accuracy. He has to classify his decision according to different confidence levels (using probability, Likert scale, binary report, or verbal report) in order to discriminate between good and wrong answers. With a binary confidence report, for simplification, his possible answers are the following:

	Correct decision	Incorrect decision
Confident	Type II Hit	Type II False Alarm
Not confident	Type II Miss	Type II Correct Rejection

We can translate the Type I analysis to the Type II framework and compute similar measures. Yet we need a strong assumption that confidence judgments are based on the same evidence than the Type I decision (see Figure 4).⁸

Thus, a Type II d' can be computed as a measure of confidence discrimination. It is based on the Type II False Alarm rate and Type II Hit rate and can be expressed as a function of the

8. The debate on the nature of confidence is still open and has been discussed before in the Scientific Agenda.

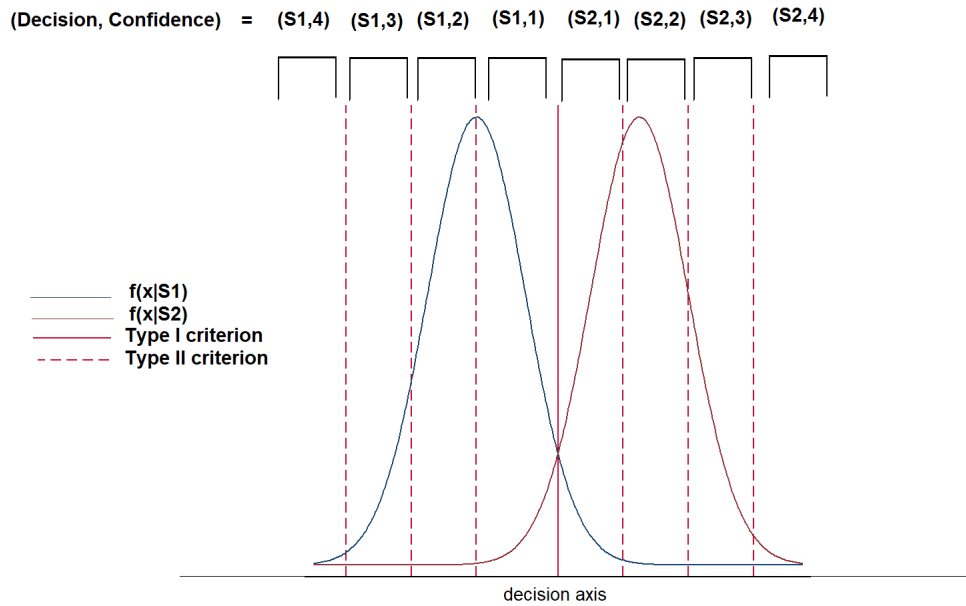


FIGURE 4 – Type II decision criteria according to the level of evidence of the Type I decision. Each criterion represents a confidence level with a symmetry with respect to the type I criterion. e.g. (S1,1) and (S2,1) indicate a confidence of 1 (on a 4-point scale) for the stimulus 1 (noise) and the stimulus 2 (signal).

Type I d' and the Type I and II decision criteria. A Type II ROC curve can also be estimated and its area will measure the discrimination ability. Yet we will see that these two measures suffer from multiple issues and are not ideal confidence discrimination measurements.

Perceptual Task

While SDT could be applied to any type of perceptual decision (and even to any detection of a signal in a noisy environment), my studies were always based on the same perceptual task: a dots task.⁹ This two-alternative forced choice dots-density task is known to be convenient to fit SDT models (Bogacz et al., 2006; Nieder and Dehaene, 2009). Figure 5 provides details of the stimuli while Figure 6 explains how a trial of this task is performed with decision and confidence.

The use of a perceptual task has multiple advantages in the study of the decision process and

9. A MATLAB script of the stimuli is available at https://github.com/metacoglab/meta_dots.

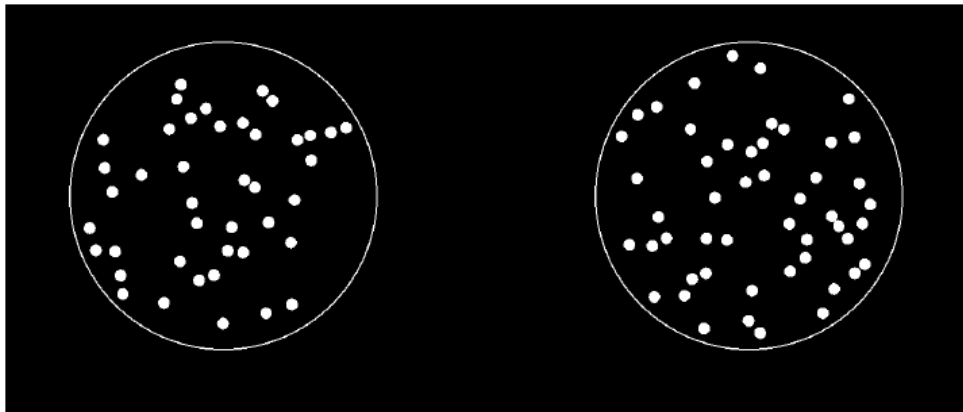


FIGURE 5 – Dots stimuli (density or numerosity two-alternative forced choice). The stimuli consisted of two circles with a variable number of dots in each circle. All dots were of the same size (diameter 0.4°) and the average distance between dots was kept constant. They appeared at random positions inside two outline circles (diameter 5.1°) first displayed with fixation crosses at their centers at eccentricities of $\pm 8.9^\circ$. One of the two circles always contained 50 dots while the other contained $50 + c$ dots. The position of the target circle (on the left or right) was randomly chosen on each trial. Before the experiment, we estimated the value of c needed to obtain a success rate of 71% using a psychophysical staircase (Levitt, 1971).

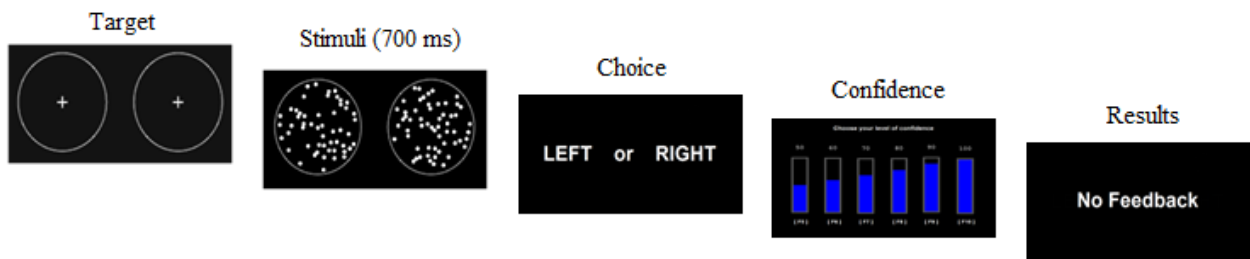


FIGURE 6 – A schematic representation of the dots task. Each trial consisted of the following sequence. First two outline circles were displayed with fixation crosses at their centers. Subjects were free to initiate the trial when they wished by pressing the "space" key on a standard computer keyboard. The dot stimuli then appeared at random positions inside each circle for 700 ms, and subjects were asked to respond as to whether the left or right circle contained a higher number of dots by pressing the "f" or "j" keys, respectively. After responding subjects were asked to indicate their level of confidence in their choice (from 0% - or 50% - to 100% by steps of 5% or 10%). No feedback or feedback was then given following either choices or confidence ratings.

the formation of confidence. First, as we saw, we can use SDT as an analytical framework to know what an optimal Bayesian classifier will do facing the stimuli (decision, confidence, metacognition). Second, the number of trials a subject can perform during a session in the lab is quite high: 150 to 300 trials can be done on "experimental economics lab students" and even higher on "psychology lab students". Third, an interesting aspect is the opportunity offers to control for individual performances heterogeneity. Indeed, performance in the perceptual task can be adjusted to adapt for visual abilities. The number of dots difference in the dots task (Figure 5) can be determined before the main part of the experiment to have a mean accuracy of 71% for all subjects. Subjects initially performed practice trials without confidence ratings and with feedback. These trials are used to calibrate difficulty of the dots task.¹⁰ The procedure I used in my studies is a one-up two-down static staircase (Levitt, 1971): after two consecutive correct answers one dot is removed, and after one failure one dot is added. The procedure stops after 30 reversals and the value of dots difference is the mean dot number across the two last reversals of the staircase. This value stays the same during all the experiment.¹¹ Controlling for performance in a confidence's study allows the researcher to obtain a common benchmark between subjects for the decision part. Thus, all differences on subjective beliefs can be linked to metacognitive components.

All results presented thereafter are not dependent of the stimuli chosen and they should have been similar with another visual perceptual discrimination task (e.g. Gabor task or random dots movement task). Evidence showing similar levels of metacognition in similar, and even

10. As subjects are unaware that this training phase is used for calibrating the main task, it can open the question of deception by omission. Subjects cannot be informed of the procedure to prevent strategic behaviors that will invalidate the calibration. A way to do can be to indicate in the instructions that the choices made in the training phase could also affect the main task. Still I see this procedure as a tool to make the most of the perceptual task rather than a way to deceive participants. Furthermore, what constitutes deception in economic experiments is still under debate: see Ortmann and Hertwig (2002); Cooper (2014); Charness, Samek and van de Ven (2019); Krawczyk (2019); Ortmann (2019).

11. Other adaptative psychophysical procedures have been proposed (staircase, maximum likelihood, sequential testing) and some allows the experimenter to calibrate the difficulty all along the experiment instead of only in the training phase. See Treutwein (1995) and Leek (2001) for a review of the available procedures. But also Rahnev and Fleming (2019) on how continuous staircase might interfere with metacognitive measures.

different, perceptual tasks (Song et al., 2011; Ais et al., 2016; Garfinkel et al., 2016; Faivre et al., 2018; Mazancieux et al., 2020) support this statement (see also Rouault et al., 2018, for a review on metacognition across domains).

Measurements of Metacognition

One fundamental question is then to know how to measure the quality of confidence i.e. the metacognitive abilities. This leads to two different (and uncorrelated) aspects: the calibration (or bias or over/under-confidence) and the discrimination (or sensitivity or reliability). The first one refers to the quality of beliefs on average: how well average confidence matches average performances i.e. how calibrated (or biased) is the confidence. The second one is linked to the ability of confidence to discriminate between levels of accuracy: how well confidence correlates with performance i.e. how the variations of confidence inform about the variations of performance. These abilities are uncorrelated. An overconfident individual can still have a good discrimination or a perfectly calibrated individuals could report non-informative confidence.¹² Figure 7 illustrates this distinction between metacognitive abilities.

I will not get into the technical details of the different measures of metacognition that I used in my different studies. Fleming and Lau (2014) wrote an extensive review on the topic.¹³

A first measure of overall quality of confidence is the *Brier Score* (Brier, 1950). For an individual giving his probability forecasts p_i about n events E_i and with x_i a dummy variable taking 1 if the event E_i is correctly predicted; the Brier Score is computed as follows:

$$BS = \frac{1}{n} \sum_{i=1}^n (p_i - x_i)^2$$

12. An intuitive example of this dissociation can be found in the quality of gender predictions of newborns (Lieberman and Tversky, 1993). A physicist predicting always a boy with a confidence of 50% will be almost perfectly calibrated but his confidence will have a null discrimination.

13. I also wrote, in French, a literature review on SDT for confidence and the different measures of metacognition for a special issue of *L'Actualité Economique* (Massoni, 2016). Chapter 1 in Massoni (2013) summarized and formalized all these measures.

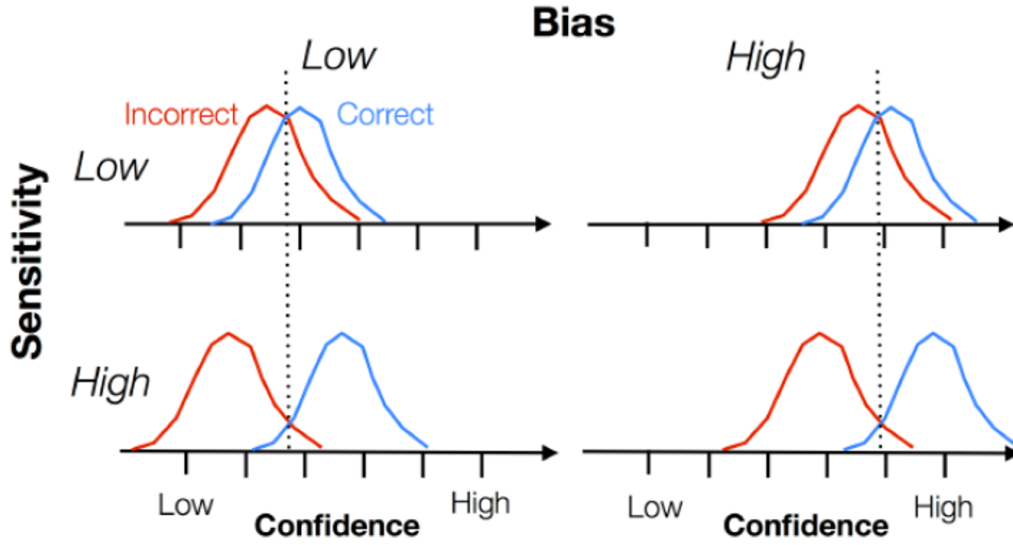


FIGURE 7 – Dissociation between calibration (bias) and discrimination (sensitivity) as illustrated in Fleming and Lau (2014). Hypothetical probability densities of confidence ratings for correct and incorrect trials. Calibration is the overall level of confidence irrespective of the curves while discrimination is the separation between distributions.

The lower the value the better the subjective judgment. Based on this measure the Murphy's decomposition (Murphy, 1972; Yates, 1982) shows that this score aggregates a calibration (CI) and a discrimination (DI) index.

$$BS = f(1 - f) - \frac{1}{n} \sum_{p \in P} N_p (f_p - f)^2 + \frac{1}{n} \sum_{p \in P} N_p (p - f_p)^2 = \text{Uncertainty} - DI + CI$$

with $f = \frac{1}{n} \sum_{i=1}^n (x_i)$ the success rate, P the number of confidence levels, N_p the number of times the level of confidence p is used, and f_p the success rate within the level of confidence p and *uncertainty* the variance of success which is independent of confidence. In addition to this calibration index (measured as the difference between the observed rate of correct detection f_p and the confidence), the bias is also estimated by the level of under/over confidence i.e. the distance between success rate and mean confidence (Lichtenstein, Fischhoff and Phillips, 1982; Harvey, 1997):

$$\text{over/under-confidence} = \frac{1}{n} \sum_{i=1}^n (p_i - x_i)$$

with a positive (negative) value indicating over (under)-confidence and a null value a perfect calibration.

Bias measurements are not under debate and both CI and overconfidence are used and capture different aspect of this confidence bias. Discrimination measurements are a more complex problem: many measures suffer from important limitations and the golden standard changed over time.

A first intuitive way to do it is to measure the correlation between confidence and success. ϕ -correlation is the Pearson correlation between accuracy trial-by-trial and a binarized confidence level while γ -correlation is the Goodman-Kruskall correlation for multiple confidence levels. Unfortunately, both are dependent of the calibration level (see Nelson, 1984, for ϕ -correlation and Masson and Rotello, 2009, for γ -correlation).

This dependence of discrimination to the bias can be solved by using Type II SDT. Discrimination as a Type II d' and the Type II ROC Area (AU2ROC) are independent of the bias. Yet the Type II d' suffers from multiple methodological issues while the AU2ROC is dependent on the Type I sensitivity d' and its bias (Galvin et al., 2003; Evans and Azzopardi, 2007; Barrett, Dienes and Seth, 2013).

The best measure of discrimination so far is based on the concept of $meta - d'$ (Maniscalco and Lau, 2012, 2014). The underlying idea is to measure the signal available for an observer to perform the Type II task. $Meta - d'$ is the Type I d' that an optimal SDT observer (in terms of choices and confidence) would have required to reach the observed Type II sensitivity (see Figure 8). An immediate implication is that $meta - d'$ and d' are expressed in same units and thus their comparison (difference or ratio) offers some insight about the ability of individuals to discriminate between correct and incorrect answers. In case of equality the observer uses all the information available for the Type I decision to make is Type II decision. He has thus an SDT optimal metacognitive ability. If $meta - d'$ is lower than d' his metacognition is imperfect. Methods for computing $meta - d'$ and supporting codes in R or MATLAB have been proposed

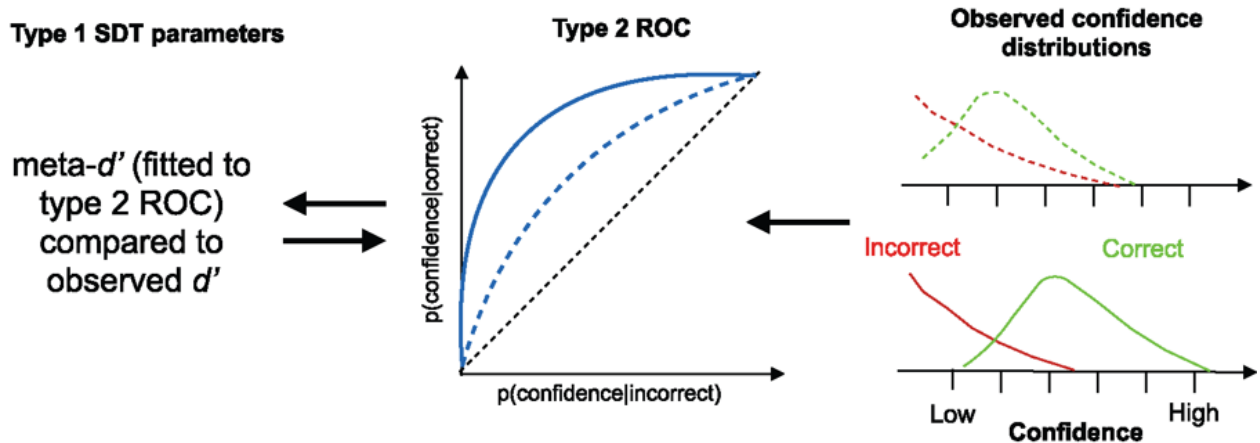


FIGURE 8 – The meta- d' model as illustrated in Fleming (2017). The right-hand panel presents confidence-rating distributions conditional on correct and incorrect decisions. High metacognitive sensitivity leads to higher (lower) confidence ratings when correct (incorrect) and these distributions will only weakly overlap (solid lines). Low metacognitive sensitivity means a greater overlap between these distributions (dotted lines). The overlap between distributions can be calculated through Type II ROC analysis (middle panel). The theoretical Type II ROC is determined by the SDT model and the model can be inverted to determine the type I d' that best fits the observed confidence rating data i.e. the *meta* - d' .

by Maniscalco and Lau (2012) and Barrett, Dienes and Seth (2013) as well as a hierarchical Bayesian estimation by Fleming (2017).¹⁴

Based on this methodological framework my aim was to understand different questions on subjective beliefs and metacognition. How to reveal in the best way the subjective beliefs of subjects in the lab? What is the nature of these beliefs and their quality? And how are they used?

1.2 Elicitation of Beliefs

My first research on this topic dealt with a methodological point: how to find the best way to help subjects to reveal their true subjective beliefs in the lab?¹⁵ I focused on the question

14. Note that another measure of discrimination controlled for performance confound has been proposed by Yaniv, Yates and Smith (1991). They adjusted for the number of confidence levels used and normalized for the performance the DI of the Brier Score (ANDI).

15. See Schlag, Tremewan and Van der Weele (2015) for a survey on beliefs elicitation.

of confidence in own performance and decided to compare three different types of elicitation mechanisms.

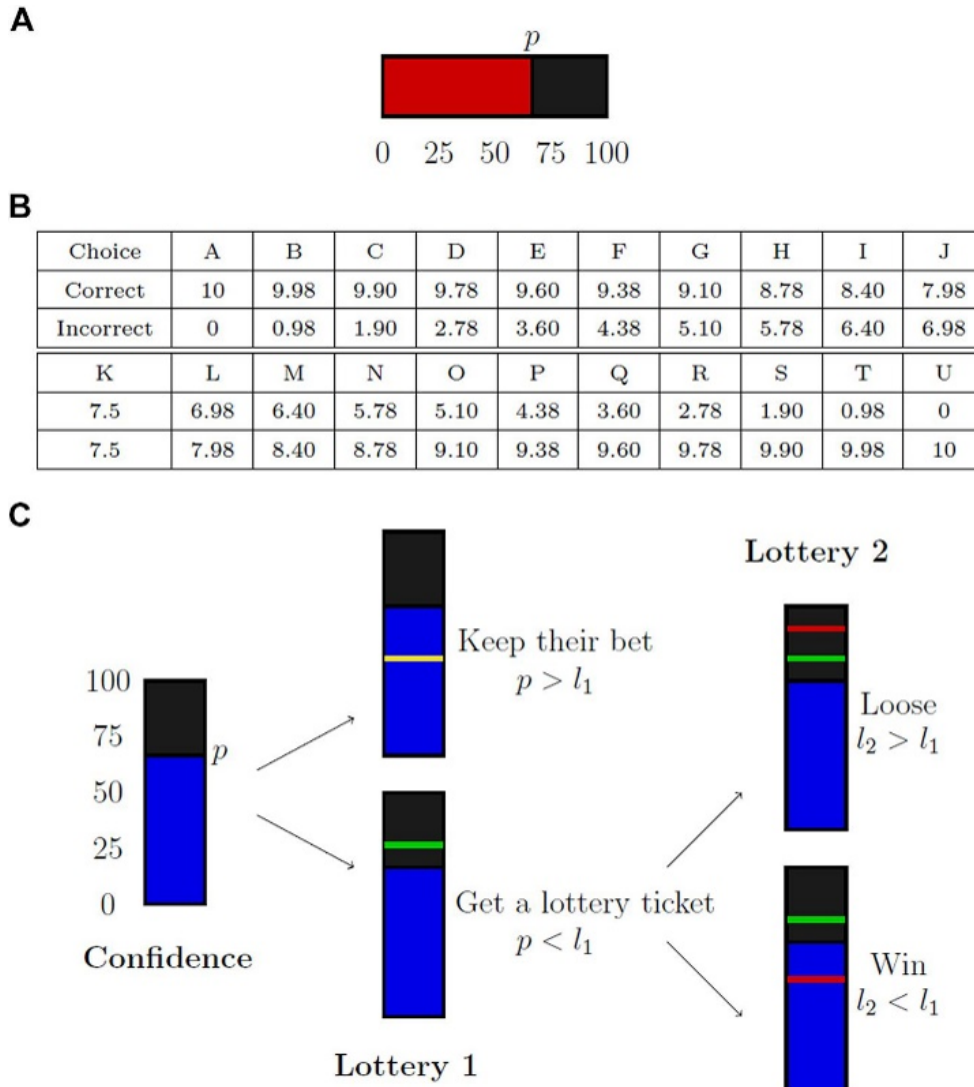


FIGURE 9 – Confidence elicitation mechanisms.

A: Simple scoring rule; **B:** Quadratic Scoring Rule; **C:** Matching Probability mechanism.

The first one was a rule without monetary incentives attached, i.e. to ask subjects their confidence after their decision in a scale going from 0 to 100% (see Figure 9A). The rationale of this rule was its widespread use in psychology but also the assumption that people can directly assess their confidence after the decision with a low effort. The second rule was the Quadratic Scoring Rule (Brier, 1950; Murphy, 1972; Nyarko and Schotter, 2002) which consists to choose

between different bets based on the accuracy of their answer (see Figure 9B). They can win an amount of money if their answer is correct and a smaller or equal amount if their answer is wrong. This rule is a *strictly proper scoring rule*, i.e. the best strategy is to report their beliefs without distortions (see Gneiting and Raftery, 2007, for a survey on proper scoring rules). Indeed, for a confidence level p , subjects will win $a - b \times (1 - p)^2$ if their answer is correct and $a - b \times (1 - (1 - p))^2$ otherwise (with a and b positive constants).¹⁶ In the vein of revealed preferences, we asked subjects to choose between the different possible bets without explicit references to confidence levels. The third rule implemented was the *Matching Probability* method (Winkler and Murphy, 1968; Holt and Smith, 2009) (see Figure 9C) which is based on a Becker-DeGroot-Marshak mechanism (Becker, DeGroot and Marschak, 1964). Subjects are asked to provide the probability p about an event E that makes them indifferent between:

- a lottery $L(E)$ that pays a positive reward s if E happens, and 0 otherwise;
- a lottery $L(p)$ that pays a positive reward s with probability p , and 0 with probability $(1 - p)$.

A random number q is then drawn in the interval $[0, 1]$. If q is smaller than p , the subject is paid according to the lottery $L(E)$. Otherwise, the subject is paid according to a lottery $L(q)$ which pays s with probability q , and 0 with probability $(1 - q)$. This rule is also a strictly proper scoring rule and has the advantage of not being affected by risk preferences.¹⁷ The

16. The QSR is a strictly proper scoring rule under the assumption of risk neutrality. With non-risk neutrality some corrections have to been made on the stated beliefs (see e.g. Offerman et al., 2009).

17. Suppose that subjects think the probability of success is p but report a probability $r \neq p$. First, if $r < p$, the lotteries according to which subjects (given their subjective probabilities) are paid are represented in the following table.

	$q < r < p$	$r < q < p$	$r < p < q$
reports p	$L(E)$	$L(E)$	$L(q)$
reports $r < p$	$L(E)$	$L(q)$	$L(q)$

Similarly, assume $r > p$. Payments (according their subjective probabilities) are described in the following table.

	$q < p < r$	$p < q < r$	$p < r < q$
reports p	$L(E)$	$L(q)$	$L(q)$
reports $r > p$	$L(E)$	$L(E)$	$L(q)$

Thus, subjects obtain a lottery that give them a higher or equal chance to win s , if they report p instead of r . See Karni (2009) for a formal proof.

main uncertainty about this rule was the potential difficulty for the subjects to understand its mechanism.¹⁸

To identify which rule is the best, I compared their performances with respect to two main approaches: a normative one (which rule gives the best fit to theoretical predictions) and a prescriptive one (which rule gives the best confidence quality).

With Thibault Gajdos and Jean-Christophe Vergnaud we compared the three rules to what subjects should have reported according to SDT predictions in the perceptual dots task (Massoni, Gajdos and Vergnaud, 2014). We tested the following set of predictions:

- Prediction 1: an elicited confidence close to that predicted by SDT2 model;
- Prediction 2: an elicited AU2ROC close to the predicted one;
- Prediction 3: an elicited AU2ROC not greater than the predicted one;
- Prediction 4: the closer the elicited confidence distribution is to the predicted confidence distribution, the closer the elicited AU2ROC is to the predicted one;
- Prediction 5: a positive correlation between performance in perceptual task and elicited AU2ROC.

Our results strongly supported the Matching Probability mechanism over the two other rules. Indeed, this rule elicited confidence compatible with all the predictions and had the best performance on four predictions over five (see Figure 10 for the results on Prediction 1). An additional insight of this study was the relatively good performance of the rule without incentive. It suggested that even without any incentives attached to it, subjects reveal informative confidence on their past performance.

With Guillaume Hollard and Jean-Christophe Vergnaud we compared in Hollard, Massoni and Vergnaud (2016) the three rules according to the metacognitive abilities expressed by subjects

¹⁸. Burfurd and Wilkening (2020) showed recently the different ways to present Matching Probability mechanisms and their relative efficiency.

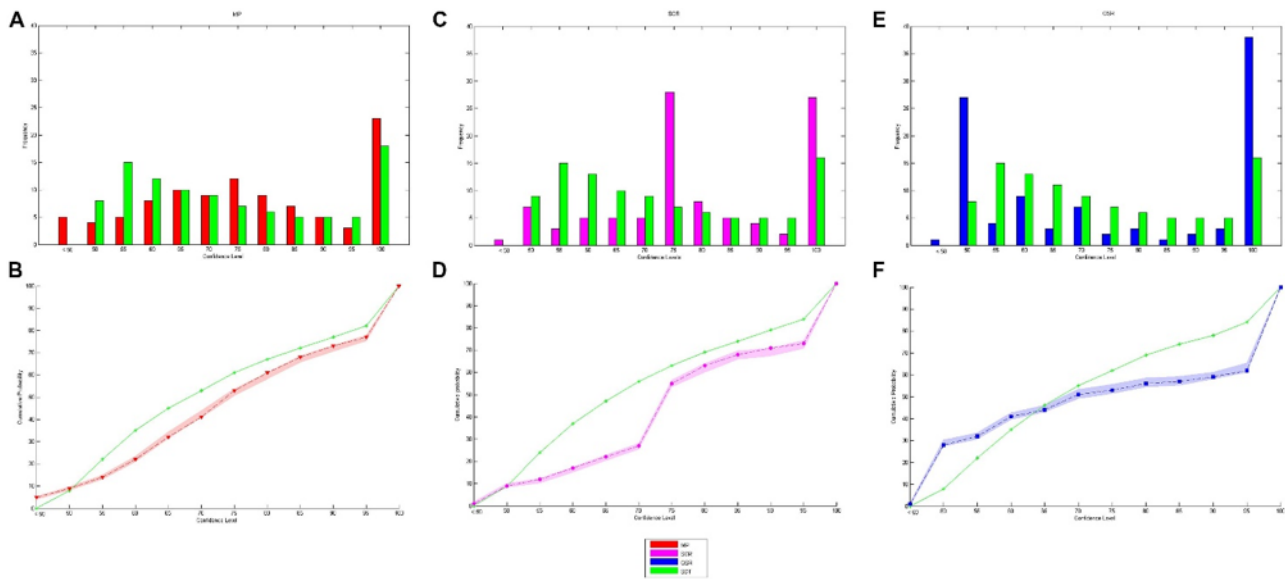


FIGURE 10 – Observed and predicted distributions and cumulative distributions of confidence. (A,C,E) are respectively the observed and predicted distributions of confidence for MP, SCR, and QSR while (B,D,F) are the observed and predicted cumulative distributions of confidence for MP, SCR, and QSR.

facing the perceptual dots task and a cognitive one (general knowledge and IQ questions). The best rule is thus defined according to stated level of calibration and discrimination. Anew we found evidence in favor of the Matching Probability mechanism. It elicited the best beliefs in terms of discrimination abilities (DI and ROC Area) and similar calibration and overconfidence levels than the Quadratic Scoring Rule¹⁹ (see Figure 11 for calibration curves). It also revealed comparable beliefs across tasks. On a side note, the rule without incentive offered the lowest performances but still was able to reveal informative beliefs.

These results in favor of the Matching Probability rule led me to use this elicitation mechanism for the study of subjective beliefs in all my subsequent experiments on beliefs.²⁰

19. Once corrected for risk aversion.

20. In addition, the relatively good performance of the rule without incentive justifies to elicit subjective beliefs with no monetary consequences when these beliefs are not at the core of the project (even more if subjects had to form them in any case prior to the decisions).

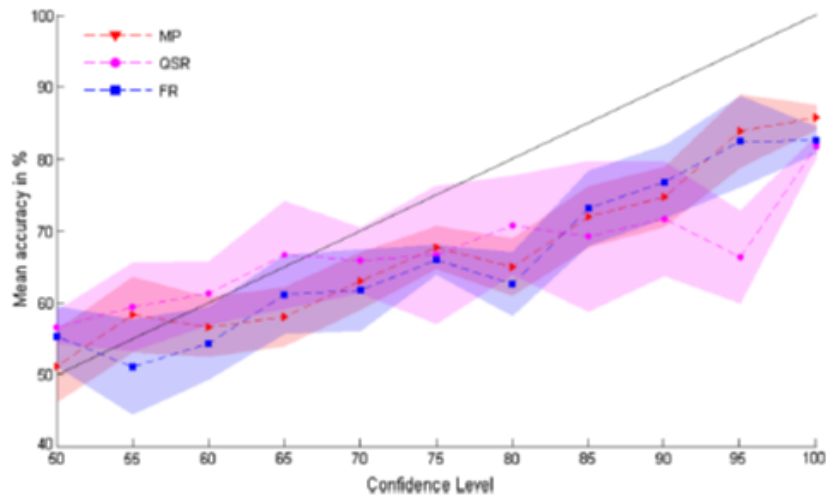


FIGURE 11 – Calibration curves. For the three rules this figure represents the mean accuracy for each level of confidence between 50 and 100.

1.3 Nature of Beliefs

Based on these previous results I identified the best way to reveal confidence in the lab. Then I wanted to understand the nature of these beliefs. My idea was to see how different types of subjective beliefs were related and how these differences affected the metacognitive abilities. I did the following works in this direction.

With Steve Fleming, Thibault Gajdos and Jean-Christophe Vergnaud we studied whether retrospective and prospective judgments were similar. In Fleming et al. (2016) we compared the quality of beliefs in terms of calibration and discrimination when subjects stated their confidence in their accuracy after a perceptual decision and when they made a prediction about their accuracy in their incoming perceptual choice i.e. before or after the dots stimuli presentation. There is some neural evidence of dissociation between prospective and retrospective metacognition (see Fleming and Dolan, 2012). But why prospective judgments are less accurate than retrospective ones (Siedlecka, Paulewicz and Wierchoń, 2016) and the influence of different cues and their temporal dynamic (Rahnev et al., 2015) need more attention. The two main results of this study were the following. In terms of metacognitive abilities, calibration

was correlated across judgment types while discrimination was not (see Figure 12). It thus

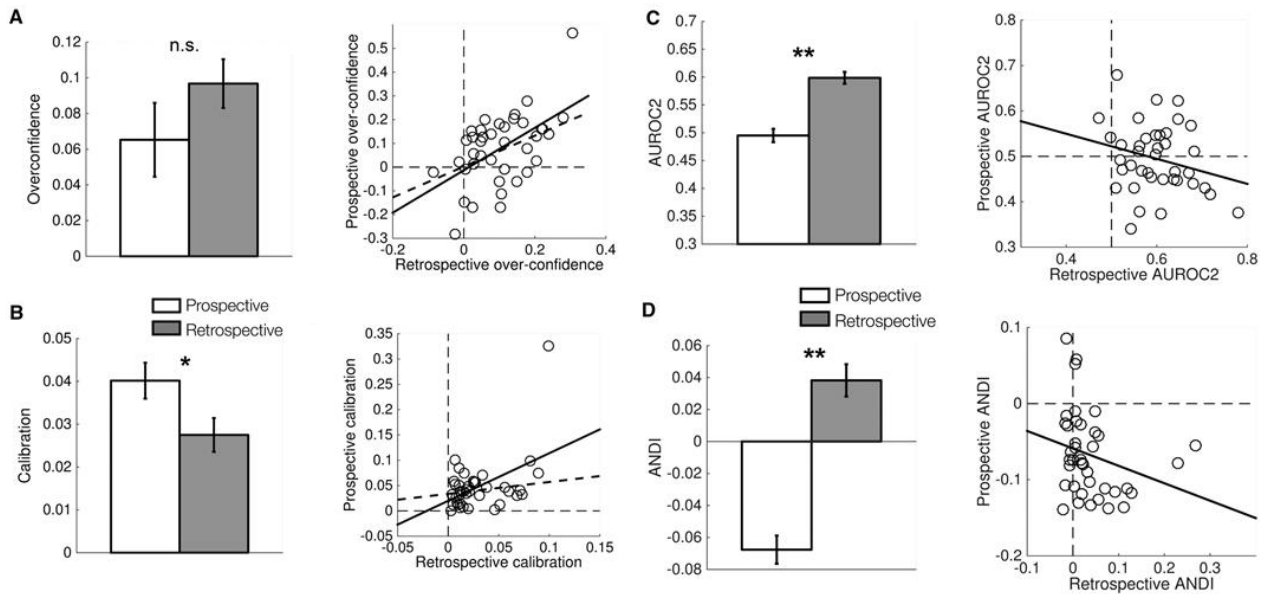


FIGURE 12 – Comparison of prospective and retrospective metacognitive abilities in levels and in terms of correlation across subjects.

A: Overconfidence; **B:** Calibration; **C:** AUROC2; **D:** ANDI. ** and * mean statistically significant at 1% and 5%.

provides evidence in favor of a domain-general overconfidence. In terms of beliefs formation, using hierarchical mixed-model and reinforcement learning model, we showed that retrospective judgments were strongly influenced by the speed and accuracy of the immediately preceding decision, whereas prospective judgments were influenced by previous confidence over a longer time window.

In an unpublished work, I compared metacognitive abilities when individuals are asked to report their probability of success and when they had to report their probability of error. While it is a pure framing effect in this study, there are recent evidence about how common mechanisms are shared in confidence judgment and errors monitoring (Yeung and Summerfield, 2012; Boldt and Yeung, 2015; Charles and Yeung, 2019). Preliminary results seem to show that quality of belief is higher when reporting success rather than errors (both in terms of calibration and discrimination).

In a different approach, I studied how confidence can be modulated by the anxiety linked to the decision. Emotions regulation is known to affect neural mechanisms of attention (Vuilleumier, 2005) and I hypothesized a direct effect of a negative emotion on the quality of confidence.²¹ In Massoni (2014) I used an experimental paradigm in which subjects faced decision for high and low stakes (€20 or €200) in a gain or loss frame. For each decision they have to stated their level of worry about the decision after knowing its characteristics and before the dots stimuli presentation. Then they stated their level of confidence in their choice. I found that subjects' feelings were affected by the type of decision with an increase of worry under loss, high stake and difficult trials. This change in anticipated emotion did not affected the decision by itself (accuracy, reaction time). But under worry individuals were better to form their confidence with a decrease of overconfidence and an increase of discrimination (see Figure 13).

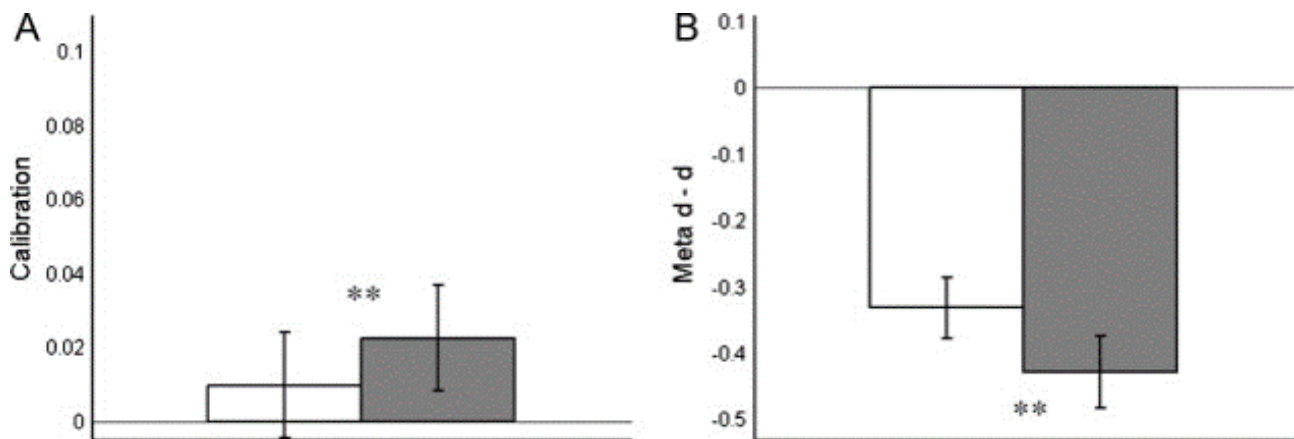


FIGURE 13 – Comparison of the mean values of the metacognitive abilities measured on the trials with worry (in white) and on the trials without worry (in gray).

A: Overconfidence; **B:** difference between meta-d' and d'. ** means statistically significant at 1%.

This gain-loss frame effect has been then documented in terms of metacognitive abilities (Lebreton et al., 2018) and reinforcement learning models of confidence (Lebreton et al., 2019).

Finally, I am currently working with Nicolas Roux on an aspect of the Bayesian nature of

21. Emotional effects on metamemory have been well-documented - see Fairfield et al. (2015) for a review.

subjective beliefs (Meyniel, Sigman and Mainen, 2015; Drugowitsch, 2016; Hangya, Sanders and Kepecs, 2016; Sanders, Hangya and Kepecs, 2016; Navajas et al., 2017b; Adler and Ma, 2018a,b). Our experiment features two treatments of the same task. In the separated treatment, subjects faced a series of trials with a weak stimulus (hard trials) and then a series of trials with a strong stimulus (easy trials), or the reverse. In the mixed treatment, subjects faced a random sequence of hard and easy trials. The separated treatment leaves room for the Bayesian mechanism to affect confidence formation, whereas the mixed treatment prevents it to play any role. The reason is that the mixed treatment makes it impossible to learn about the stimulus' strength through experience. The comparison of confidence changes across treatments should enables us to identify the presence of Bayesian inference as a driver of this confidence change. Very preliminary results seem to support our hypothesis with an improvement of the discrimination over time only for the separated difficulty treatment (see Figure 14).

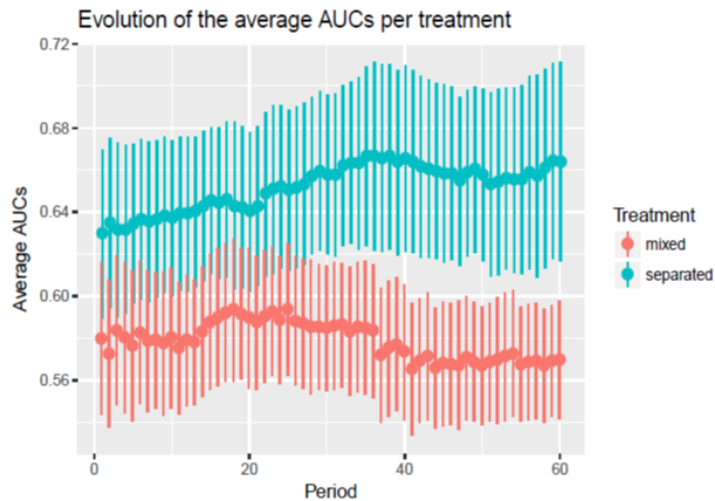


FIGURE 14 – Evolution of the AUROC2 over time on a moving window for mixed stimuli difficulty and separated ones.

1.4 Role of Beliefs

My last research trend on this topic deals with the importance of metacognition in the decision process. After studying the nature of beliefs and their quality, I tried in different studies to understand how and why they matter. The basic idea is that an adequate level of confidence is linked to the quality of decision. While overconfidence effect has been documented in a large number of studies, the role of discrimination is less known and almost absent in economic studies. I thus studied the importance of metacognition in the following contexts: social interactions, insurance decisions, market entries and tendencies to create false memories.

My first study on the role of confidence was linked to the question of group decision. Even if groups are often trusted to take better decisions than individuals (e.g. jury), knowing when and why "two heads are better than one" is crucial (Koriat, 2012*b*). In perception, an extensive work has been done by Bahrami and co-authors to study the ability of dyad to combine individual information. Based on Sorokin, Hays and West (2001)'s SDT framework of group decision, they showed that groups failed to reach optimality as soon as their members have heterogeneous performances (Bahrami et al., 2010).²² Potential explanations of this sub-optimality of group decision come from equality bias in which individuals assign equal weights to other members decisions regardless of their abilities (Mahmoodi et al., 2015) or confidence heuristic facing consensual wrong choices (Koriat, 2012*a*, 2015). With Nicolas Roux we proposed an alternative explanation in Massoni and Roux (2017): the question is not to know how confidence is shared but how well confidence carry some reliable information. We evaluated the quality of confidence in terms of calibration and showed how it can explain the observed sub-optimality. In a model-free approach we first assessed the effect of calibration heterogeneity on collective benefits (Figure 15A). Then we performed a mediation analysis to test whether calibration heterogeneity can completely mediate the performance heterogeneity effect on collective efficiency.

22. The robustness of this result has been established for multiple contexts: feedback (Bahrami et al., 2010, 2012*b*); social interactions (Bahrami et al., 2012*a*; Mahmoodi et al., 2013; Bang et al., 2014); and confidence heuristic (Bang et al., 2014).

Our results for studies with or without feedback supported this idea (Figure 15B).

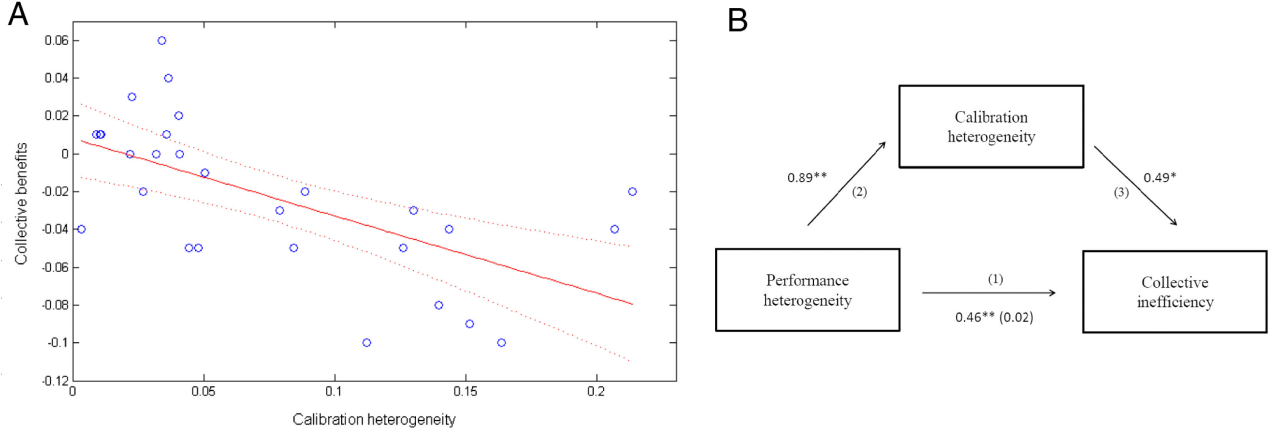


FIGURE 15 – Model free results for the study with feedback.

(A) Observations and linear fit with 95% confidence interval of the calibration heterogeneity on the actual strong collective benefits.

(B) Mediation analysis. These path diagrams show the regression coefficients of the relationship between performance heterogeneity and collective inefficiency as mediated by calibration heterogeneity. The regression coefficient between performance heterogeneity and collective inefficiency, controlling for calibration heterogeneity, is in parentheses. ** and * mean statistically significant at 1% and 5%.

To confirm these results, we derived three analytical models on how group combine individual information: optimally, sub-optimally à la Bahrami et al. (2010) and our confidence-sharing model based on beliefs.²³ In terms of goodness-of-fit (BIC and Bayes factor) results were mixed:

23. With some simplifications, models were as follows. Let x be a signal, τ the inverse of its variance, i.e. the precision of the observer, and ρ the correlation coefficient between group members' signals.

Optimal group decision is based on the sign of the sum of the signals weighted by the precision of the information: $x_G = \tau_1 x_1 + \tau_2 x_2$ and the ideal group's information precision is

$$\tau_G^* = \frac{(\tau_1 + \tau_2)^2}{(\tau_1 + \tau_2 + 2\rho\sqrt{\tau_1\tau_2})}$$

Suboptimal group decision is based on the sign of $x_G^{sub} = \sqrt{\tau_1}x_1 + \sqrt{\tau_2}x_2$ and its precision is

$$\tau_G^{sub} = \frac{(\sqrt{\tau_1} + \sqrt{\tau_2})^2}{2(1 + \rho)}$$

Confidence sharing group decision is based on the expected values of precision parameters of its members $x_G^{bel} = \tau_{1,e}x_1 + \tau_{2,e}x_2$ and the precision is then:

$$\tau_G^{bel} = \frac{\tau_1\tau_2(\tau_{1,e} + \tau_{2,e})^2}{\tau_{1,e}^2\tau_2 + \tau_{2,e}^2\tau_1 + 2\rho\sqrt{\tau_1\tau_2}\tau_{1,e}\tau_{2,e}}$$

with feedback the beliefs-based model outperformed the suboptimal one but without feedback it was only the case in the absence of correlated signals between members.

Overall this study highlighted the importance of sharing a confidence of the same quality between members to reach optimal group decision and thus to facilitate social interactions.²⁴

In an unpublished study with Jean-Christophe Vergnaud, we investigate the links between multiple types of subjective reports facing uncertain situations. We thus asked subjects to report their confidence in each trial of the perceptual dots task, their probability of success on a bet to reach a certain amount of accurate trials, an insurance premium for this bet (with a BDM mechanism) and a global level of confidence in success. Our main research question was to see whether "local" metacognition estimated on each trial was a factor of performance forecasting ("global" metacognition). We also wanted to see the links between these different types of forecasts (prediction, confidence, insurance premium). Since then, Rouault, Dayan and Fleming (2019); Rouault and Fleming (2020) showed that local confidence was a determinant factor for individuals to create their global self-performance estimates and conveyed more information than accuracy and reaction time. Our findings did not offer a strong support for this result. Indeed, local metacognitive abilities were uncorrelated to global forecasting. Yet a proper learning analysis has still to be computed to see how our data can be related to Rouault, Dayan and Fleming (2019)'s results. On a side result we found strong correlations between the different forecasts showing a common root for local self-performance estimates.

My next study on the importance of metacognitive abilities on economic behaviors dealt with a well-documented setting: decision of market entry in a competitive environment. The link between overconfidence and excess entry is known (Camerer and Lovo, 1999; Moore and Cain, 2007). But overconfidence is seen as overplacement (thinking to be better than the others) ra-

24. Note that other explanations of the performance heterogeneity effect have been provided since then: level of shared confidence sensitivity (Pescetelli, Rees and Bahrami, 2016) - our data did not support this idea; confidence matching (Bang et al., 2017); social influence (Hertz et al., 2016; Mahmoodi, Bahrami and Mehring, 2018); shared responsibility (El Zein, Bahrami and Hertwig, 2019).

ther than overestimation (of one's ability, i.e. calibration)²⁵. Results on overestimation are less clear: Bolger, Pulford and Colman (2008) found that overestimation rather than overplacement explains excess entry; while Cain, Moore and Haran (2015) found no effect of overestimation. In terms of sensitivity of confidence, no study tried to link it with market entry (but the potential role of metacognition in entrepreneurship success has been advanced by Haynie et al., 2010; Haynie, Shepherd and Patzelt, 2012). This study based on a market entry game with a perceptual dots task aimed to identify which type(s) of overconfidence explains market entry and to search for a more general effect of metacognitive abilities in this decision process. Preliminary results showed that overconfidence as overplacement and as overestimation matter in market entry decision. Also, metacognitive abilities and in particular confidence discrimination in the task could be linked to market behaviors.

My last work on the impact of metacognition focused on social influence and social contagion. With a Master student, I was interested to see the effect of trust and confidence on social contagion and in particular the tendency of people to falsely recall some items induced by others. Collective remembering has mitigated effects: groups might outperform individuals in memory tasks (Weldon and Bellinger, 1997) but might also create a collective inhibition leading to decrease performance (Basden et al., 1997).²⁶ A specific negative effect of collective remembering might be explained by social contagion resulting in people remembering events that never happened (Roediger and McDermott, 1995). Here we were interested by the introduction of false memories by a confederate in a task of visual memory (Roediger, Meade and Bergman, 2001; Meade and Roediger, 2002). We first tried to replicate previous results in terms of false memory and to mitigate the effect by the level of trust between the subject and the confederate (strangers vs. relatives). Intimate individuals have been more affected by collective inhibition (Luchies et al., 2013) and false memory (French, Garry and Mori, 2008). Our pilot study failed to replicate Roediger, Meade and Bergman (2001)'s results: social contagion,

25. See Moore and Healy (2008) on the different facets of overconfidence.

26. See Basden, Basden and Henry (2000) for costs and benefits of group remembering.

alone, did not seem to create false memories. Participants falsely recalled items only when they highly expected to find it in the scene. These results will be extended in a more proper design next year with the same Master student. Beside more control in the experiment's sessions, we expect to take into account confidence and metacognition aspects i.e. to test whether collective inhibition might be cancelled by asking individuals to state and share their level of confidence in their decision before the group remembering decision. This will open questions about the importance of metamemory (Nelson, 1990) and metacognition in groups performances.

1.5 Decisions with Implicit Beliefs

The previous studies were explicitly focused on subjective beliefs and all experimental designs involve their elicitation. I recently conducted some studies in which those beliefs were a part of the questions but I did not have a direct measure of them. My two main research questions were about decisions in situations with asymmetrical stakes and sequential decisions with an optimal stopping time.

With my PhD student Thomas Garcia, we invested in a specific decision paradigm using the SDT framework. Our question was to understand the specific decision under uncertainty in which the consequences of the actions are asymmetrical. In these cases, one state of the world implies higher stakes than its complementary. As intuitive examples we can think to the physician avoiding to miss a pathology in his patient or the judge trying not to jail an innocent accuser. One interesting aspect of this decision is that, due to the uncertainty, individuals should not try to maximize their success rate but rather their expected benefits (see e.g. Maddox and Bohil, 1998; Maddox, 2002; Maddox and Bohil, 2003; Balci et al., 2011; Ackermann and Landy, 2015). Thus, it appears an opposition between accuracy-driven and optimality-driven decision processes. Using SDT we can model both type of decision criteria and estimate where the actual behaviors fit in this trade-off. I explained in the Methodological Framework section that facing a signal detection task an individual will answer signal if the level of evidence received X is

higher than a specific threshold β , i.e. the decision criterion. This criterion is then linked to the proportion of the different answers observed (Hit, False Alarm, Correct Rejection, Miss). To get into more details we can now consider that each answer got a certain valuation $V(\cdot)$. If $V(CR) - V(FA) = V(hit) - V(miss)$ we are in the symmetrical and classic case. But if $V(CR) - V(FA) \neq V(hit) - V(miss)$ we are in our case of interest with asymmetrical payoffs. The decision facing a level of evidence X can be expressed in terms of the likelihood ratio of observing X :

$$\text{Say signal} \Leftrightarrow \frac{P(X|signal)}{P(X|noise)} > \beta.$$

We can thus derive two decision criteria (see Figure 16): β^a the accuracy driven one which maximizes the success rate and β^* the optimal driven one which maximizes the expected benefit.²⁷

$$\beta^a = 1 \quad \text{and} \quad \beta^* = \frac{V(\text{correct rejection}) - V(\text{false alarm})}{V(\text{hit}) - V(\text{miss})}$$

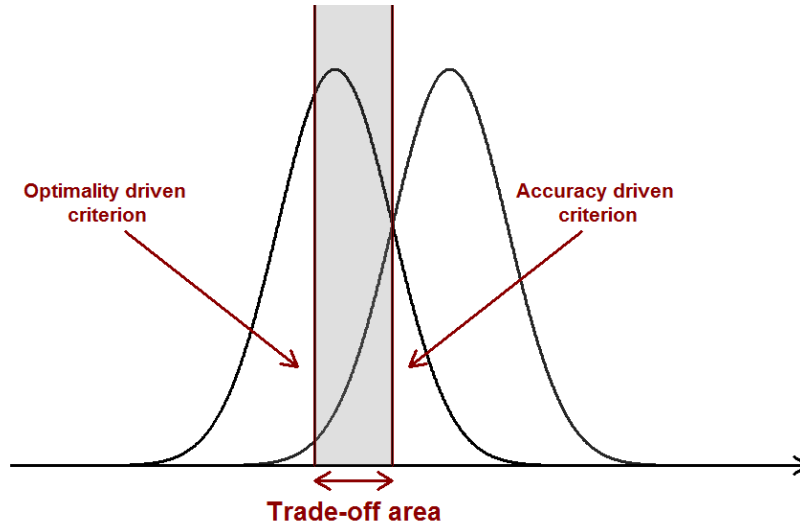


FIGURE 16 – Optimality and accuracy driven criteria for payoffs asymmetrical towards signal.

Based on this we can first compare the criterion used with the theoretical ones. Then we can predict which behaviors should be observed for an ideal Bayesian observer using each of the

²⁷. It should be noted that the criterion β has to be multiplied by the priors ratio $\frac{P(noise)}{P(signal)}$ to take into account the initial distribution of signal and noise. But in our setting, we use an equal based rate and the priors are equal i.e. $\frac{P(noise)}{P(signal)} = 1$.

criterion.

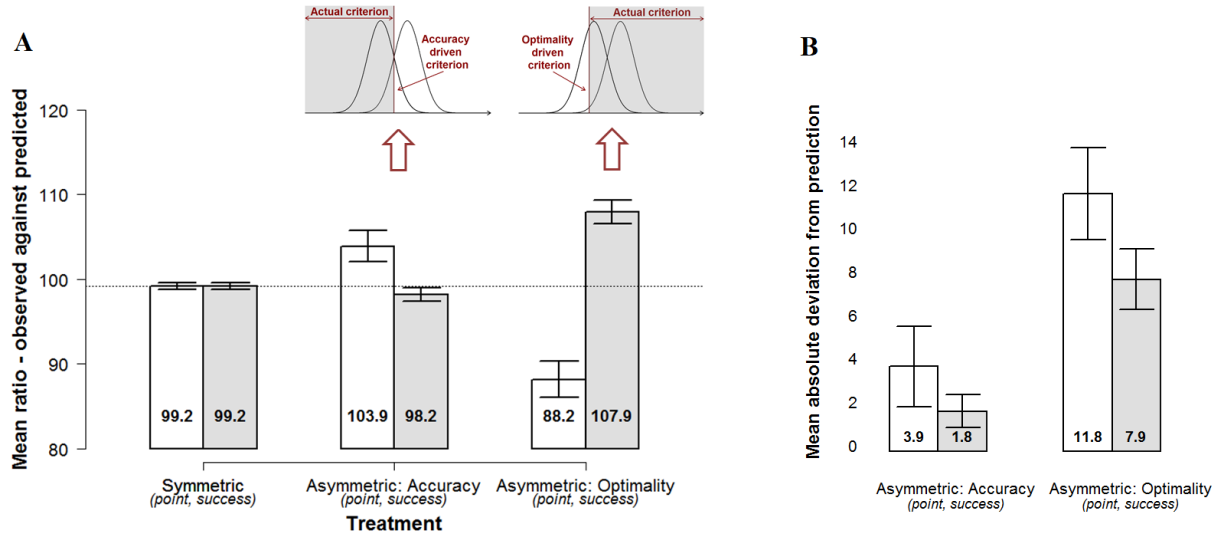


FIGURE 17 – Observed versus predicted behaviors in terms of rewards (number of points for the payoffs) and accuracy (success rate) for accuracy-driven and optimality-driven decision process. **A**: Mean ratio of observed over predicted level of points and success for accuracy-driven and optimality-driven decision process; **B**: Mean absolute deviation of points and success from prediction for accuracy-driven and optimality-driven decision process.

In Garcia and Massoni (2017) we conducted two lab studies on this question. The first study highlighted the existence of this trade-off between optimality and accuracy (see Figure 17A) and the tendency to be too close to the accuracy-driven criterion (conservatism bias - see Figure 17B). We showed that these results are robust to a utility-based criterion (replicating Ackermann and Landy, 2015’s results). The second study offered a partial explanation of this behaviors by estimating a valuation for being right using a flat-payoff scheme.²⁸ Results showed that, compared to symmetric payoffs, flat payoffs did not decrease in a large extent the accuracy. Unfortunately, this last result suffers from different limitations: first, any type of behaviors is compatible with a flat-payoffs scheme, and more generally, we were not able to prove

28. Previous explanations dealt with a biased path of optimization due to outcome bias or an insufficient steepness of the optimal reward function around the optimality (Myung and Busemeyer, 1989; Busemeyer and Myung, 1992; Erev, 1998) or with the idea that subjects attempt to maximize payoffs on each trial, but erroneously believe that maximizing accuracy fulfills this objective (Maddox, Bohil and Dodd, 2003; Maddox and Bohil, 2004).

that an intrinsic value of being right was the unique explanation of the observed decisions. The protocol will gain from more controls and, in particular, a new treatment penalizing explicitly the accuracy. Yet this paper offered me the framework for this research question and should be seen as a starting point to a more extensive program. I complemented this study with an experiment, in collaboration with Thomas Garcia and Ismael Rafai (Garcia, Rafai and Massoni, 2017), trying to correct this conservatism bias and to push individuals toward the optimal decision process. Based on a simple change of the information order we managed to change, significantly but with very low effects size, the decision criterion in the optimal direction. More precisely, revealing to subjects the payoffs matrices between the stimuli presentation and the choice improved the criterion compared to the usual scheme where the payoffs are known before the start of the trial. However, this protocol was also imperfect and more control on the attentional process is needed in case of further studies (see Carrasco, 2011 for attention in vision or Rahnev et al., 2011 for effect of attention on conservatism bias in an SDT framework).

With my PhD student Ambroise Descamps and Lionel Page we were interested in another type of decision where subjective beliefs despite central were not elicited. We studied how individuals gathered some costly information to reduce the uncertainty about their decision. They face an optimal sequential stopping problem in which they should determine when to stop the information acquisition and to decide between possible alternatives. Theoretically an optimal Bayesian decision maker should stop when the marginal expected value of information is smaller than the cost of sampling information (Wald, 1945; Fudenberg, Strack and Strzalecki, 2018). As we are in a finite horizon we can determine by backward induction the expected payoff from sampling at any period and thus the optimal stopping time (see Figure 1.5).

In Descamps, Massoni and Page (2016) we conducted a lab experiment where subjects had to determine which data generating process (under the form of risky urns of different bi-color balls composition) was used by collecting observation on the realized events (under the form of balls). We varied the cost of sampling (low - 10 cents, medium - 50 cents, high - 1 dollar) and

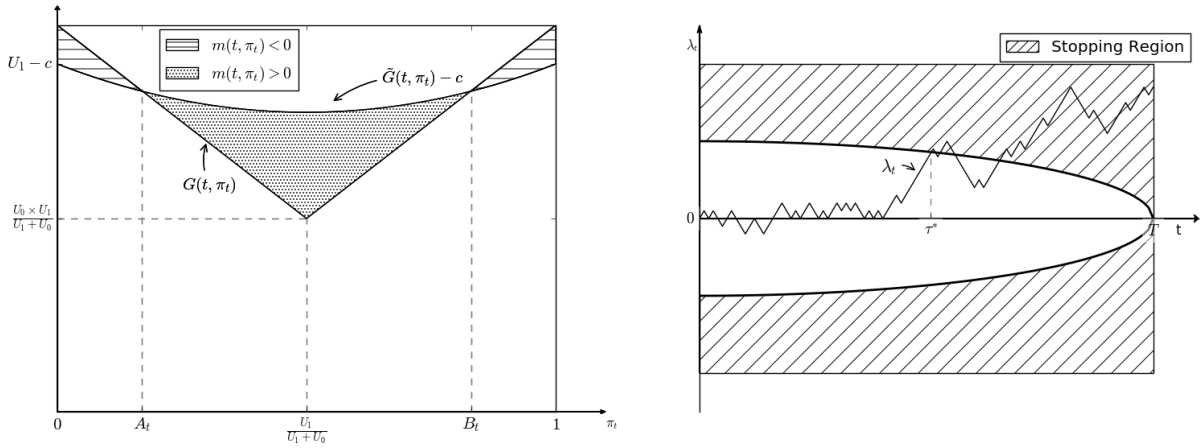


FIGURE 18 – Theoretical representation of the sampling problem at a given time and in a dynamic setting. (*Left panel*): Typical behavior of the expected utility from stopping ($G(t, \pi_t)$) and sampling ($\tilde{G}(t, \pi_t)$), at a given stopping time. The dotted area represents the expected gains from sampling when beliefs are between the boundaries of the null marginal incentives to sample (A_t and B_t). The hatched area represents the expected losses from sampling when beliefs are outside the range $[A_t, B_t]$. (*Right panel*): Typical behavior of the sequential probability ratio test statistics (λ_t). The bold parabola represents the sampling frontier. The optimal strategy is to stop as soon as λ_t crosses this frontier (at $t = \tau^*$).

the framing of the problem (gain or loss). We were able to derive the optimal stopping time for the three level of costs (see Figure 19).

We found that individuals deviate systematically from the optimal solution: they oversampled when the information is costly and undersampled when it is cheap. Yet they learned under costly information and tended to approximate the optimal rule over time. These results are robust to the framing of the problem. We searched how we can explain the observed behaviors by computing various models of decision (risk aversion, loss aversion, regret, heuristics confirmation bias). None of these models could explain the whole pattern observed (or only weakly for the confirmation bias). Recently we proposed a new explanation based on stochastic choices. The cheaper the information, the longer subjects have to wait until reaching the optimal stopping time. Thus, if we assume that individuals made random mistakes such as a Fechner error (Hey and Orme, 1994; Conte, Hey and Moffatt, 2011), this delay to the optimal solution increases the risk of stopping too early (and the undersampling). The reciprocal mechanism explains

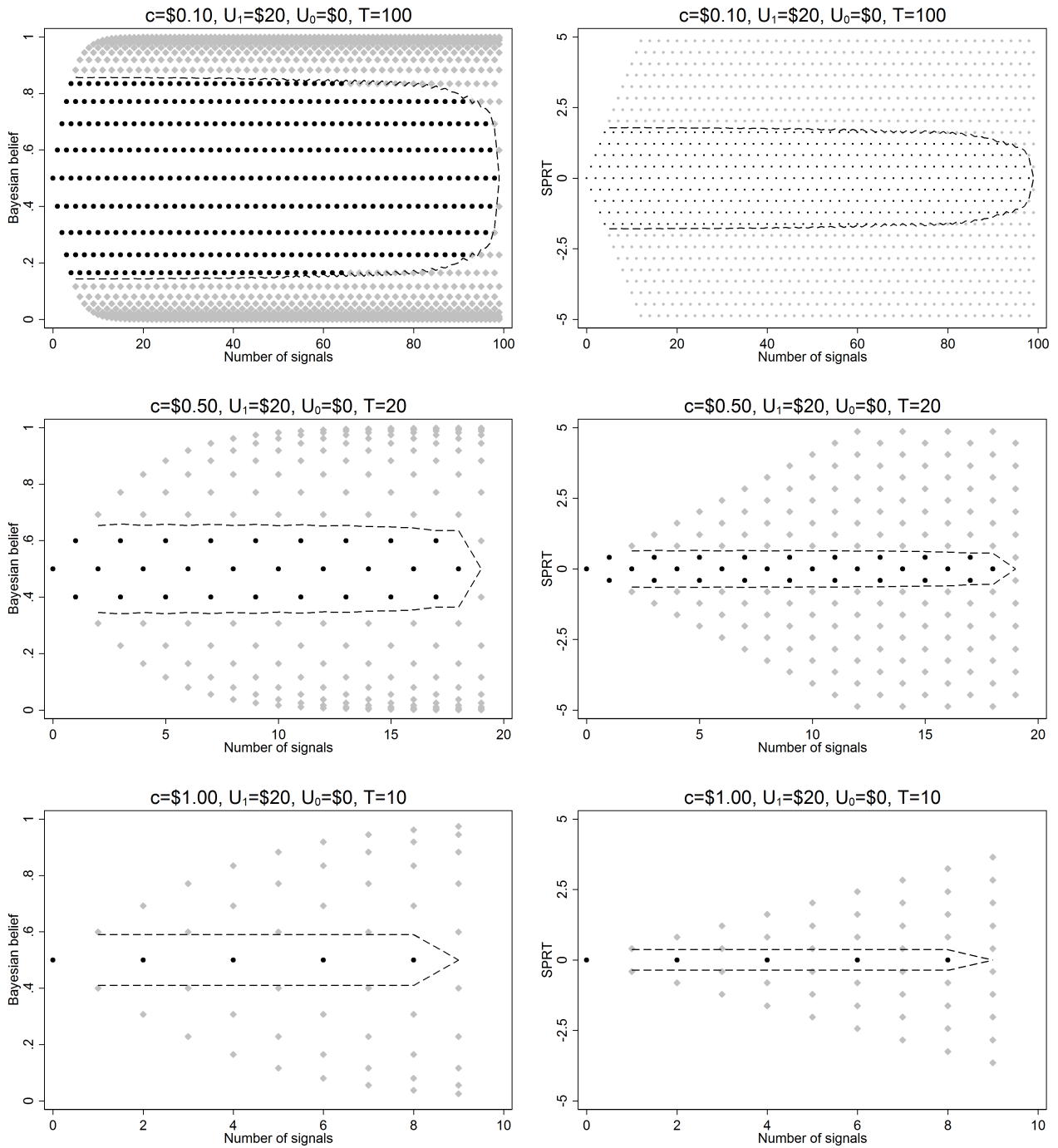


FIGURE 19 – Plot of the sampling problem in the Bayesian beliefs space (left panel) and log-likelihood space (right panel) for $c=0.10$, $c=0.50$, $c=1$. Participants’ endowment to buy signals is constant across the treatments, \$10. This endowment determines the maximum number of signals T which can be bought.

The grey dots represent the stopping region. The black dots represent the sampling region. The prior is $P(\theta = A) = 0.50$, a correct decision yields a payoff of $U_1 = 20$ and a wrong decision a payoff of $U_0 = 0$. The dashed lines represent the estimated optimal frontiers.

oversampling under costly information. Thus, this model is able to explain the whole pattern of behaviors observed.

2 Social Preferences

During my postdoctoral position I extended my research interests toward a new field, namely the social preferences (broadly speaking). More precisely I started, with my students, to engage in social preferences questions related to what I was familiar with: decision under risk and ambiguity. Then I studied some new questions explicitly focus on the social choices process itself and it became a new trend in my research agenda. I still aim to completely connect this topic with my other research on subjective beliefs and computational modeling (see Crockett, 2016, on this perspective).

2.1 Risk, Ambiguity and Social Preferences

I tried in different studies to understand how preferences under risk and ambiguity and social preferences are related and how they impact each other. How risk and ambiguity shape social preferences? And how risk preferences are affected by social context.

My main contribution on this topic is with my PhD student Thomas Garcia and Marie Claire Villeval. We studied how charitable giving behaviors are affected by the presence of risk and ambiguity on the donation's effect (Garcia, Massoni and Villeval, 2020). The idea was to see whether individuals use this uncertainty as a moral wiggle room to act less generously without feeling guilty (Dana, Weber and Kuang, 2007). This behavior has been well documented under risk (Krawczyk and Le Lec, 2010; Brock, Lange and Ozbay, 2013; Exley, 2015) but the only evidence under ambiguity are scarce and contradictory (Haisley and Weber, 2010, found that ambiguity decreases donations while Cettolin, Riedl and Tran, 2017, found similar behaviors under risk and ambiguity). In an experiment implying real charities we studied giving behaviors

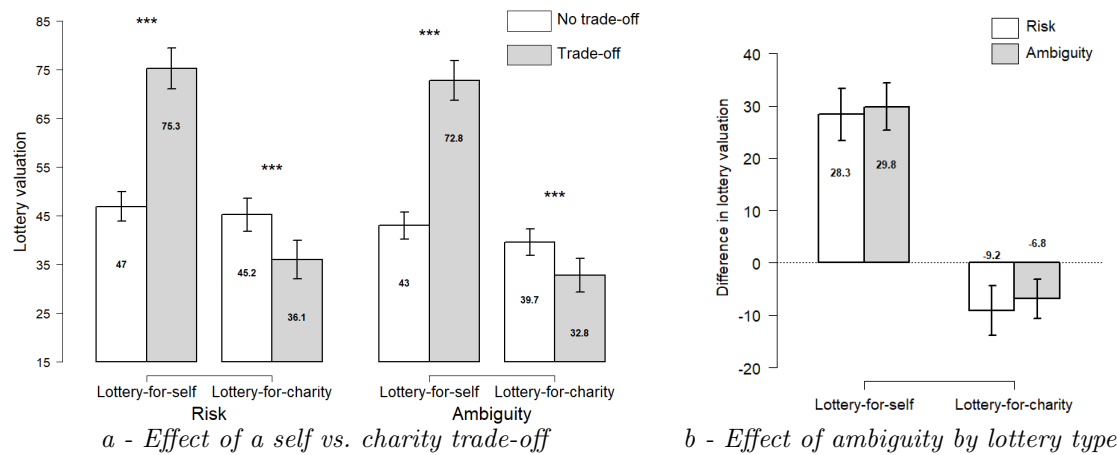


FIGURE 20 – Comparison of lottery valuations (%) under risk and under ambiguity
 Notes: (a) Mean lottery valuation for each decision. (b) Difference in mean lottery valuations between decisions with a self *vs.* charity and without this trade-off either for lotteries-for-self or lotteries-for-charity. While there is evidence of excuse-driven behavior under risk and ambiguity (a), this behavior is not reinforced under ambiguity compared to risk (b). Censored subjects are not excluded. Mean values are written at bars' centers. White bars provide valuations: (a) without a trade-off, (b) under risk. Grey bars provide valuations: (a) with a trade-off, (b) under ambiguity. The horizontal lines represent 95% confidence intervals. Stars represent the level of significance for paired t-tests. *** means $p < 0.01$.

when the cost or the benefit of the donation is subject to risk or ambiguity. Using Exley (2015)'s methodology we controlled for uncertainty preferences before offering lotteries with uncertainty on the subject oneself (cost of a donation) or on the charity itself (benefit of a donation). We found such excuse-not-to-give behaviors under risk and ambiguity. We thus replicated Exley (2015)'s results under risk but we did not find any additional decrease of donations under (partial of full) ambiguity compared to risk (see Figure 20).

We thus conclude that individuals exploit any type of uncertainty as an excuse not to give, regardless of the nature of this uncertainty.

While the previous paper was about how uncertainty could affect social behaviors, I did a couple of studies in which I wanted to see how risk preferences were affected by a social context.

With my PhD student Gevorg Ordyan we tried in an unpublished study to test how range and rank position matter on individual risk preferences. Social comparison is known to affect risk preferences in a multitude of context (Trautmann and Vieider, 2012; Maccheroni, Marinacci and Rustichini, 2012). There exists an effect of rank position among peers in the increase of risky

behaviors (Dijk, Holmen and Kirchler, 2014; Kirchler, Lindner and Weitzel, 2018). But these studies did not control for a potential range effect (see Range-Frequency theory from Parducci, 1965, for the intuition of a potential range effect or more recently Kontek and Lewandowski, 2018, in individual context). In this experiment we elicited risk preferences in a social context where the range matters but for a controlled rank level i.e. subjects can improve their range but cannot change their rank whatever their decisions. We showed that subjects increase their risky investments in social context compared to individual one. But we cannot find a direct range effect when comparing a change of range from 15% to 40% on risk preferences.

In a similar vein, I did a pilot lab study with a Master student that explicitly tried to see how social preferences can moderate peers' effect on risk preferences (Rohde and Rohde, 2011; Linde and Sonnemans, 2012, 2015; Dijk, 2017). We compared risky investments with or without information on peers and searched for a moderation effect of social preferences. Results seemed to show a small trend toward this moderation effect. Unfortunately, poor data collection (in terms of control, size and incentives) avoids any robust conclusion but still calls for new sessions.

2.2 Status and Behaviors

A second aspect of my research in the social preferences literature is directed toward the role of status in economic decisions. Social status and hierarchy have been known to be influencing factors in various aspects of economic and social behavior (see Heffetz and Frank, 2011, for a review on the topic). In different unpublished studies I aimed to understand how status could affect risky decisions, cheating behaviors and bargaining powers.

With my PhD student Gevorg Ordyan we were first interested on the effect of status hierarchy in group decisions. Subjects had to choose between low risk and high-risk investments in group of four and to find a group agreement in at most six steps of decision. Beforehand we induced high and low status according to a general knowledge quiz test (which was so hard that correctness was random) and an award ceremony (high status received a star and had to

be applauded by low status).²⁹ The existence of a choice shift has been well documented in risky group decision. Groups tend to take more extreme decisions than individuals (risky shift e.g. Shupp and Williams, 2008; or cautious shift e.g. Zhang and Casari, 2012; see Eliaz, Ray and Razin, 2006 for a theoretical approach). We formed homogeneous groups (all high or low status) and heterogeneous ones (only one high or one low status). Status effect were expected to lead the group to follow high status choice. On the contrary we found the low status were more reluctant to change their choices leading to more conflict and a shift toward their preferences. In a second experiment with Gevorg Ordyan and Lionel Page we studied how status inconsistency affects bargaining powers in an ultimatum game. High status led to more bargaining power (Ball and Eckel, 1998) but status inconsistency effect has been ignored in economics (see Zhang, 2008, for a recent sociological approach). We hypothesized that consistent status will increase the effect of single status while inconsistent status will cancel status effect. We induced two status in the lab first by score in a general knowledge quiz (again accuracy was random due to its difficulty) and then a perceptual task. Ultimatum games (with three repetitions) were played between single high and single low status, then between double high and double low status and between high and low and low and high status. In all stages of the game we did not find any significant effect in terms of offering or rejection rate between the different status members.

In a last study about status, I searched with a Master student to find the effect of status on dishonest behaviors. Status has already been linked to unethical behaviors (Charness, Masclet and Villeval, 2014). We assigned randomly high and low status to students and made them play a double auction market (with high status always in the role of sellers) and a communication game in which the sender had the opportunity to send dishonest message (Erat and Gneezy, 2012; Rosenbaum, Billinger and Stieglitz, 2014) as well as a chat option. Our market game showed that high status earned significantly more than low status over all the periods. It thus replicated Ball et al. (2001)'s findings. In terms of dishonesty, high status tended to send dis-

²⁹. This procedure has been widely used to induce artificial status in the lab - see Ball and Eckel (1998); Ball et al. (2001).

honest messages more often and to be more often trusted about their message. Unfortunately, a low number of observations (20 subjects) did not allow for a strong significant result. This study was supposed to be complemented by the effect of status on cheating through Garbarino, Slonim and Villeval (2018)'s method to allow and measure for cheating behaviors. This link between status and tendency to cheat has been documented in Piff et al. (2012) but a proper cheating experiment on it has still to be done. It should become an extension of the current study in a near future.

In a weakly related topic, I did an experiment with Thibault Gajdos, H el ene Huber and Jean-Christophe Vergnaud on how different status (in terms of wealth, health, prevention) matter on health insurance decision. More precisely we studied which factors influenced the tendency to join a mutual insurance scheme in which risks and premiums are pooled between status (Gajdos et al., 2017). We can disentangle what come from luck (health is randomly assigned), talent (wealth depends of performance in a task) and effort (prevention is based on a costly effort). Following Dworkin (1981*a,b*)'s idea of fairness we assumed that individuals will not react in the same way according to the source of inequality (see also Fleurbaey and Maniquet, 2011, for a review). Finally, we implemented a group identity in some sessions to create an in-group feeling among subjects (Chen and Li, 2009). Our results showed that there exists a willingness to contribute to mutual insurance and its level increases depending on the sources of inequality, health framing, in-group feeling and information about transfers' impacts. Thus, social preferences can be linked to mutual insurance decision and could depend on the context.

3 Applied Public Economics

In addition to my main research topics I am interested to study some more applied questions related to public policy issues. To do so I am using different types of methodology: lab experiments, lab-in-the-field experiments, field experiments, surveys, statistical data and algorithms. I will briefly present my previous works on the following topics: health, education, catastrophic

risks and labor market trajectories.

3.1 Health

My main interest in health is related to the analysis of behaviors facing infectious disease.

I developed with Olivier Chanel, Stéphane Luchini and Jean-Christophe Vergnaud a lab-in-the-field experiment on a general audience to increase the intentions of vaccinations against the (A)H1N1 virus during the 2009 pandemic. We showed in Chanel et al. (2011) that individual attitudes to vaccination are based on rational appraisal of the situation, and that it is information of a purely scientific nature (through experts' advice) that has the only significant positive effect on intentions to vaccinate (compared to information related to others' intentions, public opinion, and other's beliefs).

I am currently working within the *Psychological Science Accelerator* team (Moshontz et al., 2018) to understand different behaviors related to the ongoing Covid-19 pandemic (Forscher, Primbs and Coles, 2020).³⁰ In three online studies, we try to understand: how the framing of information impacts the efficiency of health recommendations (Dorison et al., 2020); how some cognitive reappraisal interventions could help to build psychological resilience during the pandemic and beyond (Wang et al., 2020); and how different communication styles could improve individuals' motivations to follow social distancing measures (Legate et al., 2020).

3.2 Catastrophic Risks

While it can be partially linked to my works on disease, I also explicitly focused on behaviors facing catastrophic risks in different studies.

With Olivier Chanel, Graciela Chichilnisky and Jean-Christophe Vergnaud we conducted a field

30. See Van Bavel et al. (2020) on how behavioral sciences might be helpful in this situation.

study to understand how past traumatic experiences impact attitudes toward environmental risk. The study dealt with the risk of flooding and we surveyed individuals from four different categories in South of France: those who have been affected 20 years ago in a flood disaster (37 deaths); those who have been affected 2 years ago in a flood disaster (23 deaths); those who lived in an area with a potential risk of flooding; and those at no risk of flooding. Based on 599 face-to-face interviews we found the following effects. A recent experience of flooding increases the subjective estimation of the risk, its anticipated emotions and the willingness-to-pay (WTP) for protection compared to the no-risk population. On the contrary, a distant experience of flooding decreases these estimations, anticipated emotions and WTP. In Chanel et al. (2016) we linked these results to different emotional components (anticipated, anticipatory, incidental, immediate and past emotions as well as Post-Traumatic Stress Disorder - see Lerner et al., 2015, for a recent review of emotions and decision-making) and highlighted the importance on emotions and past experience on behaviors under catastrophic risks. While the data collection was done several years ago we are still working on an additional paper on the topic.

Using the same database, we highlighted an additional effect regarding the WTP mechanism. For 30 years, most of empirical studies on non-market valuation relied on individuals' stated preferences, as consumers on fictitious (or contingent) markets, by choosing the share of their disposable income they accept to renounce to for the provision of the good proposed (Carson, 2012). However stated preferences are criticized for their sources of bias/error which are not always controlled, and for the reliability of the values obtained (McFadden and Train, 2017). In Chanel, Massoni and Vergnaud (2020) we were interested in a more ethical problem: we showed a plutocratic aspect of stated preferences techniques. Indeed, if preferences are elicited through the willingness to trade-off money for an increase in the provision of the quality / quantity of the good, the ability to pay of the respondents limits the realm of possibility. Thus, the poorest cannot express their true preferences while the wealthiest might impose their view.

By comparing standard WTP and normalized WTP (within a same budget for everyone), we measured the extend of this effect and proposed some *ex-post* techniques for its correction.

On a more theoretical aspect, I conducted, with Théodora Dupont-Courtade, a lab experiment focusing on how people react to the source of information in the case of catastrophic risks (Dupont-Courtade and Massoni, 2015). This study aimed to contribute to the experimental literature on insurance under catastrophic risk (see Kunreuther et al., 2002, for a review and Cabantous, 2007; Cabantous et al., 2011, for insurance under conflicting information) but also on decision under conflict (see Crès, Gilboa and Vieille, 2011; Gajdos and Vergnaud, 2013, for theoretical approaches; Baillon, Cabantous and Wakker, 2012, for experimental evidence; and Smithson, 2015, for a review). We studied insurance premiums according to the source of the information (risk, imprecision, conflict and imprecise conflict) in different context: low-probability high-consequence or high-probability low-consequence events; side of the insurance market (WTP or WTA); and increase of information's divergence. Results showed that individuals underestimate catastrophic risk and exhibit the following pattern of preferences for information sources: risk \succ imprecision \succeq conflict \succ imprecise conflict.

3.3 Education

In education, I was involved in the design and the evaluation of two educative programs in France and in Australia as well as an experiment on different incentives schemes to improve effort.

With Jean-Christophe Vergnaud, we did a cost-effectiveness evaluation (Levin, 2001) of the *Programme Action Lecture* designed to improve the literacy skills of 400 primary schools' students in Paris. In Hainaut, Massoni and Vergnaud (2010) and Massoni and Vergnaud (2012) we showed that an intensive one-week intervention focused on reading is worth 40% of the annual progression. This program is also most cost-effective that different policies (e.g. a class-size

reduction as estimated by Piketty and Valdenaire, 2006).

With Uwe Dulleck, Dipa Sarkar and Juliana Silva Goncalves we designed a behavioral intervention to increase the take-up in kindergarten of toddlers from disadvantaged families in Melbourne. We tried different types of basic nudges but only found null to very moderated effects (Dulleck et al., 2015).

Finally, in a more abstract setting, I searched, with Uwe Dulleck, Azhar Potia and Benno Torgler, the best way to motivate individuals to make effort (see DellaVigna and Pope, 2018 for a comparison of 18 treatments to increase effort on MTurk workers). In Potia et al. (2020) we conducted a lab experiment to compare different incentives schemes to increase performances in an effort task.³¹ We compared the following schemes in their efficiency to reach a predefined target (Locke and Latham, 2006): conditional reward and upfront reward, both with or without promises signed beforehand. These schemes are based on monetary incentives as well as their psychological foundations (Fehr and Falk, 2002): upfront reward should trigger some gift-exchange and reciprocity mechanisms (Gneezy and List, 2006; Fehr and Falk, 2007; Kube, Maréchal and Puppe, 2012); while promises should play on guilt aversion (Charness and Dufwenberg, 2006; Vanberg, 2008). We found the two following main results. First upfront rewards performed at least as well as conditional ones (even better but not significant) while they are cheaper (e.g. no need for monitoring). Promises were counterproductive and in particular for upfront schemes. It gave evidence of a crowding-out effect of intrinsic motivation (gift exchange) by extrinsic motivation (to sign a promise) (Frey and Oberholzer-Gee, 1997; Deci, Koestner and Ryan, 1999).

31. While this study is a lab experiment, the idea was first to test different schemes before trying the most promising one in the field on primary school students.

3.4 Labor Market

My studies on the labor market are mostly statistical. During my collaboration with the SAMM lab at the University of Paris 1, I developed with Madalina Olteanu some algorithms to cluster the career-paths of new entrants on the job market. Using the *Génération 98* database³², we used a Self-Organizing Map (Kohonen and Somervuo, 1998) based on different types of distances to define some typologies of career-paths (see Figure 21 for the whole market structure, an example of a 8×8 Self-Organizing Map and the final typologies).

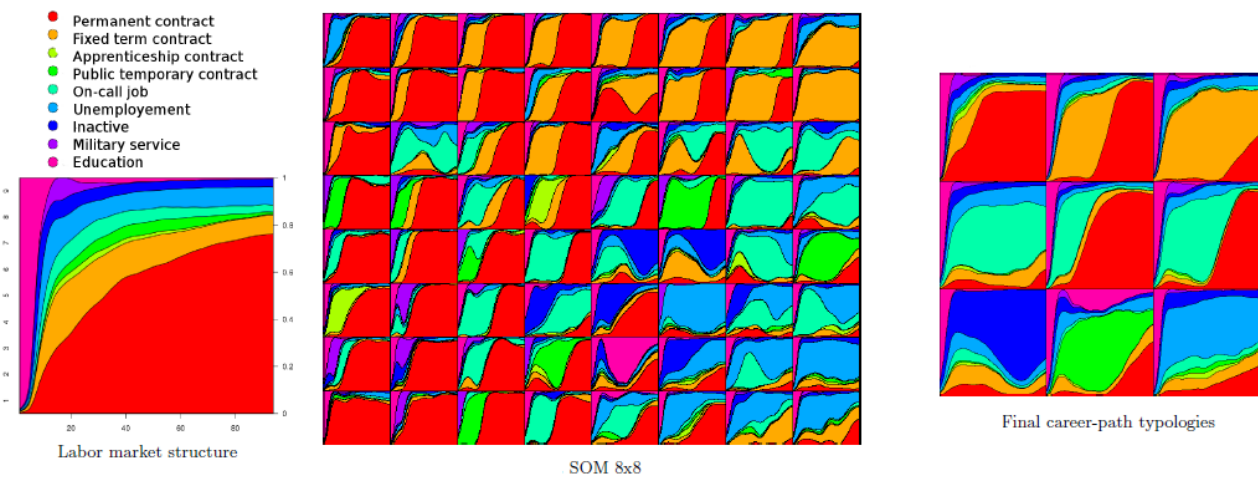


FIGURE 21 – Clustering of career-paths using Self-Organizing Map and Optimal Matching.

The main challenge for clustering such data is to find the adequate dissimilarity measures. Inspired by bioinformatics we first proposed to combine the Self-Organizing Map with an optimal matching algorithm for the distance (Massoni, Olteanu and Rousset, 2009); then we used an optimal convex combination of different dissimilarities that minimized within-class variance (Massoni, Olteanu and Villa-Vialaneix, 2013).

These studies allowed me to explore different perspectives on data analysis and to develop my interests in pure algorithms research. I should continue this kind of research with Madalina Olteanu on clustering and Joseph Rynkiewicz on deep learning.

³². This data set contains information on 16040 young people having graduated in 1998 and monitored during 94 months after having left school.

3.5 Perspectives

While the aforementioned studies are quite disconnected from my main research topics, I am enjoying the possibility of getting out of the lab and to work with field or statistical data on concrete policy questions. I do not plan to develop explicitly such studies in my research program. But I am convinced that I will continue to work on these types of topics during my career.

Research Program

This program will present the main directions of my future research. It is composed of four main projects that might be more or less linked.

- (i) The first one is dealing with my primary research field and aims to pursue my works into the questions of confidence, subjective beliefs and metacognition.
- (ii) The second one is focused on the related field of decision under risk and uncertainty. Links between this topic and the first project are obvious but in this second project the main aspect is not the metacognitive process itself.
- (iii) While some aspects of the two previous projects deal with social component questions I also have an independent project on social preferences with quite independent research questions.
- (iv) Finally a long-yearned objective is to apply previous knowledge about the decision processes on a concrete and applied type of decision and to develop some decision-support tools to improve actual behaviors. The last project is dealing with this objective and targets judicial decision-making.

These four projects comprise different work projects (WP) that can be more or less advanced in their degrees of preparation. It also comprises short or long run projects. Finally, some of them are collaborative by essence while others can be individually planned or targeting for future (PhD) students' supervisions.

Project 1 Subjective Beliefs

Project 2 Risk and Ambiguity

Project 3 Social Preferences

Project 4 Judicial Decision-Making

[The four main research programs and the associated work projects are available upon request.]

References

- Ackermann, J.F., and M.S. Landy.** 2015. “Suboptimal decision criteria are predicted by subjectively weighted probabilities and rewards.” *Attention, Perception, & Psychophysics*, 77(2): 638–658.
- Adena, M., and S. Huck.** 2017. “Matching donations without crowding out ? Some theoretical considerations, a field, and a lab experiment.” *Journal of Public Economics*, 148: 32–42.
- Adler, W.T., and W.J. Ma.** 2018*a*. “Comparing Bayesian and non-Bayesian accounts of human confidence reports.” *PLoS computational biology*, 14(11): e1006572.
- Adler, W.T., and W.J. Ma.** 2018*b*. “Limitations of proposed signatures of Bayesian confidence.” *Neural computation*, 30(12): 3327–3354.
- Ais, J., A. Zylberberg, P. Barttfeld, and M. Sigman.** 2016. “Individual consistency in the accuracy and distribution of confidence judgments.” *Cognition*, 146: 377–386.
- Aitchison, L., D. Bang, B. Bahrami, and P.E. Latham.** 2015. “Doubly Bayesian analysis of confidence in perceptual decision-making.” *PLoS Computational Biology*, 11(10): e1004519.
- Arslan, R.C., M. Brümmer, T. Dohmen, J. Drewelies, R. Hertwig, and G.G. Wagner.** 2020. “How people know their risk preference.” *Scientific reports*, 10(1): 1–14.
- Asano, T., H. Okudaira, and M. Sasaki.** 2015. “An experimental test of a search model under ambiguity.” *Theory and Decision*, 79(4): 627–637.

REFERENCES

- Bahrami, B., K. Olsen, D. Bang, A. Roepstorff, G. Rees, and C. D. Frith.** 2012a. “Together, slowly but surely: the role of social interaction and feedback on the build-up of benefit in collective decision-making.” *Journal of Experimental Psychology: Human Perception and Performance*, 38(1): 3–8.
- Bahrami, B., K. Olsen, D. Bang, A. Roepstorff, G. Rees, and C. D. Frith.** 2012b. “What failure in collective decision-making tells us about metacognition.” *Philosophical Transactions of the Royal Society B: Biological Sciences*, 367(1594): 1350–1365.
- Bahrami, B., K. Olsen, P. E. Latham, A. Roepstorff, G. Rees, and C. D. Frith.** 2010. “Optimally interacting minds.” *Science*, 329(5995): 1081–1085.
- Baillon, A., L. Cabantous, and P.P. Wakker.** 2012. “Aggregating imprecise or conflicting beliefs: an experimental investigation using modern ambiguity theories.” *Journal of Risk and Uncertainty*, 44(2): 115–147.
- Balci, Fuat, Patrick Simen, Ritwik Niyogi, Andrew Saxe, Jessica A Hughes, Philip Holmes, and Jonathan D Cohen.** 2011. “Acquisition of decision making criteria: reward rate ultimately beats accuracy.” *Attention, Perception, & Psychophysics*, 73(2): 640–657.
- Ball, S., and C. Eckel.** 1998. “The economic value of status.” *The Journal of socio-economics*, 27(4): 495–514.
- Ball, S., C. Eckel, P.J. Grossman, and W. Zame.** 2001. “Status in markets.” *The Quarterly Journal of Economics*, 116(1): 161–188.
- Banca, P., M.D. Vestergaard, V. Rankov, K. Baek, S. Mitchell, T. Lapa, M. Castelo-Branco, and V. Voon.** 2015. “Evidence accumulation in obsessive-compulsive disorder: the role of uncertainty and monetary reward on perceptual decision-making thresholds.” *Neuropsychopharmacology*, 40(5): 1192–1202.

- Bang, D., L. Aitchison, R. Moran, S.H. Castanon, B. Rafiee, A. Mahmoodi, J.Y.F. Lau, P.E. Latham, B. Bahrami, and C. Summerfield. 2017. "Confidence matching in group decision-making." *Nature Human Behaviour*, 1(6): 1–7.
- Bang, D., R. Fusaroli, K. Tylen, K. Olsen, P. E. Latham, J.Y.F. Lau, A. Roepstorff, G. Rees, C.D. Frith, and B. Bahrami. 2014. "Does interaction matter? Testing whether a confidence heuristic can replace interaction in collective decision-making." *Consciousness and Cognition*, 26: 13–23.
- Barrett, A.B., Z. Dienes, and A.K. Seth. 2013. "Measures of metacognition on signal-detection theoretic models." *Psychological methods*, 18(4): 535.
- Basden, B.H., D.R. Basden, and S. Henry. 2000. "Costs and benefits of collaborative remembering." *Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition*, 14(6): 497–507.
- Basden, B.H., D.R. Basden, S. Bryner, and R.L. Thomas III. 1997. "A comparison of group and individual remembering: Does collaboration disrupt retrieval strategies?" *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 23(5): 1176.
- Becker, G.M., M.H. DeGroot, and J. Marschak. 1964. "Measuring utility by a single-response sequential method." *Behavioral Science*, 9(3): 226–232.
- Bekkers, R. 2015. "When and why matches are more effective subsidies than rebates." *Replication in experimental economics*, 18.
- Bogacz, R., E. Brown, J. Moehlis, P. Holmes, and J. D. Cohen. 2006. "The physics of optimal decision making: a formal analysis of models of performance in two-alternative forced choice tasks." *Psychological Review*, 113(4): 700–765.

REFERENCES

- Boldt, A., and N. Yeung.** 2015. “The physics of optimal decision making: a formal analysis of models of performance in two-alternative forced choice tasks.” *The Journal of Neuroscience*, 35(8): 3478–3484.
- Bolger, F., B.D. Pulford, and A.M. Colman.** 2008. “Market entry decisions: Effects of absolute and relative confidence.” *Experimental Psychology*, 55(2): 113–120.
- Bossaerts, P., and C. Murawski.** 2015. “From behavioural economics to neuroeconomics to decision neuroscience: the ascent of biology in research on human decision making.” *Current Opinion in Behavioral Sciences*, 5: 37–42.
- Brier, G.W.** 1950. “Verification of forecasts expressed in terms of probability.” *Monthly Weather Review*, 78(1): 1–3.
- Brock, J.M., A. Lange, and E.Y. Ozbay.** 2013. “Dictating the risk: Experimental evidence on giving in risky environments.” *American Economic Review*, 103(1): 415–37.
- Burfurd, I., and T. Wilkening.** 2020. “Cognitive heterogeneity and complex belief elicitation.” *mimeo*.
- Burks, S., J. Carpenter, Goette L., and A. Rustichini.** 2013. “Overconfidence and social signalling.” *Review of Economic Studies*, 80(3): 949–983.
- Busemeyer, Jerome R, and In Jae Myung.** 1992. “An adaptive approach to human decision making: Learning theory, decision theory, and human performance.” *Journal of Experimental Psychology: General*, 121(2): 177.
- Busemeyer, J.R., and J.T. Townsend.** 1993. “Decision field theory: a dynamic-cognitive approach to decision making in an uncertain environment.” *Psychological Review*, 100(3): 432–459.
- Cabantous, L.** 2007. “Ambiguity aversion in the field of insurance: Insurers’ attitude to imprecise and conflicting probability estimates.” *Theory and Decision*, 62(3): 219–240.

- Cabantous, L., D. Hilton, H. Kunreuther, and E. Michel-Kerjan.** 2011. “Is imprecise knowledge better than conflicting expertise? Evidence from insurers’ decisions in the United States.” *Journal of Risk and Uncertainty*, 42(3): 211–232.
- Cain, D.M., D.A. Moore, and U. Haran.** 2015. “Making sense of overconfidence in market entry.” *Strategic Management Journal*, 36(1): 1–18.
- Calford, E.M.** 2020. “Uncertainty aversion in game theory: Experimental evidence.” *Journal of Economic Behavior & Organization*, 176: 720–734.
- Camerer, C., and D. Lovallo.** 1999. “Overconfidence and excess entry: an experimental approach.” *The American Economic Review*, 89(1): 306–318.
- Camerer, C.F.** 2013. “Goals, methods, and progress in neuroeconomics.” *Annual Review of Economics*, 5(1): 425–455.
- Carlebach, N., and N. Yeung.** 2020. “Subjective confidence acts as an internal cost-benefit factor when choosing between tasks.” *Journal of Experimental Psychology: Human Perception and Performance*.
- Carrasco, M.** 2011. “Visual attention: The past 25 years.” *Vision research*, 51(13): 1484–1525.
- Carson, R.** 2012. *Contingent valuation: a comprehensive bibliography and history*. Edward Elgar Publishing.
- Cettolin, E., A. Riedl, and G. Tran.** 2017. “Giving in the Face of Risk.” *Journal of Risk and Uncertainty*, 55(2): 95–118.
- Chanel, O., G. Chichilnisky, S. Massoni, and J.-C. Vergnaud.** 2016. “Exploring the Role of Emotions in Decisions Involving Catastrophic Risks: Lessons from a Double Investigation.” In *The Economics of the Global Environment - Catastrophic Risks in Theory and Practice*, ed. A. Rezaei G. Chichilnisky. Springer Berlin / Heidelberg.

REFERENCES

- Chanel, O., S. Luchini, S. Massoni, and J.-C. Vergnaud. 2011. “Impact of Information on Intentions to Vaccinate in a Potential Epidemic: Swine-origin Influenza A(H1N1).” *Social Science & Medicine*, 72(2): 142–148.
- Chanel, O., S. Massoni, and J.-C. Vergnaud. 2020. “Do Stated Preferences Favour Plutocratic Choices?” *mimeo*.
- Charles, L., and N. Yeung. 2019. “Dynamic sources of evidence supporting confidence judgments and error detection.” *Journal of experimental psychology: human perception and performance*, 45(1): 39.
- Charles, L., J.-R. King, and S. Dehaene. 2014. “Decoding the dynamics of action, intention, and error detection for conscious and subliminal stimuli.” *Journal of Neuroscience*, 34(4): 1158–1170.
- Charness, G., and M. Dufwenberg. 2006. “Promises and partnership.” *Econometrica*, 74(6): 1579–1601.
- Charness, G., A. Rustichini, and J. Van de Ven. 2018. “Self-confidence and strategic behavior.” *Experimental Economics*, 21(1): 72–98.
- Charness, G., A. Samek, and J.J. van de Ven. 2019. “What is Deception in Experimental Economics? A Survey.” *Mimeo*.
- Charness, G., D. Masclet, and M.C. Villeval. 2014. “The dark side of competition for status.” *Management Science*, 60(1): 38–55.
- Charness, G., E. Karni, and D. Levin. 2013. “Ambiguity attitudes and social interactions: An experimental investigation.” *Journal of Risk and Uncertainty*, 46(1): 1–25.
- Charness, G., T. Garcia, T. Offerman, and M.C. Villeval. 2020. “Do measures of risk attitude in the laboratory predict behavior under risk in and outside of the laboratory?” *Journal of Risk and Uncertainty*, 60(2): 99–123.

- Cheng, X., and F. Riedel.** 2013. "Optimal stopping under ambiguity in continuous time." *Mathematics and Financial Economics*, 7(1): 29–68.
- Chen, Y., and S.X. Li.** 2009. "Group identity and social preferences." *American Economic Review*, 99(1): 431–57.
- Clarke, C.** 2020. "Functionalism and the Role of Psychology in Economics." *Journal of Economic Methodology*, 1–19.
- Conte, A., J.D. Hey, and P.G. Moffatt.** 2011. "Mixture models of choice under risk." *Journal of Econometrics*, 162(1): 79–88.
- Cooper, D.J.** 2014. "A note on deception in economic experiments." *Journal of Wine Economics*, 9(2): 111–114.
- Crès, H., I. Gilboa, and N. Vieille.** 2011. "Aggregation of multiple prior opinions." *Journal of Economic Theory*, 146(6): 2563–2582.
- Crockett, M.J.** 2016. "How formal models can illuminate mechanisms of moral judgment and decision making." *Current directions in psychological science*, 25(2): 85–90.
- Croson, R.** 2009. "Experimental law and economics." *Annual Review of Law and Social Science*, 5: 25–44.
- Dal Bó, P., A. Foster, and L. Putterman.** 2010. "Institutions and behavior: Experimental evidence on the effects of democracy." *American Economic Review*, 100(5): 2205–29.
- Dana, J., R.A. Weber, and J.X. Kuang.** 2007. "Exploiting moral wiggle room: experiments demonstrating an illusory preference for fairness." *Economic Theory*, 33(1): 67–80.
- Davis, D.D.** 2006. "Rebate subsidies, matching subsidies and isolation effects." *Judgment and Decision Making*, 1(1): 13–22.

REFERENCES

- Davis, D.D., and E.L. Millner.** 2005. “Rebates, matches, and consumer behavior.” *Southern Economic Journal*, 410–421.
- Davis, D.D., E.L. Millner, and R.J. Reilly.** 2005. “Subsidy schemes and charitable contributions: a closer look.” *Experimental economics*, 8(2): 85–106.
- Deci, E.L., R. Koestner, and R.M. Ryan.** 1999. “A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation.” *Psychological bulletin*, 125(6): 627.
- de Finetti, B.** 1937. “La prévision: ses lois logiques, ses sources subjectives.” *Ann. Inst. Poincaré*, 7: 1–68.
- Del Cul, A., S. Dehaene, P. Reyes, E. Bravo, and A. Slachevsky.** 2009. “Causal role of prefrontal cortex in the threshold for access to consciousness.” *Brain*, 132(9): 2531–2540.
- Della Seta, M., S. Gryglewicz, and P. Kort.** 2014. “Willingness to wait under risk and ambiguity.” *Berkeley: Mimeo.*
- DellaVigna, S., and D. Pope.** 2018. “What motivates effort? Evidence and expert forecasts.” *The Review of Economic Studies*, 85(2): 1029–1069.
- De Martino, B., S.M. Fleming, N. Garrett, and R.J. Dolan.** 2013. “Confidence in value-based choice.” *Nature Neuroscience*, 16(5787): 105–110.
- Descamps, A., S. Massoni, and L. Page.** 2016. “Optimal Hesitation, an Experiment,.” *mimeo.*
- Desender, K., A. Boldt, and N. Yeung.** 2018. “Subjective confidence predicts information seeking in decision making.” *Psychological science*, 29(5): 761–778.
- Dietrich, F., and C. List.** 2016. “Mentalism versus behaviourism in economics: a philosophy-of-science perspective.” *Economics & Philosophy*, 32(2): 249–281.

- Dijk, O.** 2017. “For whom does social comparison induce risk-taking?” *Theory and Decision*, 82(4): 519–541.
- Dijk, O., M. Holmen, and M. Kirchler.** 2014. “Rank matters—The impact of social competition on portfolio choice.” *European Economic Review*, 66: 97–110.
- Dorison, C.A., J.S. Lerner, B.H. Heller, A.J. Rothman, I.I. Kawachi, K. Wang, V.W. Rees, B.P. Gill, N. Gibbs, Psychological Science Accelerator COVID, and N.A. Coles.** 2020. “A global test of message framing on behavioural intentions, policy support, information seeking, and experienced anxiety during the COVID-19 pandemic.” *mimeo*.
- Drugowitsch, J.** 2016. “Becoming confident in the statistical nature of human confidence judgments.” *Neuron*, 90(3): 425–427.
- Drugowitsch, J., R. Moreno-Bote, A.K. Churchland, M.N. Shadlen, and A. Pouget.** 2012. “The cost of accumulating evidence in perceptual decision making.” *Journal of Neuroscience*, 32(11): 3612–3628.
- Dulleck, U., and R. Kerschbamer.** 2006. “On doctors, mechanics, and computer specialists: The economics of credence goods.” *Journal of Economic literature*, 44(1): 5–42.
- Dulleck, U., S. Massoni, D. Sarkar, and J. Silva Goncalves.** 2015. “An exploratory analysis of how to increase the Early Start Kindergarten (ESK) grant take-up rate.” *Report for Department of Education and Training - Victoria State Government*.
- Dupont-Courtade, T., and S. Massoni.** 2015. “Insurance Behaviors of Buyers and Sellers Facing Risky, Imprecise or Conflictual Information.” *mimeo*.
- Dworkin, R.** 1981a. “What is equality? Part 1: Equality of welfare.” *Philosophy & public affairs*, 185–246.
- Dworkin, R.** 1981b. “What is equality? Part 2: Equality of resources.” *Philosophy & public affairs*, 283–345.

REFERENCES

- Eckel, C.C., and P.J. Grossman.** 2003. “Rebate versus matching: does how we subsidize charitable contributions matter?” *Journal of Public Economics*, 87(3-4): 681–701.
- Eckel, C.C., and P.J. Grossman.** 2006. “Subsidizing charitable giving with rebates or matching: Further laboratory evidence.” *Southern Economic Journal*, 794–807.
- Eckel, C.C., and P.J. Grossman.** 2008. “Subsidizing charitable contributions: a natural field experiment comparing matching and rebate subsidies.” *Experimental Economics*, 11(3): 234–252.
- Eliasz, K., D. Ray, and R. Razin.** 2006. “Choice shifts in groups: A decision-theoretic basis.” *American Economic Review*, 96(4): 1321–1332.
- El Zein, M., B. Bahrami, and R. Hertwig.** 2019. “Shared responsibility in collective decisions.” *Nature human behaviour*, 3(6): 554–559.
- Epperson, R., and C. Reif.** 2019. “Matching subsidies and voluntary contributions: A review.” *Journal of Economic Surveys*, 33(5): 1578–1601.
- Erat, S., and U. Gneezy.** 2012. “White lies.” *Management Science*, 58(4): 723–733.
- Erev, Ido.** 1998. “Signal detection by human observers: a cutoff reinforcement learning model of categorization decisions under uncertainty.” *Psychological review*, 105(2): 280.
- Erev, I., E. Ert, O. Plonsky, D. Cohen, and O. Cohen.** 2017. “From anomalies to forecasts: Toward a descriptive model of decisions under risk, under ambiguity, and from experience.” *Psychological review*, 124(4): 369.
- Evans, N.J., A.J. Bennett, and S.D. Brown.** 2019. “Optimal or not; depends on the task.” *Psychonomic Bulletin & Review*, 26(3): 1027–1034.
- Evans, N.J., and S.D. Brown.** 2017. “People adopt optimal policies in simple decision-making, after practice and guidance.” *Psychonomic Bulletin & Review*, 24(2): 597–606.

- Evans, S., and P. Azzopardi.** 2007. "Evaluation of a 'bias-free' measure of awareness." *Spatial Vision*, 20(1-2): 61–77.
- Exley, C.L.** 2015. "Excusing selfishness in charitable giving: The role of risk." *Review of Economic Studies*, 83(2): 587–628.
- Fairfield, B., N. Mammarella, R. Palumbo, and A. Di Domenico.** 2015. "Emotional meta-memories: a review." *Brain sciences*, 5(4): 509–520.
- Faivre, N., E. Filevich, G. Solovey, S. Kühn, and O. Blanke.** 2018. "Behavioral, modeling, and electrophysiological evidence for supramodality in human metacognition." *Journal of Neuroscience*, 38(2): 263–277.
- Fehr, E., and A. Falk.** 2002. "Psychological foundations of incentives." *European economic review*, 46(4-5): 687–724.
- Fehr, E., and A. Falk.** 2007. "Gift exchange in the field." *Econometrica*, 75(5): 1501–1511.
- Fehr, E., and A. Rangel.** 2011. "Neuroeconomics foundations of economic choices - recent advances." *Journal of Economic Perspectives*, 25(4): 3–30.
- Fetsch, Christopher R, Roozbeh Kiani, and Michael N Shadlen.** 2014. "Predicting the accuracy of a decision: a neural mechanism of confidence." Vol. 79, 185–197.
- Filevich, E., C. Koß, and N. Faivre.** 2020. "Response-related signals increase confidence but not metacognitive performance." *Eneuro*, 7(3).
- Flavell, J.H.** 1979. "Metacognition and cognitive monitoring: A new area of cognitive-developmental inquiry." *American psychologist*, 34(10): 906.
- Fleming, S.M.** 2017. "HMeta-d: hierarchical Bayesian estimation of metacognitive efficiency from confidence ratings." *Neuroscience of consciousness*, 2017(1): nix007.
- Fleming, S.M., and C.D. Frith.** 2014. *The cognitive neuroscience of metacognition*. Springer.

REFERENCES

- Fleming, S.M., and H.C. Lau.** 2014. “How to measure metacognition.” *Frontiers in Human Neuroscience*, 8: 443.
- Fleming, S.M., and N.D. Daw.** 2017. “Self-evaluation of decision-making: A general Bayesian framework for metacognitive computation.” *Psychological review*, 124(1): 91.
- Fleming, S.M., and R.J. Dolan.** 2012. “The neural basis of accurate metacognition.” *Philosophical Transactions of the Royal Society B: Biological Sciences*, 367(1594): 1338–1349.
- Fleming, S.M., S. Massoni, T. Gajdos, and J.-C. Vergnaud.** 2016. “Metacognition about the past and future: quantifying common and distinct influences on prospective and retrospective judgments of self-performance.” *Neuroscience of Consciousness*, 2016(1): niw018.
- Fleurbaey, M., and F. Maniquet.** 2011. *A theory of fairness and social welfare*. Vol. 48, Cambridge University Press.
- Folke, T., C. Jacobsen, S.M. Fleming, and B. De Martino.** 2016. “Explicit representation of confidence informs future value-based decisions.” *Nature Human Behaviour*, 1(1): 1–8.
- Fontanesi, L., S. Palminteri, and M. Lebreton.** 2019. “Decomposing the effects of context valence and feedback information on speed and accuracy during reinforcement learning: A meta-analytical approach using diffusion decision modeling.” *Cognitive, Affective, & Behavioral Neuroscience*, 19(3): 490–502.
- Forscher, P.S., M. Primbs, and N. Coles.** 2020. “PSACR: The Psychological Science Accelerator’s COVID-19 Rapid-response Project.” *mimeo*.
- French, L., M. Garry, and K. Mori.** 2008. “You say tomato? Collaborative remembering leads to more false memories for intimate couples than for strangers.” *Memory*, 16(3): 262–273.
- Frey, B.S., and F. Oberholzer-Gee.** 1997. “The cost of price incentives: An empirical analysis of motivation crowding-out.” *American Economic Review*, 87(4): 746–755.

- Friedl, A., P. Ring, and U. Schmidt. 2017. "Gender differences in ambiguity aversion under different outcome correlation structures." *Theory and Decision*, 82(2): 211–219.
- Friedman, D., R.M. Isaac, D. James, and S. Sunder. 2014. *Risky curves: On the empirical failure of expected utility*. Routledge.
- Fudenberg, D., P. Strack, and T. Strzalecki. 2018. "Speed, accuracy, and the optimal timing of choices." *American Economic Review*, 108(12): 3651–84.
- Gajdos, T., and J.-C. Vergnaud. 2013. "Decisions with conflicting and imprecise information." *Social Choice and Welfare*, 41(2): 427–452.
- Gajdos, T., H. Huber, S. Massoni, and J.-C. Vergnaud. 2017. "Testing a Boost Policy to Enhance Mutualized Health Insurance." *mimeo*.
- Galbiati, R., and P. Vertova. 2008. "Obligations and cooperative behaviour in public good games." *Games and Economic Behavior*, 64(1): 146–170.
- Galbiati, R., and P. Vertova. 2014. "How laws affect behavior: Obligations, incentives and cooperative behavior." *International review of law and economics*, 38: 48–57.
- Gallier, C. 2020. "Democracy and compliance in public goods games." *European Economic Review*, 121: 103346.
- Galvin, S. J., J. V. Podd, V. Drga, and J. Whitmore. 2003. "Type 2 tasks in the theory of signal detectability: discrimination between correct and incorrect decisions." *Psychonomic Bulletin and Review*, 10: 843–876.
- Gandullia, L. 2019. "The price elasticity of warm-glow giving." *Economics Letters*, 182: 30–32.
- Garbarino, E., R. Slonim, and M.C. Villeval. 2018. "A method to estimate mean lying rates and their full distribution." *Journal of the Economic Science Association*, 4(2): 136–150.

REFERENCES

- Garcia, T., and S. Massoni.** 2017. “Aiming to Choose Correctly or to Choose Wisely? The Optimality-Accuracy Trade-Off in Decisions Under Uncertainty.” *mimeo*.
- Garcia, T., I. Rafai, and S. Massoni.** 2017. “Manipulating Payoff Processing Order in Perceptual Decision-Making.” *mimeo*.
- Garcia, T., S. Massoni, and M.C. Villeval.** 2020. “Ambiguity and Excuse-Driven Behavior in Charitable Giving.” *European Economic Review*, 124.
- Garfinkel, S.N., M.F. Manassei, G. Hamilton-Fletcher, Y. In den Bosch, H.D. Critchley, and M. Engels.** 2016. “Interoceptive dimensions across cardiac and respiratory axes.” *Philosophical Transactions of the Royal Society B: Biological Sciences*, 371(1708): 20160014.
- Gherman, S., and M.G. Philiastides.** 2015. “Neural representations of confidence emerge from the process of decision formation during perceptual choices.” *Neuroimage*, 106: 134–143.
- Gneezy, U., and J.A. List.** 2006. “Putting behavioral economics to work: Testing for gift exchange in labor markets using field experiment.” *Econometrica*, 74(5): 1365–1384.
- Gneiting, T., and A. E. Raftery.** 2007. “Strictly proper scoring rules, prediction, and estimation.” *Journal of the American Statistical Association*, 102(477): 359–378.
- Green, D. M., and J. A. Swets.** 1966. *Signal Detection Theory and Psychophysics*. John Wiley and Sons.
- Gul, F., and W. Pesendorfer.** 2008. “The case for mindless economics.” *The foundations of positive and normative economics: A handbook*, 1: 3–42.
- Guthrie, C., J.J. Rachlinski, and A.J. Wistrich.** 2000. “Inside the judicial mind.” *Cornell L. Rev.*, 86: 777.
- Guthrie, C., J.J. Rachlinski, and A.J. Wistrich.** 2007. “Blinking on the bench: How judges decide cases.” *Cornell L. Rev.*, 93: 1.

- Hainaut, M., S. Massoni, and J.-C. Vergnaud. 2010. "Apprendre à bien lire: une étude coût-efficacité des Actions Lecture." *Revue d'Economie Politique*, 120(5): 823–843.
- Haisley, E.C., and R.A. Weber. 2010. "Self-serving interpretations of ambiguity in other-regarding behavior." *Games and Economic Behavior*, 68(2): 614–625.
- Hangya, B., J.I. Sanders, and A. Kepecs. 2016. "A mathematical framework for statistical decision confidence." *Neural computation*, 28(9): 1840–1858.
- Harrison, G.W. 2008. "Neuroeconomics: A critical reconsideration." *Economics & Philosophy*, 24(3): 303–344.
- Harvey, N. 1997. "Confidence in judgment." *Trends in Cognitive Sciences*, 1(2): 78–82.
- Haynie, J.M., D.A. Shepherd, and H. Patzelt. 2012. "Cognitive adaptability and an entrepreneurial task: The role of metacognitive ability and feedback." *Entrepreneurship Theory and Practice*, 36(2): 237–265.
- Haynie, J.M., D.A. Shepherd, E. Mosakowski, and P.C. Earley. 2010. "A situated metacognitive model of the entrepreneurial mindset." *Journal of business venturing*, 25(2): 217–229.
- Heffetz, O., and R.H. Frank. 2011. "Preferences for status: Evidence and economic implications." In *Handbook of social economics*. Vol. 1, 69–91.
- Hertz, U., M. Romand-Monnier, K. Kyriakopoulou, and B. Bahrami. 2016. "Social influence protects collective decision making from equality bias." *Journal of Experimental Psychology: Human Perception and Performance*, 42(2): 164.
- Hey, J.D., and C. Orme. 1994. "Investigating generalizations of expected utility theory using experimental data." *Econometrica*, 62(6): 1291–1326.

- Hey, J.D., G. Lotito, and A. Maffioletti.** 2010. “The descriptive and predictive adequacy of theories of decision making under uncertainty/ambiguity.” *Journal of risk and uncertainty*, 41(2): 81–111.
- Hollard, G., S. Massoni, and J.-C. Vergnaud.** 2016. “In Search of Good Probability Assessors: An Experimental Comparison of Elicitation Rules for Confidence Judgments.” *Theory and Decision*, 80(3): 363–387.
- Holt, C., and M. Smith.** 2009. “An update on Bayesian updating.” *Journal of Economic Behavior and Organization*, 69(2): 125–134.
- Holzmeister, F., and M. Stefan.** 2020. “The risk elicitation puzzle revisited: Across-methods (in) consistency?” *Experimental Economics*, 1–24.
- Huang, Y., and R.P.N. Rao.** 2013. “Reward optimization in the primate brain: A probabilistic model of decision making under uncertainty.” *PloS one*, 8(1): e53344.
- Huck, S., and I. Rasul.** 2011. “Matched fundraising: Evidence from a natural field experiment.” *Journal of Public Economics*, 95(5-6): 351–362.
- Hungerman, D.M., and M. Ottoni-Wilhelm.** 2018. “Impure Impact Giving: Theory and Evidence.” *NBER Working Paper*, , (w24940).
- Karni, E.** 2009. “A mechanism for eliciting probabilities.” *Econometrica*, 77(2): 603–606.
- Keck, S., E. Diecidue, and D.V. Budescu.** 2014. “Group decisions under ambiguity: Convergence to neutrality.” *Journal of Economic Behavior & Organization*, 103: 60–71.
- Kepecs, A., and Z.F. Mainen.** 2012. “A computational framework for the study of confidence in humans and animals.” *Philosophical Transactions of the Royal Society B: Biological Sciences*, 367(1594): 1322–1337.
- Kepecs, A., N. Uchida, H. Zariwala, and Z.F. Mainen.** 2008. “Neural correlates, computation and behavioural impact of decision confidence.” *Nature*, 455(7210): 227–231.

- Kerschbamer, R., and M. Sutter.** 2017. “The economics of credence goods—a survey of recent lab and field experiments.” *CESifo Economic Studies*, 63(1): 1–23.
- Kerschbamer, R., D. Neururer, and M. Sutter.** 2019. “Credence goods markets and the informational value of new media: A natural field experiment.” *MPI Collective Goods Discussion Paper*, , (2019/3).
- Kiani, R., and M. Shallden.** 2009. “Representation of confidence associated with a decision by neurons in parietal cortex knowledge: some calibration studies.” *Science*, 324(5928): 759–764.
- Kirchler, M., F. Lindner, and U. Weitzel.** 2018. “Rankings and risk-taking in the finance industry.” *The Journal of Finance*, 73(5): 2271–2302.
- Kohonen, T., and P. Somervuo.** 1998. “Self-organizing maps of symbol strings.” *Neurocomputing*, 21(1-3): 19–30.
- Kontek, K., and M. Lewandowski.** 2018. “Range-dependent utility.” *Management Science*, 64(6): 2812–2832.
- Koriat, A.** 2012a. “The self-consistency model of subjective confidence.” *Psychological Review*, 119: 80–113.
- Koriat, A.** 2012b. “When are two heads better than one and why?” *Science*, 336(6079): 360–362.
- Koriat, A.** 2015. “When Two Heads Are Better Than One and When They Can Be Worse: The Amplification Hypothesis.” *Journal of Experimental Psychology: General*, 144(5): 934–950.
- Korobkin, R.B., and T.S. Ulen.** 2000. “Law and behavioral science: Removing the rationality assumption from law and economics.” *Calif. L. Rev.*, 88: 1051.
- Kovářík, J., D. Levin, and T. Wang.** 2016. “Ellsberg paradox: Ambiguity and complexity aversions compared.” *Journal of Risk and Uncertainty*, 52(1): 47–64.

REFERENCES

- Krajbich, I., B. Oud, and E. Fehr.** 2014. “Benefits of Neuroeconomic Modeling: New Policy Interventions and Predictors of Preference.” *American Economic Review*, 104(5): 501–06.
- Krawczyk, M.** 2019. “What should be regarded as deception in experimental economics? Evidence from a survey of researchers and subjects.” *Journal of Behavioral and Experimental Economics*, 79: 110–118.
- Krawczyk, M., and F. Le Lec.** 2010. ““Give me a chance!’An experiment in social decision under risk.” *Experimental Economics*, 13(4): 500–511.
- Kube, S., M.A. Maréchal, and C. Puppe.** 2012. “The currency of reciprocity: Gift exchange in the workplace.” *American Economic Review*, 102(4): 1644–1662.
- Kunreuther, H., R. Meyer, R. Zeckhauser, P. Slovic, B. Schwartz, C. Schade, M. Luce, S. Lippman, D. Krantz, B. Kahn, and R. Hogarth.** 2002. “High stakes decision making: Normative, descriptive and prescriptive considerations.” *Marketing Letters*, 13(3): 259–268.
- Kvam, P.D., T.J. Pleskac, S. Yu, and J.R. Busemeyer.** 2015. “Interference effects of choice on confidence: Quantum characteristics of evidence accumulation.” *Proceedings of the National Academy of Sciences*, 112(34): 10645–10650.
- Lebreton, M., K. Bacily, S. Palminteri, and J.B. Engelmann.** 2019. “Contextual influence on confidence judgments in human reinforcement learning.” *PLoS computational biology*, 15(4): e1006973.
- Lebreton, M., S. Langdon, M.J. Sliker, J.S. Nooitgedacht, A.E. Goudriaan, D. Denys, R.J. van Holst, and J. Luigjes.** 2018. “Two sides of the same coin: Monetary incentives concurrently improve and bias confidence judgments.” *Science advances*, 4(5): eaaq0668.
- Leek, M.R.** 2001. “Adaptive procedures in psychophysical research.” *Perception & psychophysics*, 63(8): 1279–1292.

- Legate, N., T.-V. Nguyen, A. Moller, L. Legault, Psychological Science Accelerator COVID, and N. Weinstein. 2020. "Effect of message framing on motivation to follow vs. defy social distancing guidelines during the COVID 19 pandemic." *mimeo*.
- Lerner, J.S., Y. Li, P. Valdesolo, and K.S. Kassam. 2015. "Emotion and decision making." *Annual review of psychology*.
- Levin, H. 2001. "Waiting for Godot: cost-effectiveness analysis in education." *New directions for evaluation*, 2001(90): 55–68.
- Levitt, H. 1971. "Transformed up-down methods in psychoacoustics." *Journal of the Acoustical Society of America*, 49(2): 467–477.
- Liberman, V., and A. Tversky. 1993. "On the evaluation of probability judgments: calibration, resolution, and monotonicity." *Psychological Bulletins*, 114: 162–173.
- Lichtenstein, S., B. Fischhoff, and L. Phillips. 1982. "Calibration of probabilities: the state of the art to 1980." In *Judgment under Uncertainty: Heuristic and biases.*, ed. D. Kahneman, P. Slovic and A. Tversky, 306–334. Cambridge, UK: Cambridge University Press.
- Li, C., U. Turmunkh, and P.P. Wakker. 2019. "Trust as a decision under ambiguity." *Experimental Economics*, 22(1): 51–75.
- Li, C., U. Turmunkh, and P.P. Wakker. 2020. "Social and strategic ambiguity versus betrayal aversion." *Games and Economic Behavior*, 123: 272–287.
- Linde, J., and J. Sonnemans. 2012. "Social comparison and risky choices." *Journal of Risk and Uncertainty*, 44(1): 45–72.
- Linde, J., and J. Sonnemans. 2015. "Decisions under risk in a social and individual context: The limits of social preferences?" *Journal of Behavioral and Experimental Economics*, 56: 62–71.

REFERENCES

- Locke, E.A., and G.P. Latham.** 2006. "New directions in goal-setting theory." *Current directions in psychological science*, 15(5): 265–268.
- Luchies, L.B., J. Wieselquist, C.E. Rusbult, M. Kumashiro, P.W. Eastwick, M.K. Coolson, and E.J. Finkel.** 2013. "Trust and biased memory of transgressions in romantic relationships." *Journal of personality and social psychology*, 104(4): 673.
- Lukas, I., C.C. Eckel, and P.J. Grossman.** 2010. "Preference or confusion: Understanding the differential impact of rebate and matching subsidies." *Saint Cloud State University Working Paper*.
- Maccheroni, F., M. Marinacci, and A. Rustichini.** 2012. "Social decision theory: Choosing within and between groups." *Review of Economic Studies*, 79(4): 1591–1636.
- Maddox, W.T.** 2002. "Toward a unified theory of decision criterion learning in perceptual categorization." *Journal of the experimental analysis of behavior*, 78(3): 567–595.
- Maddox, W.T., and C.J. Bohil.** 1998. "Base-rate and payoff effects in multidimensional perceptual categorization." *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 24(6): 1459.
- Maddox, W.T., and C.J. Bohil.** 2003. "A theoretical framework for understanding the simultaneous base-rate and payoff manipulations on decision criterion learning in perceptual categorization." *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 29(2): 307.
- Maddox, W.T., and C.J. Bohil.** 2004. "Probability matching, accuracy maximization, and a test of the optimal classifiers independence assumption in perceptual categorization." *Attention, Perception & Psychophysics*, 66(1): 104–118.

- Maddox, W.T., C.J. Bohil, and J.L. Dodd.** 2003. “Linear transformations of the payoff matrix and decision criterion learning in perceptual categorization.” *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 29(6): 1174.
- Mahmoodi, A., B. Bahrami, and C. Mehring.** 2018. “Reciprocity of social influence.” *Nature communications*, 9(1): 1–9.
- Mahmoodi, A., D. Bang, K. Olsen, Y.A. Zhao, Z. Shi, K. Broberg, S. Safavi, S. Han, M.N. Ahmadabadi, C.D. Frith, A. Roepstorff, G. Rees, and B. Bahrami.** 2015. “Equality bias impairs collective decision-making across cultures.” *Proceedings of the National Academy of Sciences*, 112(12): 3835–3840.
- Mahmoodi, A., D. Bang, M.N. Ahmadabadi, and B. Bahrami.** 2013. “Learning to make collective decisions: the impact of confidence escalation.” *PLoS One*, 8(12): e81195.
- Maniscalco, B., and H. Lau.** 2012. “A signal detection theoretic approach for estimating metacognitive sensitivity from confidence ratings.” *Consciousness and Cognition*, 21(1): 422–430.
- Maniscalco, B., and H. Lau.** 2014. “Signal Detection Theory Analysis of Type 1 and Type 2 Data: Meta-d’, Response-Specific Meta-d’, and the Unequal Variance SDT Model.” In *The Cognitive Neuroscience of Metacognition.*, ed. S.M. Fleming and C. Frith, 25–66. Springer: Berlin, Heidelberg.
- Maniscalco, B., and H. Lau.** 2016. “The signal processing architecture underlying subjective reports of sensory awareness.” *Neuroscience of Consciousness*, 2016(1).
- Massoni, S.** 2013. “Essays on Subjective Probabilities and Metacognition.” PhD diss. University of Paris 1.
- Massoni, S.** 2014. “Emotion as a boost to metacognition: how worry enhances the quality of confidence.” *Consciousness and Cognition*, 29: 189–198.

REFERENCES

- Massoni, S.** 2016. “Confiance, métacognition et perception.” *L’Actualité Economique. Special issue on Experimental / Behavioral economics*, N. Jacquemet, O. L’Haridon, B. Shearer (Eds.), 90(1-2).
- Massoni, S., and J.-C. Vergnaud.** 2012. “How to Improve Pupils’ Literacy? A Cost-Effectiveness Analysis of a French Educational Project.” *Economics of Education Review*, 31(1): 84–91.
- Massoni, S., and N. Roux.** 2017. “Optimal group decision: a matter of confidence calibration.” *Journal of Mathematical Psychology*, 79: 121–130.
- Massoni, S., M. Olteanu, and N. Villa-Vialaneix.** 2013. “Which Dissimilarity is to be used when Extracting Typologies in Sequence Analysis? A Comparative Study.” In *LNCS 7902 - Advances in Computational Intelligence: IWANN 2013.*, ed. J. Cabestany I. Rojas, G. Joya, 69–79. Springer Berlin / Heidelberg.
- Massoni, S., M. Olteanu, and P. Rousset.** 2009. “Career-Path Analysis Using Optimal Matching and Self-Organizing Maps.” In *LNCS 5629 - Advances in Self-Organizing Maps: WSOM 2009.*, ed. R. Miikkulainen J. Principe, 154–162. Springer Berlin / Heidelberg.
- Massoni, S., T. Gajdos, and J.-C. Vergnaud.** 2014. “Confidence Measurement in the Light of Signal Detection Theory.” *Frontiers in Psychology*, 5: 1455.
- Masson, M.E.J., and C.M. Rotello.** 2009. “Sources of bias in the Goodman-Kruskal gamma coefficient measure of association: implications for studies of metacognitive processes.” *Journal of Experimental Psychology: Learning, Memory and Cognition*, 35: 509–527.
- Mata, R., R. Frey, D. Richter, J. Schupp, and R. Hertwig.** 2018. “Risk preference: A view from psychology.” *Journal of Economic Perspectives*, 32(2): 155–72.

-
- Mazancieux, A., S.M. Fleming, C. Souchay, and C.J.A. Moulin.** 2020. “Is there a G factor for metacognition? Correlations in retrospective metacognitive sensitivity across tasks.” *Journal of Experimental Psychology: General*.
- McFadden, D., and K. Train.** 2017. *Contingent valuation of environmental goods: a comprehensive critique*. Edward Elgar Publishing.
- Meade, M.L., and H.L. Roediger.** 2002. “Explorations in the social contagion of memory.” *Memory & cognition*, 30(7): 995–1009.
- Meyniel, F., M. Sigman, and Z.F. Mainen.** 2015. “Confidence as Bayesian probability: From neural origins to behavior.” *Neuron*, 88(1): 78–92.
- Migdał, P., J. Rączaszek-Leonardi, M. Denkiewicz, and D. Plewczynski.** 2012. “Information-sharing and aggregation models for interacting minds.” *Journal of Mathematical Psychology*, 56(6): 417–426.
- Mimra, W., A. Rasch, and C. Waibel.** 2016a. “Price competition and reputation in credence goods markets: Experimental evidence.” *Games and Economic Behavior*, 100: 337–352.
- Mimra, W., A. Rasch, and C. Waibel.** 2016b. “Second opinions in markets for expert services: Experimental evidence.” *Journal of Economic Behavior & Organization*, 131: 106–125.
- Moore, D.A., and D.M. Cain.** 2007. “Overconfidence and underconfidence: When and why people underestimate (and overestimate) the competition.” *Organizational Behavior and Human Decision Processes*, 103(2): 197–213.
- Moore, D.A., and P.J. Healy.** 2008. “The trouble with overconfidence.” *Psychological review*, 115(2): 502.

- Moran, R., A.R. Teodorescu, and M. Usher. 2015. "Post choice information integration as a causal determinant of confidence: Novel data and a computational account." *Cognitive Psychology*, 78: 99–147.
- Moshontz, H., L. Campbell, C.R. Ebersole, H. IJzerman, H.L. Urry, P.S. Forscher, J.E. Grahe, R.J. McCarthy, E.D. Musser, J. Antfolk, C.M. Castille, T.R. Evans, S. Fiedler, K.K. Flake, D.A. Forero, S.M.J. Janssen, J.R. Keene, J. Protzko, B. Aczel, S. Álvarez Solas, D. Ansari, D. Awlia, E. Baskin, C. Batres, M.L. Borrás-Guevara, C. Brick, P. Chandel, A. Chatard, W.J. Chopik, D. Clarence, N.A. Coles, K.S. Corker, B.J.W. Dixon, V. Dranseika, Y. Dunham, N.W. Fox, G. Gardiner, S.M. Garrison, T. Gill, A.C. Hahn, B. Jaeger, P. Kačmár, G. Kaminski, P. Kanske, Z. Kekecs, M. Kline, M.A. Koehn, P. Kujur, C.A. Levitan, J.K. Miller, C. Okan, J. Olsen, O. Oviedo-Trespalacios, A.A. Özdoğan, B. Pande, A. Parganiha, N. Parveen, G. Pfuhl, S. Pradhan, I. Ropovik, N.O. Rule, B. Saunders, V. Schei, K. Schmidt, M.M. Singh, M. Sirota, C.N. Steltenpohl, S. Stieger, D. Storage, G.B. Sullivan, A. Szabelska, C.K. Tamnes, M.A. Vadillo, J.V. Valentova, W. Vanpaemel, M.A.C. Varella, E. Vergauwe, M. Verschoor, M. Vianello, M. Voracek, G.P. Williams, J.P. Wilson, J.H. Zickfeld, J.D. Arnal, B. Aydin, S.-C. Chen, L.M. DeBruine, A.M. Fernandez, K.T. Horstmann, P.M. Isager, B. Jones, A. Kapucu, H. Lin, M.C. Mensink, G. Navarrete, M.A. Silan, and C.R. Chartier. 2018. "The Psychological Science Accelerator: Advancing Psychology Through a Distributed Collaborative Network." *Advances in Methods and Practices in Psychological Science*, 1(4): 501–515.
- Murphy, A.H. 1972. "Scalar and vector partitions of the probability score. Part I: two-states situation." *Journal of Applied Meteorology*, 11: 273–282.
- Myung, In Jae, and Jerome R Busemeyer. 1989. "Criterion learning in a deferred decision-making task." *The American journal of psychology*, 102(2): 1–16.

- Navajas, J., B. Bahrami, and P.E. Latham. 2016. "Post-decisional accounts of biases in confidence." *Current Opinion in Behavioral Sciences*, 11: 55–60.
- Navajas, J., C. Hindocha, H. Foda, M. Keramati, P.E. Latham, and B. Bahrami. 2017a. "The idiosyncratic nature of confidence." *Nature human behaviour*, 1(11): 810.
- Navajas, J., C. Hindocha, H. Foda, M. Keramati, P.E. Latham, and B. Bahrami. 2017b. "The idiosyncratic nature of confidence." *Nature human behaviour*, 1(11): 810–818.
- Nelson, T.O. 1984. "A comparison of current measures of the accuracy of feeling-of-knowing predictions." *Psychological Bulletin*, 95: 109–133.
- Nelson, T.O. 1990. "Metamemory: A theoretical framework and new findings." In *Psychology of learning and motivation*. Vol. 26, 125–173.
- Nieder, A., and S. Dehaene. 2009. "Representation of number in the brain." *Annual Review of Neuroscience*, 32(1): 185–208.
- Nyarko, Y., and A. Schotter. 2002. "An experimental study of belief learning using elicited beliefs." *Econometrica*, 70(3): 971–1005.
- Offerman, T., J. Sonnemans, G. Van de Kuilen, and P.P. Wakker. 2009. "A truth-serum for non-bayesian: correcting proper scoring rules for risk attitudes." *Review of Economic Studies*, 76(4): 1461–1489.
- Ortmann, A., and R. Hertwig. 2002. "The empirical cost of deception: evidence from psychology." *Experimental Economics*, 5: 111–131.
- Ortmann, Andreas. 2019. "Deception." In *Handbook of Research Methods and Applications in Experimental Economics*. , ed. A. Schram and A. Ule, 28–38. Edward Elgar.
- Ottoni-Wilhelm, M., L. Vesterlund, and H. Xie. 2017. "Why do people give? Testing pure and impure altruism." *American Economic Review*, 107(11): 3617–33.

REFERENCES

- Parducci, A.** 1965. “Category judgment: a range-frequency model.” *Psychological review*, 72(6): 407.
- Pedroni, A., R. Frey, A. Bruhin, G. Dutilh, R. Hertwig, and J. Rieskamp.** 2017. “The risk elicitation puzzle.” *Nature Human Behaviour*, 1(11): 803–809.
- Peng, H.-C.** 2020. “Effect of cognitive ability on matching and rebate subsidies.” *Research in Economics*, 74(1): 19–25.
- Persaud, N., P. McLeod, and A. Cowey.** 2007. “Post-decision wagering objectively measures awareness.” *Nature Neuroscience*, 10: 257–261.
- Pescetelli, N., G. Rees, and B. Bahrami.** 2016. “The perceptual and social components of metacognition.” *Journal of Experimental Psychology: General*, 145(8): 949–965.
- Piff, P.K., D.M. Stancato, S. Côté, R. Mendoza-Denton, and D. Keltner.** 2012. “Higher social class predicts increased unethical behavior.” *Proceedings of the National Academy of Sciences*, 109(11): 4086–4091.
- Piketty, T., and M. Valdenaire.** 2006. “L’impact de la taille des classes sur la réussite scolaire dans les écoles, collèges et lycées français: estimations à partir du panel primaire 1997 et du panel secondaire 1995.” *Direction de l’évaluation et de la prospective*.
- Pleskac, T.J., and J.R. Busemeyer.** 2010. “Two-stage dynamic signal detection: A theory of choice, decision time, and confidence.” *Psychological Review*, 117(3): 864–901.
- Potia, A., S. Massoni, B. Torgler, and U. Dulleck.** 2020. “Gift versus Conditional Incentives for Commitment and Achievement: Evidence from a Laboratory Experiment.” *mimeo*.
- Pouget, A., J. Drugowitsch, and A. Kepecs.** 2016. “Confidence and certainty: distinct probabilistic quantities for different goals.” *Nature neuroscience*, 19(3): 366.

- Purcell, B.A., and R. Kiani. 2016. “Hierarchical decision processes that operate over distinct timescales underlie choice and changes in strategy.” *Proceedings of the national academy of sciences*, 113(31): E4531–E4540.
- Rahnev, D., A. Koizumi, L.Y. McCurdy, M. D’Esposito, and H. Lau. 2015. “Confidence leak in perceptual decision making.” *Psychological science*, 26(11): 1664–1680.
- Rahnev, D., and S.M. Fleming. 2019. “How experimental procedures influence estimates of metacognitive ability.” *Neuroscience of consciousness*, 2019(1): niz009.
- Rahnev, D., B. Maniscalco, T. Graves, E. Huang, F.P. De Lange, and H. Lau. 2011. “Attention induces conservative subjective biases in visual perception.” *Nature neuroscience*, 14(12): 1513–1515.
- Rahnev, D., K. Desender, A.L.F. Lee, W.T. Adler, D. Aguilar-Lleyda, B. Akdoğan, P. Arbuzova, L.Y. Atlas, F. Balci, J.W. Bang, I. Bègue, D.P. Birney, T.F. Brady, J. Calder-Travis, A. Chetverikov, T.K. Clark, K. Davranche, R.N. Denison, T.C. Dildine, K.S. Double, Y.A. Duyan, N. Faivre, K. Fallow, E. Filevich, T. Gajdos, R.M. Gallagher, V. de Gardelle, S. Gherman, N. Haddara, M. Hainguerlot, T.-Y. Hsu, X. Hu, I. Iturrate, M. Jaquierey, J. Kantner, M. Koculak, M. Konishi, C. Koß, P.D. Kvam, S. Kwok, M. Lebreton, K.M. Lempert, C. Ming Lo, L. Luo, B. Maniscalco, A. Martin, S. Massoni, J. Matthews, A. Mazancieux, D.M. Merfeld, D. O’Hora, E.R. Palser, B. Paulewicz, M. Pereira, C. Peters, M.G. Philiastides, G. Pfuhl, F. Prieto, M. Rausch, S. Recht, G. Reyes, M. Rouault, J. Sackur, S. Sadeghi, J. Samaha, T.X.F. Seow, M. Shekhar, M.T. Sherman, M. Siedlecka, Z. Skóra, C. Song, D. Soto, S. Sun, J.J.A. van Boxtel, S. Wang, C.T. Weidemann, G. Weindel, M. Wierzchoń, X. Xu, Q. Ye, J. Yeon, F. Zou, and A. Zylberberg. 2020. “The Confidence Database.” *Nature Human Behaviour*, 4(3): 317–325.

REFERENCES

- Ramsey, F.** 1931. "Truth and probability." In *The Foundations of Mathematics and Other Logical Essays*, ed. R. Braithwaite, 156–198. London: Kegan Paul.
- Ratcliff, R., and J.J. Starns.** 2009. "Modeling confidence and response time in recognition memory." *Psychological Review*, 116(1): 59–83.
- Riedel, F.** 2009. "Optimal stopping with multiple priors." *Econometrica*, 77(3): 857–908.
- Roediger, H.L., and K.B. McDermott.** 1995. "Creating false memories: Remembering words not presented in lists." *Journal of experimental psychology: Learning, Memory, and Cognition*, 21(4): 803.
- Roediger, H.L., M.L. Meade, and E.T. Bergman.** 2001. "Social contagion of memory." *Psychonomic bulletin & review*, 8(2): 365–371.
- Roe, Robert M, Jermone R Busemeyer, and James T Townsend.** 2001. "Multialternative decision field theory: A dynamic connectionist model of decision making." *Psychological review*, 108(2): 370.
- Rohde, I., and K. Rohde.** 2011. "Risk attitudes in a social context." *Journal of Risk and Uncertainty*, 43(3): 205–225.
- Rosenbaum, S.M., S. Billinger, and N. Stieglitz.** 2014. "Let's be honest: A review of experimental evidence of honesty and truth-telling." *Journal of Economic Psychology*, 45: 181–196.
- Rouault, M., A. McWilliams, M.G. Allen, and S.M. Fleming.** 2018. "Human metacognition across domains: insights from individual differences and neuroimaging." *Personality neuroscience*, 1.
- Rouault, M., and S.M. Fleming.** 2020. "Formation of global self-beliefs in the human brain." *Proceedings of the National Academy of Sciences*.
- Rouault, M., P. Dayan, and S.M. Fleming.** 2019. "Forming global estimates of self-performance from local confidence." *Nature communications*, 10(1): 1–11.

- Rutstrom, E., and N. Wilcox.** 2009. “Stated versus inferred beliefs: A methodological inquiry and experimental test.” *Games and Economic Behavior*, 67(2): 616–632.
- Sanders, J.I., B. Hangya, and A. Kepecs.** 2016. “Signatures of a statistical computation in the human sense of confidence.” *Neuron*, 90(3): 499–506.
- Savage, L. J.** 1954. *The Foundations of Statistics*. New York, NY: John Wiley and Sons.
- Schlag, K. H., J. Tremewan, and J. Van der Weele.** 2015. “A penny for your thoughts: A survey of methods for eliciting beliefs.” *Experimental Economics*, 18(3): 457–490.
- Schwardmann, P., and J. Van der Weele.** 2019. “Deception and self-deception.” *Nature Human Behaviour*, 3(10): 1055–1061.
- Shupp, R.S., and A.W. Williams.** 2008. “Risk preference differentials of small groups and individuals.” *The Economic Journal*, 118(525): 258–283.
- Siedlecka, M., B. Paulewicz, and M. Wierzchoń.** 2016. “But I was so sure! Metacognitive judgments are less accurate given prospectively than retrospectively.” *Frontiers in psychology*, 7: 218.
- Siedlecka, M., Z. Skóra, B. Paulewicz, S. Fijałkowska, B. Timmermans, and M. Wierzchoń.** 2019. “Responses improve the accuracy of confidence judgements in memory tasks.” *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 45(4): 712.
- Smithson, M.** 2015. “Probability judgments under ambiguity and conflict.” *Frontiers in psychology*, 6: 674.
- Song, C., R. Kanai, S.M. Fleming, R.S. Weil, D.S. Schwarzkopf, and G. Rees.** 2011. “Relating inter-individual differences in metacognitive performance on different perceptual tasks.” *Consciousness and Cognition*, 20(4): 1787–1792.
- Sonsino, D., U. Benzion, and G. Mador.** 2002. “The complexity effects on choice with uncertainty—Experimental evidence.” *The Economic Journal*, 112(482): 936–965.

REFERENCES

- Sorkin, R. D., C. J. Hays, and R. West. 2001. "Signal detection analysis of group decision making." *Psychological Review*, 108: 183–203.
- Spiliopoulos, L., and A. Ortmann. 2018. "The BCD of response time analysis in experimental economics." *Experimental economics*, 21(2): 383–433.
- Summerfield, C., and K. Tsetsos. 2012. "Building bridges between perceptual and economic decision-making: neural and computational mechanisms." *Frontiers in Neuroscience*, 6(70): 1–20.
- Teslovich, T., M. Mulder, N.T. Franklin, E.J. Ruberry, A. Millner, L.H. Somerville, P. Simen, S. Durston, and B.J. Casey. 2014. "Adolescents let sufficient evidence accumulate before making a decision when large incentives are at stake." *Developmental Science*, 17(1): 59–70.
- Ting, C.-C., S. Palminteri, J.B. Engelmann, and M. Lebreton. 2020. "Robust valence-induced biases on motor response and confidence in human reinforcement learning." *Cognitive, Affective, & Behavioral Neuroscience*, 1–16.
- Trautmann, S. T., and F. M. Vieider. 2012. "Social influences on risk attitudes: Applications in economics." In *Handbook of risk theory*. 575–600. Springer Verlag.
- Treutwein, B. 1995. "Adaptive psychophysical procedures." *Vision research*, 35(17): 2503–2522.
- Tyran, J.-R., and L.P. Feld. 2006. "Achieving compliance when legal sanctions are non-deterrent." *scandinavian Journal of Economics*, 108(1): 135–156.
- Van Bavel, J.J., K. Baicker, P.S. Boggio, V. Capraro, A. Cichocka, M. Cikara, M.J. Crockett, A.J. Crum, K.M. Douglas, J.N. Druckman, J. Drury, O. Dube, N. Ellemers, E.J. Finkel, J.H. Fowler, M. Gelfand, S. Han, S.A. Haslam, J. Jetten, S. Kitayama, D. Mobbs, L.E. Napper, D.J. Packer, G. Pennycook, E. Peters, R.E.

-
- Petty, D.G. Rand, S.D. Reicher, S. Schnall, A. Shariff, L.J. Skitka, S.S. Smith, C.R. Sunstein, N. Tabri, J.A. Tucker, Sander. van der Linden, P. van Lange, K.A. Weeden, M.J.A. Wohl, J. Zaki, S.R. Zion, and R. Willer. 2020. “Using social and behavioural science to support COVID-19 pandemic response.” *Nature Human Behaviour*, 4(5): 460–471.
- Vanberg, C. 2008. “Why do people keep their promises? An experimental test of two explanations.” *Econometrica*, 76(6): 1467–1480.
- Vandekerckhove, J., F. Tuerlinckx, and M.D. Lee. 2011. “Hierarchical diffusion models for two-choice response times.” *Psychological methods*, 16(1): 44.
- Vesterlund, L. 2016. “Using experimental methods to understand why and how we give to charity.” *Handbook of experimental economics*, 2: 91–151.
- Viefers, P. 2012. “Should i stay or should i go?-a laboratory analysis of investment opportunities under ambiguity.” *DIW Berlin Discussion Paper*.
- Vuilleumier, P. 2005. “How brains beware: Neural mechanisms of emotional attention.” *Trends in Cognitive Sciences*, 9(12): 584–594.
- Wakker, P.P. 2010. *Prospect Theory: For Risk and Ambiguity*. Cambridge University Press.
- Wald, A. 1945. “Sequential tests of statistical hypotheses.” *The Annals of Mathematical Statistics*, 16(2): 117–186.
- Wang, K., A. Goldenberg, C.A. Dorison, J.K. Miller, A. Uusberg, J.S. Lerner, Psychological Science Accelerator COVID, and J.J. Gross. 2020. “A global test of brief reappraisal interventions on emotions during the COVID-19 pandemic.” *mimeo*.
- Weldon, M.S., and K.D. Bellinger. 1997. “Collective memory: collaborative and individual processes in remembering.” *Journal of experimental psychology: Learning, memory, and cognition*, 23(5): 1160.

REFERENCES

- Wickens, T.D.** 2002. *Elementary Signal Detection Theory*. New-York, NY: Oxford University Press.
- Wiecki, T.V., I. Sofer, and M.J. Frank.** 2013. "HDDM: Hierarchical Bayesian estimation of the drift-diffusion model in Python." *Frontiers in neuroinformatics*, 7: 14.
- Wilcox, N.T.** 1993. "Lottery choice: Incentives, complexity and decision time." *The Economic Journal*, 103(421): 1397–1417.
- Winkler, R.L., and A.H. Murphy.** 1968. "'Good' probability assessors." *Journal of Applied Meteorology*, 7: 751–758.
- Yaniv, I., F. Yates, and K. Smith.** 1991. "Measures of discrimination skill in probabilistic judgment." *Psychological Bulletin*, 110(3): 611–617.
- Yates, J.F.** 1982. "External correspondence: decompositions of the mean probability score." *Organizational Behavior and Human Performance*, 30(1): 132–156.
- Yeung, N., and C. Summerfield.** 2012. "Metacognition in human decision-making: confidence and error monitoring." *Philosophical Transactions of the Royal Society B: Biological Sciences*, 367(1594): 1310–1321.
- Yu, S., T.J. Pleskac, and M.D. Zeigenfuse.** 2015. "Dynamics of postdecisional processing of confidence." *Journal of Experimental Psychology: General*, 144(2): 489.
- Zamir, E., and D. Teichman.** 2018. *Behavioral law and economics*. Oxford University Press.
- Zhang, J., and M. Casari.** 2012. "How groups reach agreement in risky choices: an experiment." *Economic Inquiry*, 50(2): 502–515.
- Zhang, X.** 2008. "Status inconsistency revisited: An improved statistical model." *European Sociological Review*, 24(2): 155–168.