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Risk, reproducibility, and reproduction: Essays on scholar's analytic decisions and consumers' product purchases

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Cover: Photo generated using Dall E
(photo: painting of a brain thinking about different types of consumption such as conspicuous consumption and food)

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Risk, reproducibility, and reproduction: Essays on scholar's analytic decisions and consumers' product purchases

Abstract

This thesis investigates how evolutionary biology theories can be used to better understand consumer behavior. The first paper lays the groundwork for the methodologies used throughout the thesis. Here, the focus is on the (ab-)use of p-values and how easy it is to find a false-positive research result under different common circumstances. The second paper investigates what happens with the willingness to engage in risky choices when people have a low level of blood glucose. The third and fourth papers focus on conspicuous consumption and examine the circumstances that induce people to purchase prestigious products. The empirical studies have in common the idea that the respective choices involved in each paper are embedded in an evolutionary process. In the first paper, we find that obtaining a false positive result is easy, especially when there is no pre-registration of the hypothesis or no correction of p-values for multiple hypothesis testing. In some important cases, pre-registration alone is not sufficient to overcome the problem of inflated false positives. Applying these insights to an empirical case and using theoretical arguments from evolutionary biology, the second paper uses cross-validation and a meta-analysis to show that people with low levels of blood glucose show a higher willingness to pay for risky food items, whereas this is not the case for non-food products. The third paper shows through two studies that conspicuous consumption is particularly prevalent among single men. Building on these findings, the fourth paper shows, through a newly constructed uncertainty index, that increased uncertainty amplifies people's propensity to engage in conspicuous consumption. Overall, this thesis adds to the literature on false-positive findings and illuminates how social scientists can reach a deeper understanding of human behavior by adopting an evolutionary lens.

Keywords: false positive results, budget rule, conspicuous consumption, natural language processing, evolutionary biology, blood glucose, relationship status

Risk, reproducerbarhet och reproduktion: Essäer om forskares analytiska beslut och konsumenternas produktköp

Abstract

Denna avhandling undersöker hur evolutionsbiologiska teorier kan användas för att bättre förstå mänskligt beteende. Det första delarbetet lägger grunden för de metoder som används genom hela avhandlingen. Här ligger fokus på missbruk av p-värden och hur lätt det är att hitta ett falskt positivt forskningsresultat under olika vanliga omständigheter. Det andra delarbetet undersöker vad som händer med viljan att göra riskfyllda val när människor har en låg blodsockernivå. Det tredje och fjärde delarbetet studerar iögonfallande, statussignalerande konsumtion och under vilka omständigheter människor är benägna att konsumera sådana prestigeartade produkter. De empiriska studierna har det gemensamt att de respektive valen i varje delarbete är inbäddade i en evolutionär process. I den första artikeln finner vi att det är lätt att få ett falskt positivt resultat, särskilt när det inte finns någon förregistrering av hypotesen eller då korrigering av p-värden för multipel hypotestestning saknas. I vissa viktiga fall är förhandsregistrering inte ens tillräcklig för att övervinna problemet med en ökad sannolikhet för falska positiva resultat. Genom att tillämpa dessa insikter på ett empiriskt fall och använda teoretiska argument från evolutionär biologi, använder den andra artikeln korsvalidering och en metaanalys för att visa att människor med en låg blodsockernivå uppvisar en högre benägenhet att betala för riskfyllda matvaror, även om detta inte visar sig vara fallet för varor som ej är ätbara. Det tredje delarbetet visar genom två studier att iögonfallande, statussignalerande konsumtion är särskilt framträdande bland män som ej är i en relation. Med utgångspunkt i dessa fynd visar det sista delarbetet genom ett nykonstruerat osäkerhetsindex att en ökad osäkerhet leder till en högre grad av sttaussignalerande konsumtion. Sammantaget bidrar denna avhandling till litteraturen om falska positiva resultat och belyser hur forskare inom samhällsvetenskaperna kan nå en djupare förståelse for mänskligt beteende genom att anamma ett evolutionärt synsätt.

Nyckelord: falska positiva resultat, budgetregeln, statussignalerande konsumtion, språkteknologi, evolutionär biologi, blodsocker, relationsstatus

Dedication

Mia, without you, none of this would have ever been possible. You have been my rock through all this. You are the reason why it was even possible to do this work. I will forever be grateful!

Contents

List of publications

This thesis is based on the work contained in the following papers, referred to with Roman numerals in the text:

I. J.C. Dalgaard, J.L. Orquin, S. Perkovic, C.J. Lagerkvist. Inflated false-positive risk in common regression analyses: A combinatorial analysis of model sets.

II. J.L. Orquin, J.C. Dalgaard, C.J. Lagerkvist. A meta-analytical and experimental examination of blood glucose effects on decision making under risk. *Judgment and Decision Making, 15* (6) (2020), pp. 1024-1036.

III. J.C. Dalgaard, T. Otterbring, C.J. Lagerkvist, J. Sundie. Salient signaling by single men: The impact of relationship status on men's conspicuous consumption (Submitted to *Proceedings of the National Academy of Sciences*).

IV. J.C. Dalgaard, M.S. Andres, C.J. Lagerkvist. Does information about the state of the world around us direct competitive consumption?

Paper II is reproduced with the permission of the publishers.

The contribution of Jacob Dalgaard Christensen to the papers included in this thesis is as follows:

I. Together with the co-authors, I came up with the idea for the paper. I coded the simulation and wrote the full results section. The code was later reviewed together with a co-author. I wrote the first draft of the paper, and along with the co-authors, I revised it to arrive at the final manuscript.

II. I conducted all the analyses of the two experiments, and I also planned and conducted the second study of the paper. I wrote the different sections of the paper and, along with the other authors, wrote the final draft of the paper.

III. For Study 1, I designed it together with the co-authors. I wrote the first draft of the pre-registration and planned and edited it together with the co-authors. I did all the testing of the manipulations and all the testing of the dependent variable. For both studies, I collected and cleaned the data, designed the analysis plan, and ran all analyses. I wrote the first draft of the paper.

IV. Together with the co-author, I collected the data and cleaned and wrote the code for developing the indices. I cleaned the consumption data and wrote up a forecasting model of consumption. I wrote the first draft of the manuscript and, along with a co-author, rewrote it into the manuscript in the thesis.

Abbreviations

CEX	Consumer Expenditure Survey
EPU	Economic policy uncertainty
FPP	False-positive probability
FPR	False-positive ratio
LDA	Latent Dirichlet allocation
LOO	Leave-one-out
MSE	Mean square error
NLP	Natural language processing
RF	Random forest
RMSE	Root mean square error

1. Introduction

For many years, economic literature was based on the idea that all agents make rational choices that result in outcomes aligned with their best interests (Levin & Milgrom, 2004). Over the more recent decades, however, economic research has increasingly incorporated ideas from the fields of psychology and cognitive science. This created a string of new research, a novel field called behavioral economics (Camerer, 1999; Hursh, 1984; Kahneman et al., 1991) to understand how and why people behave the way they do in the real world. In a similar fashion, economics has been shaped by neuroscientific insights, resulting in the emergence of neuroeconomics as a subfield (Fehr & Rangel, 2011). In other words, economics has benefited from opening up to other disciplines and engaging in interdisciplinary exchanges. Based on the idea that economic analysis can learn from other disciplines, in this thesis, I will adopt theories from evolutionary biology and psychology and use them to examine two central aspects of consumer behavior, namely conspicuous consumption and preference stability and decision-making under risk.

The present thesis is based on four separate studies. Paper I provides a meta-methodological perspective for the thesis. It is the foundation of the methodological decisions taken throughout my thesis, and, as such, the paper illustrates my experiences as an early-career scholar and demonstrates my commitment to open science practices. In other words, I have tried to overcome the issues I have learned in the process of writing this thesis and apply them to the empirical parts of the thesis (Papers II, III, and IV). Paper II investigates preference stability by examining the role of blood glucose in decision-making. We find that when humans are under an energy constraint (low levels of blood glucose), they are more willing to engage in risky decision-making regarding food objects, but this does not hold for non-food

objects. This different effect could be due to a shift in preference as blood glucose decreases. Paper III and Paper IV study conspicuous consumption. Conspicuous consumption refers to goods that are visible and signal economic power through wealth (Veblen, 1899). These goods might be of high interest to economic policy, as they are normally seen as an externality (Ireland, 1994), and it could therefore be argued that we need to adequately tax the consumption of these goods. However, this interpretation rests on the assumption that conspicuous goods have no other value than just signaling social status. Because demand for conspicuous goods is increasing in tandem with their price, taxing these goods could lead to a loss in welfare (Corneo & Jeanne, 1997). Paper III relies on an experiment and observational data to show that single men use conspicuous salient consumption more than men in relationships. It first shows the causal effect of relationship status on conspicuous consumption. The second part of the paper uses expenditure data from the Consumer Expenditure Survey (CEX). As Paper III gives evidence that conspicuous consumption is used to achieve reproductive goals and might lower uncertainty about fitness in the mating game (De Fraja, 2009), Paper IV investigates what happens when uncertainty increases in the external environment. Here, we find that as uncertainty in the environment increases, conspicuous consumption also increases. In contrast, there is a decrease in the use of other goods. Both these results are consistent with theories from evolutionary biology: conspicuous consumption is used to signal status to attract a mate, and as uncertainty increases, the mating goals move closer and make conspicuous consumption more valuable. Figure 1 provides an overview of the four papers and how they relate to each other.

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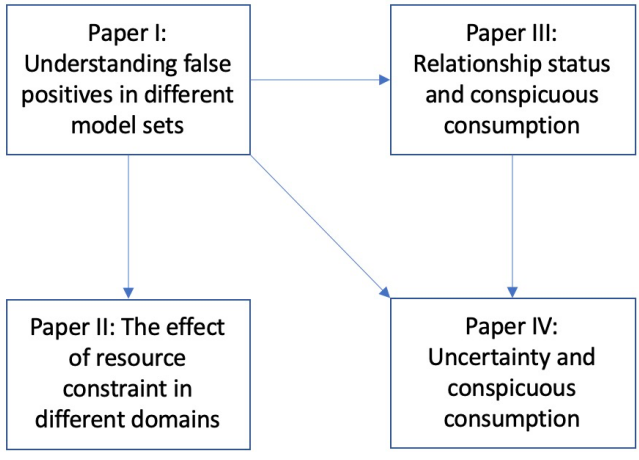

Figure 1. *Link between the studies presented in this thesis*

This thesis contributes to the ongoing debate in meta-science and the discussion on p-hacking and problems with false positives (Pham & Oh, 2021; Simmons et al., 2021) by identifying issues that can happen when increasing the model set both with the number of covariates but also within interactions included in the model set. First, I show how different model sets can be built from a set of covariates and how these affect false positives. Finding a significant result within these sets is not difficult, as we already know (Simmons et al., 2016), but what might be overlooked so far is how interaction terms in regressions can play a key role in obtaining false-positive research results. Adjusting statistical procedures when deciding on the alpha level for type I error risk in statistical analysis is important when using interaction terms in particular. Second, as the case of behavioral economics has shown (the value of including theories from other disciplines), I show how evolutionary biology and psychology theories may help in understanding human behavior.

The remainder of this cover is organized as follows: Section 2 describes different theories from evolutionary biology and how we can expect these to predict consumer behavior. Section 3 explains why method selection matters and why it is important to discuss this topic. Section 4 details the methods used in the four papers included in this thesis. Section 5 provides an overview of the papers included in the thesis and their main results. Finally, Section 6 discusses the results and their implications.

2. Theory for empirical papers

The theories that form the foundation of this thesis come from evolutionary biology. The basic assumption of evolutionary biology is that animals, including humans, strive to survive and reproduce (Penn, 2003; Saad, 2007). In this process, they must select how to spend resources to survive and attract a mate today or in the future. This means that throughout life, organisms need to make some decisions and choose how and when to act in a certain way (Kaplan & Gangestad, 2015). Using ideas from evolutionary biology is nothing new within economics, as scholars such as Friedman (1953) and Alchian (1950) saw a firm's profit maximization as a selection criterion between firms that followed the ideas from evolutionary biology. There is also a strand of literature in institutional economics that borrows ideas from Darwinism (Hodgson, 1996). However, only more recently has it been argued that our evolutionary roots should also influence consumer behavior (Griskevicius & Kenrick, 2013).

In this thesis, I test some of the ideas from evolutionary biology on consumer behavior. I mainly focus on three theories from the literature: budget rule (Stephens, 1981), sexual selection (Darwin, 1871), and life history theory (Stearns, 1992).

2.1 Budget rule

For a human to reproduce, survival is a prerequisite. Paper II provides a better understanding of what happens when human energy is limited, and the focus, therefore, should be more on survival than reproduction. To do so, we take a closer look at the budget rule (Stephens, 1981) and how it helps explain why humans are willing to accept different levels of risk for different

types of products under different biophysical conditions. The budget rule describes an animal's choices when faced with resource constraints concerning food. If energy use is higher than energy consumption, it is expected that animals will increase their willingness to engage in risky choices to obtain more energy. This is because animals who have a negative budget value often fear facing death. With a negative energy budget, which could mean death for the animal, it would thus be more beneficial to choose a higher variance option (more risky option), as this would give a higher likelihood of surviving (Caraco et al., 1980).

Because budget rule theory is concerned only with energy, it would be expected that animals would only increase their willingness to engage in risky behavior regarding food-related items and not non-food items. A previous meta-analysis found that humans with low blood glucose follow budget rule strategies and are more willing to pay and work for food-related items but not for non-food items (Orquin & Kurzban, 2016). However, this meta-analysis does not directly study risky options and the willingness to pay for them. In Paper II, we test whether the results from the meta-analysis also hold when looking at risky choices for human consumers.

2.2 Sexual selection

If animals survive, the next important step is reproduction. However, finding a partner that would be a good match and have the resources to care for the offspring might not be straightforward, as ample resources might not always be available. Darwin (1871) developed the theory of sexual selection to explain why we observe sex differences in display in nature. As one sex (in general) bears the cost of carrying the offspring, it is normally the one carrying this cost that makes a choice of whom to reproduce with. This also means that in the case of offspring, men and women have not faced the same kinds of evolutionary risks (Buss, 1989; Buss et al., 2020). These differences might be one reason why we see sex-specific mate preferences (Bech-Sørensen & Pollet, 2016; Conroy-Beam et al., 2015). Across cultures, it has been observed that women value status and resources more than men when looking for partners (Walter et al., 2020). In contrast, men have a stronger preference for youth and physical attractiveness (Walter et al., 2020). In this mating game of finding a suitable partner, sending signals about resources and status would be beneficial, particularly for males.

Zahavi (1975) argued that for a male to send trustworthy signals about potential resources, these signals must be costly. If they are not costly, any male would be able to send these signals. This is where conspicuous consumption comes into play. In economics, these goods were first discussed by Veblen (1899) in his book *The Theory of the Leisure Class: An Economic Study of Institutions*. Conspicuous consumption was here defined as the act of spending money on consumption goods that signal wealth through the display of these luxury goods. This means that it is not enough for these goods to be expensive, they should also be publicly visible.

More formally, De Fraja (2009) developed a model of status signaling. Under the assumption that men have different resources that are beneficial to their partners, which are not visible, conspicuous goods could arise if they are a meaningful signal of these unobservable benefits. This means that in this model, given that it is the females who commonly chose a partner, males would be the ones who should signal status through conspicuous consumption.

There have already been some empirical contributions to this idea, as it has been shown that men, more than women, are willing to buy status-signaling products, especially in a mating context (Griskevicius et al., 2007; Sundie et al., 2011). It is still true that females also engage in conspicuous consumption (Durante et al., 2014; Hudders et al., 2014; Wang & Griskevicius, 2014), but for attracting partners, the use of conspicuous consumption is more prevalent among men (Griskevicius et al., 2007; Sundie et al., 2011). All these papers have, however, one thing in common: they do not directly investigate the link between relationship status and conspicuous consumption. To overcome this issue, Paper III in this thesis directly investigates the link between relationship status and conspicuous consumption. Based on arguments from sexual selection theory, it is hypothesized that single men should consume conspicuous goods more than mated men and women in general.

2.3 Life History Theory

Life history theory is a framework for understanding how organisms allocate their limited resources to growth, reproduction, and other biological processes and how environmental conditions influence these allocation

decisions. One key aspect of life history theory is the idea that in uncertain environments, animals may be more likely to adopt a "fast" life history strategy in which they invest fewer resources in growth and maintenance and start reproducing at an earlier age. This strategy may be advantageous because it allows individuals to use available resources and reproduce before they are depleted (Stearns, 1992). Across cultures with a high level of uncertainty in the environment, individuals generally choose to have children at an earlier stage compared to more stable environments (Griskevicius et al., 2011; Low et al., 2008).

One potential way that individuals could signal their fitness and reproductive success in uncertain environments is by engaging in conspicuous consumption. Following the results of Griskevicius et al. (2007) (and those in Paper III), it could be expected that conspicuous consumption becomes more valuable in uncertain times.

Overall, the three theories used in this thesis describe both what we could expect to happen when humans are in a depleted state and hence need to acquire resources to survive, as well as what happens when survival is secured and which strategies they then use to reproduce. These theories give a good idea of the fundamental needs of humans from an evolutionary perspective. These theories are still rarely tested within the field of economics, which constitutes the first main contribution of this thesis. Thus, Paper II investigates risky gambles to determine whether humans would follow the budget rule. Paper III examines real expenditure data to estimate the effect of being single on the consumption of conspicuous goods. Lastly, Paper IV uses the level of perceived uncertainty measured through newspapers to predict conspicuous consumption.

Importantly, and as the second main contribution of this thesis, to test the predictability of the above theories, methods must be discussed. In the following section, I elaborate on the methodological choices in the three empirical papers presented in this thesis. The first part of this section first identifies some issues within the literature and explains why it is necessary to discuss methods and the use of p-values.

3. Understanding why methods matter

The first paper in this thesis revolves around p-values, especially the risks that we encounter when using them. This paper is the offset of the statistical and analytical methods used in the other papers. Therefore, interpretations of the p-value, how the p-value has historically been misunderstood, and finally, what to do about these issues will be briefly discussed.

3.1 Definition of a p-value

When defining the p-value, we can use Fisher's (1925) framework. Following null hypothesis H0 and test statistic T, we define the p-value as the probability of observing the test statistic or a more extreme value than we did in the data, given that the null hypothesis is true. For a one-sided test, this can be written as $P(T < t|\mathrm{H}_0)$. Writing the p-value as the probability might help understand why the p-value has been hard to interpret for researchers within different fields (Gigerenzer, 2018; Heckelei et al., 2021). The p-value is not about the hypothesis concerning the population but the data (a test statistic calculated from the data) conditional on a specific hypothesis in the population being true. In performing a hypothesis test, some significance level is set (also known as the alpha level). When the p-value is lower than the significance level, we would reject the null hypothesis and say that we do not believe that our data were drawn from a distribution where the null hypothesis was true. However, since we are talking about probabilities, the data could still have been drawn from where the null hypothesis was true, but we observe this value just by chance. We normally refer to this error as a type I error (a false positive). If everything were well

specified, the type I error would be equal to the alpha level we set. Generally, setting this cut-off to 5% has been accepted. This means that we would reject the null hypothesis in 5% of the cases, even though the data were drawn from a distribution where the null hypothesis was true, meaning they were false positives.

3.2 The replication crises

The definition of the p-value and what the alpha level gives us could incorrectly lead to the conclusion that the replication rate in published work would be around 5%. However, this is not the case. Remember that the p-value is about observing the data, given that the hypothesis is true, and therefore not a test if the hypothesis is true or not. However, we could assume that if there are a high number of false positives in published work, we would also assume a lower level of them to replicate. However, the replication rate of studies still comes down to factors other than just the false-positive rate, such as the power of replication studies.

One of the first attempts to replicate a large body of psychological literature was the Open Science Collaboration (2015). They found that of the 100 studies they tried to replicate, only 37% were replicated. A later analysis of these results has found that context sensitivity seems to matter for the replication of these studies (Van Bavel et al., 2016), meaning studies that were rated as being more sensitive to context had a lower likelihood of being successfully replicated. Within experimental economics, slightly more positive results were found, as 2/3 of the studies that scholars tried to replicate truly replicated (Camerer et al., 2016). It is important to remember that the replication rate is a function of the power of a study in which the power of a study measures how often one would find an effect if it were truly there (Cohen, 1992). In the case of Camerer et al. (2016), the estimated power of the study was set at 90%, meaning that if there was truly an effect (of the expected size, as estimated by the published studies), 90% of the studies should have been replicated. This is off from the 66% replication rate they found. Therefore, it is important to understand what the reasons behind these failures could be to replicate them and what we can do about them.

3.3 Why has it happened?

There might be several reasons why a replication crisis exists. One reason already discussed in the literature is researchers' degrees of freedom (Wicherts et al., 2016). When we, as researchers, conduct and analyze a study, we have freedom regarding how to collect the data (i.e., what data to collect to test our hypothesis, how to analyze the data, and in the end, what we choose to report in our final paper). Even if a researcher is only interested in one variable, there is still the choice of what covariates to include in the model, should there be any outlier deletion, and, if so, how should this be done and how the dependent variable should be treated. With this type of flexibility, it has already been shown that the chance of a false positive can go above 60% (Simmons et al., 2016). However, this is under the assumption that the researcher is willing to test a set of models and only report the one where there is a significant effect. In this literature, there is a focus on what we call the false-positive probability (FPP) in Paper I. With this, I mean the probability of all the possible models to test that one of them would have a significant effect. This measure is important to understand why it could be that some studies could not replicate (Collaboration, 2015), but this is only important if there is selective reporting of results, and researchers are truly using these flexibilities. Brodeur et al. (2016) found some evidence that this is what might be going on. They collected p-values and transformed them into z-values from the top five economic journals. Plotting these values, it is clear that across journals, there is a hump of values just around 1.96. This value corresponds to a p-value of 0.05 and means that there is an overreporting of these values in the literature compared to what could have been expected from the distribution of z-values. Similar results are found in other fields when conducting online studies using Mechanical Turk (Brodeur et al., 2022). Brodeur et al. (2022) found strong indications of both the use of flexibilities (p-hacking) and publication bias across fields when studies used online samples. The use of this selective reporting and indications of the use of flexibilities could be part of why we see a higher number of papers failing to replicate.

There is no doubt that there is an issue with p-values and the reporting of these values within social science fields. However, the more important part is how to solve this problem.

3.4 Solutions to the issue

A series of solutions to overcome the issues with p-values and their misuse have been offered. These range from completely abandoning the p-value to lowering the threshold where we call something significant to using completely different methods to test our hypothesis (Benjamin et al., 2018; Gigerenzer, 2004; Meng, 1994; Vidgen & Yasseri, 2016).

One of the first suggestions in the literature is to abandon p-values completely, as they are too easy to manipulate (Gigerenzer, 2004). The suggestion has then been to instead use effect sizes and focus more on economic or practical significance rather than statistical significance (Ziliak & McCloskey, 2008). There have already been some implementations of these ideas, as the journals Basic and Applied Social Psychology and Political Analysis have banned the use of p-values (Gill, 2018; Trafimow & Marks, 2015). However, this has been challenged from multiple sides, but the most important is that any alternative method selected can also be manipulated (Savalei & Dunn, 2015; Simonsohn, 2014). Furthermore, an analysis of the impact of not using p-values found that researchers would still overstate results, and even, in some instances, more if p-values had been allowed in the journal (Fricker et al., 2019).

Another suggested solution has been to use Bayesian statistics or even Bayesian p-values (Meng, 1994; Vidgen & Yasseri, 2016). This method might have a very clear interpretation, as one would use the posterior probability of an event combined with the likelihood of the data to give a posterior probability. This allows a researcher to talk about the probability of an effect rather than, as in the world of p-values, the probability of observing the data. Even though this might be a good idea, it has some drawbacks. First, it might be difficult to determine the posterior probability. There are some solutions to this, but in general, the posterior probability is specific to the case at hand, and it can be difficult for researchers to make an implementation that is easy to use. Another issue is that the use of Bayesian statistics, or, more specifically, Bayesian p-values can be manipulated just as easily as p-values (Simonsohn, 2014). This result builds on the issue of creating the prior and suggests that in these cases, it would be optimal to have a uniform prior distribution. However, this will lead to the same issues as with p-values, as they are mathematically identical (Simonsohn, 2014).

For those who want and still see value in using p-values, one suggestion has been to lower the cutoff point for when to call an effect significant

(Benjamin et al., 2018; Vidgen & Yasseri 2016). There are different arguments for lowering this threshold. The argument by Benjamin et al. (2018) comes from Bayesian statistics, as they want to see how low a p-value should be for it to be comparable to a meaningful Bayes ratio used when doing Bayesian statistics. Here, Benjamin et al. (2018) argue that a threshold of 0.005 is comparable to a Bayes factor between 14 and 24 in favor of the alternative hypothesis, which corresponds to a "substantial" or "strong" finding (Kass & Raftery, 1995). As with any other threshold, it could still be argued to be arbitrary to set it at 0.005, which has also been criticized in the literature (Amrhein & Greenland, 2018).

Furthermore, the argument that lowering the significance threshold to 0.005 will lower the false discovery rate is only true if no researchers engage in p-hacking (Crane, 2018). Others have argued that it should not be set to any specific level but should be set for the situation (Lakens et al., 2018). Lakens et al. (2018) still agree that an alpha of around 0.05 might not be the best, but going from 0.05 to 0.005 and still having the same amount of power for the test would require an increase of 10% for the sample size. It should, however, be mentioned that even the authors of the paper Redefine statistical significance (2018) do not seem to follow the recommendation of using 0.005 instead of 0.05, so implementing this might be difficult (Białek et al. 2021).

Therefore, one option could be to focus more on replications and meta-analyses. Meta-analysis is an old statistical tool, and one of the first was done in 1907 by Karl Pearson (O'rourke, 2007). However, it grew in popularity when the replication crisis was announced (Fontelo & Liu, 2018). Meta-analysis uses the effect sizes from different studies to test whether this aggregate effect can be assumed to be "true" or, alternatively, due to something like publication bias (Field & Gillett, 2010). In this thesis, the method that has been used takes validity into consideration when conducting the meta-analysis, but there are multiple ways to conduct an analysis like this (Hunter & Schmidt, 2004).

One issue that meta-analysis cannot completely overcome is p-hacking and publication bias (Friese & Frankenbach, 2020). Therefore, even though the meta-analytic method might be good for summarizing results within a field, it cannot stand alone. Therefore, there is a need to replicate previous studies.

The use of replication studies has increased dramatically over the last decade (Mueller-Langer et al., 2019). Here, instead of looking at old published work, researchers try to either do a conceptual replication or a direct replication (Derksen & Morawski, 2022). The conceptual replication tries to replicate a published study but only using the concepts and not the same study material, manipulation, stimuli, or dependent variables. This might be a good choice for replication, as the effect could have been driven by the method chosen in the data collection. Direct replication, on the other hand, uses the exact same method and analysis plan. This type of replication might have been better if it were truly just a type I error in the original paper, so a false positive.

The final factor that could help overcome the rate of false positives in the scientific literature is the pre-registration of analysis. With this, I mean that before researchers even start collecting the data, they would more or less write the whole method section of the paper and explicitly state the hypothesis, what data are going to be collected, what the sample should be (and why), and precisely how the data will be analyzed (Van't Veer & Giner-Sorolla, 2016). These plans are then submitted to a repository that will timestamp the plan so that there can be no changes after the data have been collected. This prevents any fishing in the data from obtaining significant results. More importantly, it clarifies the difference between true hypothesis testing and exploratory analysis. This later point might be very important to emphasize. Using pre-registration does not eliminate the use of exploratory analysis, as there might still be very important information to gather here (Rubin & Donkin, 2022). Instead, it makes it very clear what exploratory analysis is. There has been some debate over the use of these pre-registration plans (Pham & Oh, 2021), but there seems to be an overall movement toward using these more (Simmons et al., 2021). It is, however, important to keep discussing these methods, as the first generation of pre-registered analysis still seems to contain errors (Claesen et al., 2021), and even in some cases, there was a massive difference between the published article and the pre-registration (Van den Akker et al., 2022).

Notwithstanding the strengths associated with the above tools, all analysis strategies bring some risks. The methods used in this thesis were selected to overcome some of the risks mentioned above. The next section, therefore, goes through the different methods used in each paper, along with the data used.

4. Types of data and analytical methods

4.1 Data used

In this section, I discuss the different types of data that have been used in the thesis, as these guide the choice of the analytical method.

4.1.1 Simulations

In the first paper, all data were simulated. This means that we created our own data-generating process to ensure that we controlled exactly what was happening. This was done to investigate the impact of the data type (and other factors) on FPP and the false-positive ratio (FPR). Simulations in this field are common (Simmons et al., 2016). However, we expanded on the data type and what we were interested in.

Another place where simulating data can be helpful is when calculating the statistical power of a study (Arend & Schäfer, 2019). This was done in Paper III when conducting the power analysis for the survey experiment. Here, we created data with a specific effect size and subsequently examined what happened with the power of the study when we changed different parameters (such as the sample size and the interclass correlation). This was done to determine how large a sample is needed to ensure a specific power, given the effect size.

4.1.2 Experimental data

Experimental data were collected from two of the papers in this thesis (Papers II and III). For Paper II, two experiments were conducted in the COBE lab at Aarhus University. The first study included 107 participants,

while the second study included 162. The first used a consumer panel to recruit participants, meaning that it might also be more representative of the whole population compared to Study 2, which used the local student participant pool from the university. Both studies used a 2 × 2 × 2 mixed within-between subjects design. This means that there were 16 observations per participant for the first study, leading to a total of 2,568 observations, whereas Study 2 had 82 observations per participant, resulting in a total of 13,608 observations. In the second study, we collected effect sizes from 20 experimental studies (including those conducted in the paper) to perform the meta-analysis. These other studies were identified on the Web of Science following a series of keyword searches. Gray literature was identified on Google Scholar. Finally, all identified papers were searched using backward and forward citation analyses.

For Paper III, the first study used experimental data. Here, we conducted a survey experiment with 420 men. For each participant, there were 20 observations, meaning a total of 8,400 observations. As mentioned above, the sample size for this study was based on power simulations for the experiment. Before the study, a series of tests were run to test whether the manipulation was working and for which products to include as dependent variables. For the manipulation, we recruited 201 men with a balance between being in a relationship and being single. This was done to ensure that our treatment performed as intended. For the dependent variable pretest, we recruited 50 participants to test which products would truly signal wealth. The final study of Paper III also used observational data (see the section below), but we collected 100 participants to classify the products used in the observational study. These participants rated a total of 20 product categories regarding the extent to which each product category signaled wealth and visibility.

4.1.3 Observational data

Both Paper III and Paper IV used observational data from the CEX (US Department of Labor, 2022). This is a rotating survey that collects the consumption of different goods for a representative set of households in the United States. The dataset is also used to calculate the consumer price index (CPI) for the United States. I have used observational data collected from 1990 until 2020. This is not the first time that this dataset has been used in relation to conspicuous consumption (Charles et al., 2009), but here we used

an updated classification instead of using the overall groups classified by Harris and Sabelhaus (2000).

In Paper III, the observational dataset was used at the household level. In contrast, in Paper IV, consumption was aggregated on a monthly (and quarterly) basis to investigate the effect of uncertainty on conspicuous consumption.

However, generating data on uncertainty is not straightforward. To measure uncertainty, we collected newspaper articles from six major news companies (New York Times, USA Today, Salt Lake Tribune, Star Tribune, Philadelphia Inquire, Tampa Bay Times, and Pittsburgh Post-Gazette) from 1990 to 2020. The newspapers were selected so that some of them would cover overall news across the United States (New York Times and USA Today), whereas others were chosen to cover specific regions (Salt Lake Tribune, Star Tribune, Philadelphia Inquire, Tampa Bay Times, and Pittsburgh Post-Gazette), with the regions classified as in the CEX. For the newspapers covering specific regions, we saved only the news coverage of that region. Including regional newspapers ensured that it would be possible to calculate an uncertainty index for each region.

4.2 Methods used in the thesis

The methods used in this thesis can be split into two sections: predictive modeling and frequentist modeling. Table 1 features an overview of the data used, the methods applied to analyze the data, and how the effects have been evaluated.

The main reason for choosing different methods across the thesis was to overcome the risk of false positives, as discussed in Paper I.

4.2.1 Predictive modeling

In Papers II[1] and IV, there was a focus on the predictability of the models instead of how well the data fit the given model. Paper II used linear mixed models to analyze the data, as there were repeated measures for both Study 1 and Study 2. This means that each model had a random effect on each study participant. Instead of using p-values to test the treatment effects in these studies, we used cross-validation. The idea here is that instead of focusing

[1] Paper II still presents p-values as these were put in as part of the publication process.

on how well the model fits the data, you want to try to predict data that are not used in the model estimation (Berrar, 2019). When using cross-validation, there are normally two ways to evaluate models: k-fold or leave-one-out (LOO). In both cases, the data are split into a training and a testing set. The k-fold splits the data into k partitions, where the training sets become k-1 parts of the sample, and the k'th split becomes the test set. LOO instead takes one observation out to become the test set. The model is then fitted to the training set, and a prediction error for the test set is calculated. This is then done for each of the observations and a set of models, either each of the folds in k-fold or each of the observations in LOO. Finally, all the prediction errors are then averaged within the models. The model that is then chosen is the one with the lowest average prediction error. Doing this can overcome issues with the overfitting of the data (Cawley & Talbot, 2010). In the case of Paper II, the LOO was chosen. Here, a set of possible models that included the different variables of interest was chosen. Each model was then estimated on the sample, excluding one participant, and then the prediction error for that model was calculated. The participant was then included in the training set again; another participant was the test set. This was done for each participant.

Paper IV uses some of the same ideas. Here, the idea was also to predict part of the sample that was not included in the estimation. However, instead of individuals being taken out, consumption was forecasted in the next period, meaning that the training set was all observations up to time t, and the training set would then be the observation in t + 1. Another major difference is in the possible models. Although the paper's interest is in the forecasting performance of the indices developed from newspapers, this has to be compared to something. In this case, the performance was compared to a model that included hard economic variables from the FRED-MD dataset. However, this leaves an issue with dimensionalities, as there are many variables but not many time periods to estimate the models. Therefore, the models were estimated using a random forest (RF) (Breiman, 2001). RF builds on the idea from decision trees, but adding a random element lowers the estimates' variance without affecting the bias (Hastie et al., 2009). The random part of this comes from the fact that every time the model is estimated, it uses only a random subset of available variables. The performance of the models is then evaluated the same way as with the LOO cross-validation, just with the test set being the next period's consumption.

4.2.2 Frequentist modeling

Instead of predictive modeling, Paper III used p-values to test for effects. However, as outlined in the discussion about p-values, this brings some challenges and some important things to be clarified. First, the analytical model in Study 1 in this paper was the same as in Paper II, as the data also came from an experiment with repeated measures for each participant. Study 2 of the paper was the part that uses the observational data of the expenditure for households in the United States. Here, the type of model was selected based on the bias of the variables that needed to be controlled for. We wanted to control for permanent income, as this should affect consumption decisions (Friedman, 2018). However, doing so with these data creates some problems. First, as the data in the survey focus on the expenditure side of the household and not the income, it can be expected that there could be some measurement error for the income variables. We could instead use expenditure as a proxy for income, but this leaves us with a simultaneous issue, as both our dependent and independent variables would be decided simultaneously. To overcome this issue, we used 2SLS with the income variables as instruments for the expenditure variables. This should overcome both issues.

However, this still leaves the issue of being clear and transparent about the testing and interpreting of the p-values to ensure a lower FPR. Therefore, we used pre-registration in Study 1 (for the experiment) and the same analysis strategy used earlier in the literature in Study 2 (for the observational data). The pre-registration would bind our hands and force us only to make one hypothesis test, ensuring a low FPP. Using a previous analysis plan for Study 2 makes it apparent that we did not try out different models to obtain the results reported in the paper. Of course, the latter approach still leaves some flexibility. Therefore, we did not test against the normal 0.05 but only reported p-values lower than 0,005, as suggested by the literature (Benjamin et al., 2018).

Table 1. This table shows the data, analytical approach, and evaluation that have been used in the papers presented in this thesis.

	Data	Analytical approach	Evaluation
Paper I	Simulated data	Linear regressions	False positive probability and false positive ratio
Paper II	Experimental data and effect sizes from the literature	Linear mixed model meta-analysis	Cross validation using RMSE
Paper III	Survey experiment and bigger survey data	Linear mixed model and 2SLS	P-values following pre-reregistered model and analysis plan from earlier paper
Paper IV	Newspapers and time series data	Latent dirichlet allocation and random forest	Forecasting error

5. Summaries of appended papers

The following section provides a brief summary of the four papers included in this thesis.

5.1 I – Inflated false-positive risk in common regression analyses: A combinatorial analysis of model sets

In the first paper of this thesis, we attempt to understand how different types of flexibilities affect type I errors. As the evidence points toward an inflated number of false positives (Camerer et al., 2016; Collaboration, 2015), it is important to understand why this happens. Previous literature has already shown that with simple flexibilities, it is easy to get a false positive (Simmons et al., 2016), but in this paper, we try to go a bit deeper to understand why it is happening and what to do about it. When we do research and use p-values for our hypothesis testing, we have an expectation that the FPR will be at the critical values, normally put at 5%. It has been shown that different kinds of misspecifications in the model can increase the risk of type I errors (Dennis et al., 2019; Litière et al., 2007). Therefore, the goal of this paper was to see how easy it would be to get one variable of interest significant, even though it would have zero correlation with the dependent variable. The first step is to define what we mean when talking about model sets. In this case, we can define two overall types of model sets: those that only contain main effects and those that also contain interactions. The sets where interactions are present can be further split into two different sets: sets where there are interactions between the variables of interest and sets where there are interactions between the covariates themselves. We can then have combinations of these three sets, leaving us with seven different model sets.

If we restricted our model set so that for any interaction, the main effect should follow, there would be four different sets. A table of the different types of sets can be seen in Table 2. We then define two outcomes of interest: FPP and FPR. The FPP measures the probability that one model in the full model set will have a false positive, while the FPR measures the number of models within the model set with a false positive. Therefore, the FPP can be seen with regard to the chance of getting a false positive if a researcher would p-hack, and the FPR measures the risk of getting a false positive if the researcher ran only one single model from the model set.

Table 2 *An overview of the model sets when there are two covariates and one dependent variable depending on the restriction that the corresponding main effects must follow the interaction effects. The model sets are the once that are developed in Paper I. The x + z set contains all of the main effects; the x + z + x × z set includes the main effects and interactions between the variable of interest and the covariates; the x + z + z × z set contains the main effects and interactions between the covariates; the x + z + x × z + z × z set contains the main effects, the interactions between the variable of interest and covariates, and the interactions between the covariates; and the x × z, z × z and x × z + z × z sets are empty sets due to the restriction that main effects must follow interaction effects.*

Model set	Models with restrictions	Models without restrictions
$x + z$	$y = x_1$ $y = x_1 + z_1$ $y = x_1 + z_2$ $y = x_1 + z_1 + z_2$	$y = x_1$ $y = x_1 + z_1$ $y = x_1 + z_2$ $y = x_1 + z_1 + z_2$
$x \times z$	Empty set	$y = x_1 + x_1z_1$ $y = x_1 + x_1z_2$ $y = x_1 + x_1z_1 + x_1z_2$
$z \times z$	Empty set	$y = x_1 + z_1z_2$
$x + z + x \times z$	$y = x_1 + z_1 + x_1z_1$ $y = x_1 + z_2 + x_1z_2$ $y = x_1 + z_1 + z_2 + x_1z_1$ $y = x_1 + z_1 + z_2 + x_1z_2$ $y = x_1 + z_1 + z_2 + x_1z_1 + x_1z_2$	$y = x_1 + z_1 + x_1z_1$ $y = x_1 + z_1 + x_1z_2$ $y = x_1 + z_1 + x_1z_1 + x_1z_2$ $y = x_1 + z_2 + x_1z_1$ $y = x_1 + z_2 + x_1z_2$ $y = x_1 + z_2 + x_1z_1 + x_1z_2$ $y = x_1 + z_1 + z_2 + x_1z_1$ $y = x_1 + z_1 + z_2 + x_1z_2$ $y = x_1 + z_1 + z_2 + x_1z_1 + x_1z_2$
$x + z + z \times z$	$y = x_1 + z_1 + z_2 + z_1z_2$	$y = x_1 + z_1 + z_1z_2$ $y = x_1 + z_2 + z_1z_2$ $y = x_1 + z_1 + z_2 + z_1z_2$
$x \times z + z \times z$	Empty set	$y = x_1 + x_1z_1 + z_1z_2$ $y = x_1 + x_1z_2 + z_1z_2$ $y = x_1 + x_1z_1 + x_1z_2 + z_1z_2$
$x + z + x \times z + z \times z$	$y = x_1 + z_1 + z_2 + x_1z_1 + z_1z_2$ $y = x_1 + z_1 + z_2 + x_1z_2 + z_1z_2$ $y = x_1 + z_1 + z_2 + x_1z_1 + x_1z_2 + z_1z_2$	$y = x_1 + z_1 + x_1z_1 + z_1z_2$ $y = x_1 + z_1 + x_1z_2 + z_1z_2$ $y = x_1 + z_1 + x_1z_1 + x_1z_2 + z_1z_2$ $y = x_1 + z_2 + x_1z_1 + z_1z_2$ $y = x_1 + z_2 + x_1z_2 + z_1z_2$ $y = x_1 + z_2 + x_1z_1 + x_1z_2 + z_1z_2$ $y = x_1 + z_1 + z_2 + x_1z_1 + z_1z_2$ $y = x_1 + z_1 + z_2 + x_1z_2 + z_1z_2$ $y = x_1 + z_1 + z_2 + x_1z_1 + x_1z_2 + z_1z_2$

We ran a series of simulations to find the FPP and FPR for the different model sets and different kinds of flexibilities (using different kinds of outlier criteria, several dependent variables, and increasing the number of covariates). We generally find that getting a false positive when allowing for p-hacking is very easy. With just two covariates, it is easy to obtain a high FPP when looking at different model sets but not including any other flexibilities. What might be more interesting is that the higher the correlation between the covariates and the dependent variable, the higher the FPP. This higher correlation does not affect the FPR. For most cases, the FPR is around the expected 5%, but as soon as we allow for interactions between the variable of interest and the covariates, the FPR will also increase. However, there is a simple solution to this. The alpha level needs to be corrected as soon as these interactions occur. A simple Bonferroni correction (Dunn, 1961) is enough to get the value back to 5%. One thing that has been argued in the literature is the need for larger samples to overcome the risk of false positives (Simmons et al., 2018). Our results show that this is not true. Increasing the sample will not lower either the FPP or the FPR, and even in some cases, it goes the other way around, meaning bigger samples increase both the FPP and FPR. Bigger samples are indeed important when there is a true effect, as, with smaller sample sizes, the effect jumps more around (Gelman & Carlin, 2014). Therefore, it is not to say that big samples are unimportant; they are. They help with type II errors, but from these simulations, we see no effect on type I errors.

To sum the results into some recommendations: 1) researchers should pre-register the hypothesis they want to test, 2) when using interactions with the variable of interest, there should be a correction of the alpha level, 3) when using interactions, main effects should always be present in the model, 4) having a bigger sample does not legitimize exploratory analysis as being more “true” or not as it does not lower the FPP, and 5) exploratory analyses are important for scientific discoveries but to draw conclusions of effects, it a true hypothesis test in another study is still needed.

5.2 II – A meta-analytical and experimental examination of blood glucose effects on decision making under risk

During the day, our blood glucose levels go up and down. This is a function of our eating habits and the time of day. In recent years, some studies have looked directly at how the movement of blood glucose affects risk-taking (De Ridder et al., 2014; Symmonds et al., 2010; Williams et al., 2016). The first studies within the field showed the effect of higher risk-taking in the food domain with a lower level of blood glucose (Ditto et al., 2006). However, work that tried to replicate this study did not find similar results (Festjens et al., 2018). Therefore, it is important to understand if the shift in blood glucose levels that we all experience during the day affects our risk-taking, and if so, whether this is the same across domains (food vs. non-food). Based on previous research, two different theories might help explain what could happen. The first one from the optimal foraging model is called the budget rule (Stephens, 1981). The second theory is a compound of models but generally goes under the label of dual system theory. The first model assumes that animals, as well as humans, maximize their ability to survive. This means that when animals become hungrier, they are willing to increase the risk in an area that can help them survive but not in areas where such risky decision-making does not bring clear survival-related benefits. This means a model like this would predict that humans with low levels of blood glucose would increase their risk-taking in the food domain but not in a non-food domain. On the other hand, a theory like dual system theory assumes that humans have two different ways of making decisions: one slow, which takes more energy, and one fast, which takes less energy. This means that as there is less energy in the body (lower levels of blood glucose), the decisions are shifted faster. Under the assumption of a concave utility function, this would lead to more risk aversion. As this model is domain-general, it would predict that the risk-aversion goes for both the food and non-food domains. These two theories are tested in two experiments in which blood glucose was manipulated using Sprite vs. Sprite Zero. In the first experiment, people bid on different types of risky and non-risky products within the Becker–Degroot–Marshak auction approach (Becker et al., 1964). In this study, there were two different product categories (food vs. non-food), and each product could be represented as either risky or non-risky. Risky

products were presented to the participants that they were producing using some biotechnology such that the products would increase the performance of the product, although with a small risk of an allergic reaction. In the second study, we use a high and low level of variance in different gambles where the price was either some food or, in the other condition, a gift card for an electronic store. Finally, we conduct a meta-analysis of the studies conducted in the paper along with previous literature in the area.

In the first study, we did not find any effect of manipulating blood glucose on the willingness to pay for non-risky products compared to risky products. In the second study, we found that participants with a lower blood glucose level were more willing to choose the high-variance gambles, with the effect being more pronounced in the food domain. From the meta-analysis, we find that including food vs. non-food as a moderator best explains the effects found in the literature. This analysis shows an increase in risk-seeking in the food domain under a lower blood glucose level, which is not the case for the non-food domain. Overall, the results from the meta-analysis align best with the budget rule's predictions that lower blood glucose levels should lead to higher risk-taking in the food domain but not in the non-food domain.

5.3 III – Salient signaling by single men: The impact of relationship status on men's conspicuous consumption

The third paper of the thesis shifts the focus to conspicuous consumption and how evolutionary biology might help explain this type of behavior. Several studies have already investigated various predictors of conspicuous consumption and have found several factors linked to this consumption practice (Kruger, 2022; Otterbring et al., 2018). From an offset in evolutionary biology, we try to better understand one specific aspect of human life that can affect the consumption of status-signaling goods, namely relationships with a partner. Men are more motivated than women to engage in conspicuous consumption, especially when exposed to mating-related cues (Griskevicius et al., 2007; Sundie et al., 2011). Therefore, we investigate whether we can show this effect in a pre-registered experimental setting in which we manipulate the relationship status of men and see how this affects their willingness to purchase conspicuous goods for a potential

date. Following this, we use the CEX to test whether the potential effect found in the experiment could be replicated in real expenditure data.

All participants in the first study initially indicated their true relationship status, as this would be the foundation of which type of manipulation they would receive. This was done because there could be no true control (i.e., someone with no relationship status). If they said they were in a relationship, they would be given the manipulation to either think of themselves as going on a date with their partner or think of themselves as single and going on a date with a potential partner, and vice versa, for those who indicated they were single. The participants would then rate a series of products to indicate whether they would purchase those to wear on this date. We found that those who were in the uncommitted (single) condition had a higher purchase intention for conspicuous products than their counterparts in the committed (relationship) condition. A series of robustness tests did not alter any of these conclusions. Following this study, we used the CEX from 1990 to 2020 to investigate whether single men were purchasing more conspicuous goods than other groups. This dataset contains over 770,000 households collected from a rotating panel. We then tested a series of products to find some that could be seen as conspicuous and others that would be seen as inconspicuous. We followed the analysis plan done by Charles et al. (2009) with the only difference of adding a dummy variable that was coded as one if the household was single and zero otherwise. This variable was then interacted with the sex of the reference person in the household. This analysis showed that single men spend over 40% more on conspicuous consumption compared to single women and 15% more than a mated household. These effects are robust to a series of tests and show that it is not only in the experimental setting that we find that single men would have a higher purchase intention for conspicuous goods; also, in real data, single men spend more money on conspicuous goods compared to mated men. This adds to the notion that evolutionary biology might help explain why something like conspicuous consumption would happen.

5.4 IV – Does information about the state of the world around us direct competitive consumption?

The last paper of the thesis looks at how uncertainty affects the growth of conspicuous consumption. This might seem to be an obvious question for

economists: higher economic uncertainty should lead to lower consumption. This argument comes from the precautionary saving hypothesis (Friedman, 2018). This states that when uncertainty increases, a rational consumer who is risk averse should shift consumption to savings to safeguard against this uncertainty (Leland, 1978). However, viewing the same problem from an evolutionary perspective, the answer might be more complex. Within these theories, behavior should be routed in evolutionary conditions such that a specific behavior should help with the survival of the individual or the group (Saad, 2007). One such theory is life history theory (Stearns, 1992). One aspect of this theory is the trade-off between mate-seeking and investing resources in the future to ensure better survival. This means that within this framework, as an animal reacts to the survival of the species, a higher level of uncertainty in the environment should lead to shifting the investment into mate-seeking rather than investment into personal survival. There is already evidence that this type of shift from personal investment to reproductive goals is seen in humans (Belsky et al., 2012). One thing that humans use to attract potential partners is conspicuous consumption (Griskevicius et al., 2007; Sundie et al., 2011). Therefore, within this framework, it could be expected that consumption would shift toward conspicuous consumption rather than savings, as predicted by economic theory.

To test whether this is true, we first build an uncertainty index using American newspapers from 1990 until 2020. We build on the index creation from Baker et al. (2016) but with the big difference that we use completely unsupervised machine learning to exclude any errors that can come from human decision-making. From the newspapers, we build the uncertainty indices from 25 topics ranging from economic topics to more religious topics to a traveling topic. These topics are generated using latent Dirichlet allocation (LDA), and the measure of uncertainty is learned using Word2Vec (Blei et al., 2003; Mikolov et al., 2013). To test whether this helps predict conspicuous consumption, we compare the prediction power to a model that uses hard economic variables collected by McCracken and Ng (2016). However, as both of these prediction sets contain many variables, we use RF as the prediction model, as this has been shown to perform well in data-rich environments (Medeiros et al., 2021). In general, the model using news-based uncertainty indices outperforms the model that uses economic variables from the FRED-MD when forecasting conspicuous consumption. The gain of using the uncertainty indices, however, only seems to help with

the prediction in the short run. We do not see any performance increase for inconspicuous goods when using news-based uncertainty indices. Since we are using RF here, it is not possible to get just one coefficient out that tells something about the direction of the effect from indices. Instead, we look at the accumulated local effects (ALE) (Apley & Zhu, 2020). We plot these for the economic and political variables, as these are the ones for which it is easiest to draw a direct line with the precautionary saving hypothesis and what we would expect to happen to consumption when the uncertainty in these domains increases. We get the opposite effect of what would be expected from economic theory. As uncertainty increases for economic variables, the consumption of conspicuous goods increases. We do not see this pattern for inconspicuous goods. This means that the results that we find in this paper are better explained by life history theory than by the precautionary saving hypothesis. For robustness, we calculate the same set of uncertainty indices on a regional level in the United States and find similar results.

This paper contributes to the literature in several ways. First, it provides a way to calculate uncertainty within different domains that are completely free from human intervention. This means that it is easier to scale and include new data or even predict similar indices for other countries. Second, we contribute to the literature on conspicuous consumption and provide some foundation for further research. If these results would hold in a more general sense than what is found here, we might need to figure out a new way to model consumption patterns in economics and split the utility function by good type, as it seems that conspicuous consumption does not follow the normal economic model.

6. Discussion

In this thesis, I have used theories from evolutionary biology to understand socially embedded preferences in ways of conspicuous consumption, as well as inter-subject preference structure. Through a series of papers, I have shown why it might be important to have such evolutionary-inspired theories in mind when developing economic models. In all the empirical papers this thesis presents, there is some explanatory power from the theories tested in evolutionary biology. Therefore, it is important to keep these evolutionary goals in mind when modeling consumption behavior.

6.1 Economic implications

The findings from this thesis become increasingly important when we talk about what to do with conspicuous consumption. A series of different tax schemes in the literature for these pricey possessions has already been suggested (Ireland, 1994; Ng, 1987). One thing they have in common is that they start with the assumption that conspicuous consumption is an externality that should be taxed away. However, this might be only partially true, following the results from this thesis and prior results on conspicuous consumption. The groups with the least amount of wealth seem to use a higher proportion of their income for conspicuous consumption (Charles et al., 2009). Furthermore, as single men mainly use these goods to signal status to potential partners, with increased usage during uncertain times, higher taxation on these goods might not hit the ones intended for taxation. Any model that should try to understand how to tax conspicuous consumption should consider who is using these products and whether it changes—and the direction of such change—during uncertain times.

This thesis can also contribute to our understanding of preference order and the stability of preferences. In Paper II, it is found that a lower level of blood glucose (marginally) led to a higher willingness to pay for food objects. There is also some evidence (the meta-analysis) that this lower level of blood glucose increases the willingness to engage in risky options for the food items but not for the non-food items. The same kinds of ideas can be seen in Papers III and IV when it comes to conspicuous consumption. First, as men become single, they are more willing to engage in conspicuous consumption, as they have a higher expenditure level for these goods than mated households.

Furthermore, there are some indications that as perceived uncertainty increases in the environment, the amount spent on conspicuous goods increases. All these studies lead to the idea that some evolutionary backgrounds might drive the preference order of some goods. As with the paper by De Fraja (2009), which showed the importance of having conspicuous consumption as part of the utility function, it might also be important to have these ideas at hand when we think about preference ordering and how they might be contingent on the apparent situation for the agent. Especially for conspicuous goods. This follows with previous literature showing that men use these kinds of goods more than women in situations when they want to signal to a potential partner (Griskevicius et al., 2007; Sundie et al., 2011). Overall, the three empirical papers indicate that "outside" effects can have an effect on the stability of the preferences, as all results from the papers seem to show a shift in preferences under different conditions.

6.2 Limitations

Although this thesis tries to use methods other than relying solely on p-values, there are still some drawbacks. First, using some of the other methods used in this thesis, there is no longer a clear hypothesis test. This is especially true for Paper IV, which uses forecasting predictions to test different model sets. Even though there are derived predictions from economic and evolutionary biology theories, there is still no direct hypothesis testing, only a show of how well the data predict some outcomes and whether that prediction falls under these theories. In other words, using predictive modeling compared to hypothesis testing is not a silver bullet. The final

paper in this thesis should be seen more as a first step in the testing of the theories and not as a final conclusion.

Second, I have used various data sources to answer different questions. However, there will always be questions about internal and external validity. Some of the papers presented in this thesis use experimental settings to increase internal validity, but this sometimes comes at the expense of decreased external validity. In running lab-based experiments, we might lose touch with how humans react when confronted with information in the real world. These experiments might be good at isolating effects, providing confidence in certain causal relationships under "clean" conditions but may not replicate in the real world, where we cannot possibly control for all "noise" that may also influence consumers' decisions. As has already been pointed out in the literature, we need to use more real data and fieldwork and move our experiments closer to where humans are making their decisions to fully test the generalizability and replicability of our tested models (Otterbring, 2021). I have tried to overcome some of these issues by using observational data, as in Paper III, in combination with experimental settings. Because of the tradeoffs between collecting data in more controlled but less realistic environments, on the one hand, and in real-world settings with more noise, on the other hand, I have tried to use both these data sources throughout the thesis. Having said that, more work is needed, especially to better understand conspicuous consumption. Thus, this thesis should only be seen as one of several building blocks to further our understanding of the topics addressed herein.

One important point in this thesis that could be confusing is the combination of papers. The papers have been ordered and arranged to make the story clear, but the reason for Paper I in this thesis stems from the issues when trying to publish Paper II. Here, we were met with high resistance toward not using p-values. Therefore, Paper I was developed from the issues found when conducting Paper II in this thesis. This is not to say that using p-values, in general, is an issue. Undoubtedly, it would have been helpful for this paper to be pre-registered, but the clear need for that also came after the work on Paper I. The data and all code for Paper II are publicly available, and I learned a lot from that experience, but doing that study all over again, I would have pre-registered the analysis plan just to be more transparent with the analysis.

6.3 A note to further research

This thesis aims to understand consumer behavior from an evolutionary view and to further our knowledge of some of the issues that can happen during the data analysis stage when conducting research. The main contribution of the current research might not be the outcome of each paper but rather how they were conducted. One way or another, each of them either sheds light on risks when conducting data analysis or on how to overcome such risks using different methods. Considering the prevalent issues of replication and p-hacking within the social sciences, it is important to think in new ways to overcome these problems (Brodeur et al., 2020; Collaboration, 2015). All the methods used in this thesis have been put in place, to the best of my knowledge, to protect against false positives. There is no doubt that more methodological work is still needed, as it has already been shown that solutions, such as pre-registrations, might not be the solution to all problems (Van den Akker et al., 2022). Nonetheless, the results from Paper I in this thesis show that pre-registration is an important step, as it binds the researcher not to do multiple testing. However, more adjustments are still needed under specific circumstances. If nothing else, I think one important lesson from this thesis is that the use of pre-registration when using p-values does not mean the death of creativity, as has been argued in the literature (Pham & Oh, 2021). Rather, pre-registration forces researchers to think in new ways, and we need to be more clear about what we are actually doing and why.

I want to end the thesis with some suggestions for future research. The debate on methods within the academic community generally, and especially within the social sciences, has begun to take off. However, I fear that this is a field moving in two different directions. On the one hand, we have a series of papers showing the low replicability rate within different fields (Camerer et al., 2016; Collaboration, 2015) and papers that strongly criticize studies based on how they have been conducted (Simmons et al., 2016; Simmons et al., 2018). On the other hand, some researchers do not agree or strongly oppose the views of these movements, such as the pre-registration of the studies (Pham & Oh, 2021). It is important to have an open discussion about some earlier research in the literature that does not seem to replicate. For us, as researchers, to minimize the risk of our work, we need to be able to discuss earlier years' mistakes without pointing fingers. I, therefore, encourage all to have a vivid discussion about methods (and the use of p-values) but

remember that the issue is not in the methods themselves but in how we use them.

Another point that might be important to clarify is the need to use exploratory analysis. Even though Paper I discusses some issues with doing so, it is only in their interpretation. We still need to explore the data we have, but we need to be open about it and make it clear that the results that were found were not part of the hypothesis to begin with. Paper IV uses machine learning for predictive modeling, and one might argue that this goes under the idea of exploratory analysis. I see no issue in that. A paper like the final paper in this thesis should not be the end of looking into uncertainty and conspicuous consumption but rather could be a first step of setting up experiments to test the hypothesis in a more controlled environment where it would make sense to use pre-registration and a simple t-test. All this is to say that even though a big part of this introduction is the issues with p-values and particular p-hacking, this does not mean we should stop exploring and be creative in our search for new knowledge.

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Popular science summary

This thesis examines how theories from evolutionary biology can be used to better understand human behavior. In a series of papers, combining simulations, experiments, and observational data, the thesis centers on risk and uncertainty.

Paper I describes some of the risks that may occur when using quantitative data and discusses why we need to think about methodological aspects when doing any form of statistical analyses. For that reason, the methods and analyses in all subsequent papers were chosen in an attempt to minimize the risk of obtaining false positive results.

Paper II shows that humans with low blood glucose levels are more willing to engage in risky decision-making when the decisions are about food. Thus, consistent with evolutionary theorizing, humans as well as other species seem to make riskier decisions in the food domain when they are energy-deprived, although such risky decision-making does not generalize to non-food objects.

Paper III uses an experiment together with expenditure data from the US and shows that single men are particularly prone to engage in conspicuous consumption. Accordingly, single men are more inclined to prefer pricey products and status-signaling goods compared to mated men and women in general, probably to appear attractive to potential partners.

Paper IV investigates how uncertainty in the US has developed from the 1990s until today in relation to conspicuous consumption. In contrast to theories from economics but consistent with evolutionary theorizing, the results indicate that increased uncertainty in certain domains increases rather than decreases purchases of such prestigious products.

Overall, theories from evolutionary biology seem capable of explaining different economic behaviors reasonably well.

Populärvetenskaplig sammanfattning

Denna avhandling undersöker hur evolutionsbiologiska teorier kan främja förståelsen för mänskligt beteende. I en serie delarbeten, där simuleringar kombineras med experiment och observationsdata, fokuserar avhandlingen på risk och osäkerhet.

Delarbete I beskriver några av de risker som kan uppstå vid användandet av kvantitativt datamaterial och diskuterar varför vi behöver tänka på metodologiska aspekter när vi gör någon form av statistiska analyser. Av denna anledning var strävan i varje efterföljande delarbete att metoderna och analyserna skulle väljas på ett sådant sätt att risken för falska positiva resultat minimerades.

Delarbete II visar att människor med låga blodsockernivåer är mer villiga att engagera sig i riskfylldt beslutsfattande så länge som besluten handlar om mat. I enlighet med evolutionära teorier tyder resultaten således på att människor liksom andra arter fattar mer riskfyllda beslut kring mat när de är utarmade på energi, även om denna typ av riskfyllt beslutsfattande ej är generaliserbart till andra objekt som inte handlar om mat.

Delarbete III bygger på ett experiment tillsammans med konsumtionsdata från USA och visar att män utan partner är särskilt benägna att engagera sig i "skrytkonsumtion". Med andra ord tenderar singelmän att att föredra värdefulla varor och statussignalerande produkter i högre grad jämfört med både män i relation och kvinnor generellt, sannolikt för att signalera attraktiva attribut till potentiella partners.

Delarbete IV undersöker hur osäkerheten i USA har utvecklats från tidigt 1990-tal fram till idag i relation till statussignalerande konsumtion. Tvärtemot teorier från nationalekonomi men i linje med evolutionsbiologiska teorier visar resultaten att ökad osäkerhet inom vissa områden faktiskt ökar snarare än minskar sådan "skrytkonsumtion".

Överlag verkar evolutionsbiologiska teorier kunna förklara olika ekonomiska beteenden relativt väl.

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II

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A meta-analytical and experimental examination of blood glucose effects on decision making under risk

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Abstract

Previous research has shown that short-term changes in blood glucose influence our preferences and may affect decisions about risk as well. However, consensus is lacking about whether and how blood glucose influences decision making under risk, and we conduct two experiments and a meta-analysis to examine this question in detail. In Study 1, using a pecuniary valuation method, we find no effect of blood glucose on willingness to pay for risky products that may act as allergens. In Study 2, using risky gambles, we find that low levels of blood glucose increase risk taking for food and to a lesser degree for non-food rewards. Combining our own and previous findings in a meta-analysis, we show that low levels of blood glucose on average increase risk taking about food. Low blood glucose does not increase risk taking about non-food rewards although this is subject to heterogeneity. Overall, our studies suggest that low blood glucose increases our willingness to gamble on how much food we can get, but not our willingness to eat food that can harm us. Our findings are best explained by the energy budget rule.

Keywords: risk; blood glucose; decision making; meta-analysis; energy budget rule

1 Introduction

Physiological states are fundamental to decision making and influence how we perceive and decide about risky options (Loewenstein, Weber, Hsee & Welch, 2001; Slovic, Finucane, Peters & MacGregor, 2004). In recent years, researchers have begun studying the role of homeostasis in risk tasking. This line of research has explored homeostasis directly by manipulating blood glucose levels (de Ridder, Kroese, Adriaanse & Evers, 2014), at the experiential level by measuring hunger and satiety (Williams, Pizarro, Ariely & Weinberg, 2016), and at the hormonal level by measuring leptin, ghrelin, or insulin (Symmonds, Emmanuel, Drew, Batterham & Dolan, 2010). The earliest study concluded that presenting decision makers with appetitive food cues increase their risk taking (Ditto, Pizarro, Epstein, Jacobson & MacDonald, 2006). This effect could be due to the fact that appetitive food cues trigger a cephalic phase reaction that, among other things tend to lower blood glucose levels (Bruce & Storlien, 2010; Ott et al., 2011). However, the most recent study, which replicated the work of Ditto and colleagues, concluded that there is no, or even a diminishing, effect of appetitive food cues on risk taking (Festjens, Bruyneel & Dewitte, 2018). Considering that our blood glucose levels fluctuate as a function of time of day and food intake, it is of no small importance whether these changes impact our risk taking. Is it, for example, undesirable to operate heavy machinery before lunch, or perform surgery or trade stocks without a prior snack?

We know from several reviews, that many areas of cognition, emotion and behavior are influenced by fluctuations in blood glucose levels (Dye & Blundell, 2002; Dye, Lluch & Blundell, 2000; Gibson & Green, 2002; Hoyland, Lawton & Dye, 2008; Lieberman, 2003; Messier, 2004; Riby, 2004; Smith, Riby, Eekelen & Foster, 2011). From a biological perspective, a steady supply of calories is necessary to maintain blood glucose levels and uphold survival. Depending on our homeostatic demands, some behaviors might be more appropriate than others, and it seems that our brains are involved in shaping these behaviors in a more intricate way than merely by making us feel hungry. For instance, low blood glucose levels increase our willingness to pay for a hamburger (Briz, Drichoutis, Nayga Jr & House, 2013), but decrease our willingness to donate to charity (Briers, Pandelaere & Warlop, 2006). In general, low blood glucose seems to change our priorities towards food objects and away from non-food objects (Brendl, Markman & Messner, 2003). In line with this, Orquin and Kurzban (2016) showed that blood glucose levels influence behavior in a way consistent with domain specific models derived from evolutionary biology. They also showed that while many studies rely on domain general versions of dual systems theory to explain or predict

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results, this theory cannot account for the complete pattern of blood glucose effects, particularly how the effect of blood glucose differs across food vs non food domains.

Motivated by this literature, we review two theories in the subsequent sections; an optimal foraging model and a dual systems model that both can account for blood glucose effects on decision making under risk. The optimal foraging model, known as the *budget rule* (Stephens, 1981), predicts risk preferences as a function of energy budgets, i.e., the energy balance between consumed and expended calories which is measurable as fluctuations in blood glucose levels. The mathematically specified version of dual systems theory (Mukherjee, 2010) predicts risk preferences as a function of the relative activation in the deliberate and the affective systems, which is influenced by physiological states such as fluctuating blood glucose levels.

1.1 The budget rule

Caraco and colleagues proposed that an animal with a negative energy budget, i.e., that consume fewer calories than it expends, should be risk seeking to avoid starvation and hence maximize its chances of survival (Caraco, Martindale & Whittam, 1980). Later, Stephens formalized the idea in what is now referred to as the *budget rule*: when the rate of energy intake exceeds the rate of energy expenditure during foraging, animals will be risk averse when choosing between food sources with equal mean energy payoffs (Stephens, 1981). When energy expenditure exceeds energy gains, animals will be risk seeking when choosing between food sources with equal mean energy payoffs. The switch from risk averse to risk seeking is optimal because the probability of starvation goes towards a fifty-fifty chance of starvation as the variance of the food source goes towards infinity. The budget rule is compelling in its simplicity and several studies on animal behavior have demonstrated effects of energy budgets on switching from risk averse to risk seeking behavior (Kacelnik & El Mouden, 2013). The budget rule has also been the focus of much criticism (Lim, Wittek & Parkinson, 2015). An important point being that the budget rule may be too simple; first it collapses a sequence of foraging decisions into a single one, and second, it assumes that a single threshold for survival guides the foraging decision. Other challenges relate to how animals are supposed to perceive the state of the internal and external environments to make these optimal decisions (Kacelnik & El Mouden, 2013).

When applying the budget rule to a specific case such as a human decision maker, further problems arise; the model assumes that the animal will starve to death overnight if insufficient calories are acquired during the daily foraging (Stephens, 1981). However, few species are in danger of starvation on a day-to-day basis and it may therefore be difficult to apply the budget rule to larger species. These ancillary assumptions make it difficult to test the budget rule in many species and may explain the mixed evidence in favor of the budget rule (Kacelnik & Bateson, 1997; Kacelnik & El Mouden, 2013).

Deriving predictions from the budget rule for human behavior is subject to all of the complications outlined above. With these caveats in mind, we assume that the energy budget in humans is reflected in blood glucose levels, with low or diminishing levels signaling a negative budget and high or rising levels signaling a positive energy budget. The assumption follows from the correlation between the consumption of calories and blood glucose levels. During and immediately after consuming a meal there are more calories available than can be expended which raises blood glucose levels. When calories are not consumed for a longer period, for instance three days, blood glucose levels gradually decrease (Merimee & Tyson, 1974). From this, we assume that relative changes in blood glucose signals relative changes in energy budgets, and the budget rule therefore predicts that human decision makers will react to relative decreases in blood glucose levels by becoming more risk seeking. Since the budget rule is strictly about foraging behaviors, the prediction only applies to decisions about food.

1.2 Dual systems theory

Dual systems theory, is a compound of several theories and models that vary in their exact assumptions and degree of mathematical formalization. However, they all share the assumption that the mind consists of two major components: an affective, fast, and impulsive system I and a deliberate, slow, and calculating system II (Evans & Stanovich, 2013; Kahneman, 2011). Recently, dual process theory has been formalized with respect to decision making under risk by Mukherjee (Mukherjee, 2010) and later by Loewenstein and colleagues (Loewenstein, O'Donoghue & Bhatia, 2015). Both models assume that the subjective value of a risky prospect is determined jointly by the affective and deliberate systems and that activation of emotional states or physiological needs shifts the balance between the two systems in favor of the affective system. In other words, low levels of blood glucose which signals a physiological need increase the affective system activation and hence impulsivity. The models differ in the implementation of these assumptions; here we focus on Mukherjee's model since it aims to be a more general implementation of dual process theory. The model proposes that the value of a risky prospect, $V(G)$, is the sum of the affective and the deliberate system value functions:

$$V(G) = \gamma V_a(G) + (1-\gamma) V_d(G),$$

where $V_a(G)$ is the value of gamble G given by the affective system and $V_d(G)$ is the value of the gamble given by the deliberate system. The gamma term γ determines the relative contribution of the affective and deliberate systems.

If gamma is zero then the value of the gamble is entirely defined by the deliberate system. Gambles are defined by a set of probabilities p and outcomes x. The affective system applies a step function to probabilities so that any probability above zero takes the value one and applies a power transformation to outcomes, x^m, where $m < 1$ resulting in a concave utility function, and therefore diminishing marginal utility. Since probabilities are assumed to be greater than zero, the affective system in practice ignores probabilities. The deliberate system computes the expected value of risky prospects, kpx, where k is a scaling parameter. The equation above can therefore be rewritten as:

$$V(G) = \gamma \frac{1}{n} \sum_i x_i^m + (1-\gamma) k \sum_i p_i x_i$$

We assume that low or diminishing blood glucose levels increase the relative activation of the affective system, i.e., leading to a higher γ value, resulting in an overall more concave utility function and hence risk aversion. Since the model is domain general, we derive the prediction that lower levels of blood glucose increase risk aversion for both food and non-food rewards. Note, however, that the model does not always predict increasing risk aversion with greater reliance on system 1 since this depends on the curvature of the value function.

2 Study approach

In the following, we examine the role of blood glucose in decision making under risk through two experimental studies and a meta-analysis. In both experiments, we manipulate blood glucose levels by administering a glucose-placebo solution to our participants. This operationalization has been used in previous studies, its advantage being that it is effective in controlling blood glucose levels while also being blinded and placebo controlled thus separating the effect of blood glucose from visceral sensations or subjective feelings and beliefs about hunger and satiety. In these studies blood glucose levels ranged between 4.74–5.5 mmol/L in the baseline measure to 5.80–6.96 mmol/L in the post ingestion measure (Wang & Dvorak, 2010; Wang & Huangfu, 2017). The effect on blood glucose levels is similar to what was obtained by Rantapuska and colleagues (2017) who administered a 521 kcal meal vs no meal to fasting participants, 5.01 mmol/L at baseline measure and 6.78 mmol/L at post ingestion measure. More extreme blood glucose levels can be obtained with the glucose clamp technique as reported by Kubera and colleagues (2016), who achieved levels ranging from 2.73 to 6.18 mmol/L in the hypo- and euglycemic conditions respectively.

Previous studies have used either between- or within-subjects manipulations of blood glucose. While within-subjects manipulations increase statistical precision, there is also a risk that participants become aware of the study purpose and even of the glucose condition by the second administration of the glucose-placebo solution. To minimize awareness of the study purpose and glucose condition, we therefore manipulated blood glucose levels between-subjects. In Study 1, we measure risk preferences using a Becker-Degroot-Marshak (BDM) auction approach (Becker, Degroot & Marschak, 1964) for risky and safe food and non-food products. In Study 2, we measure risk preferences for food and non-food rewards using high and low variance gambles. We conclude by performing a meta-analysis of our own and previous studies.

3 Study 1

In Study 1, we manipulate participants' blood glucose levels using a glucose-placebo solution. As a measure of risk preferences, we obtain participants' willingness to pay for risky and non-risky food and non-food products. To manipulate the riskiness of the products, we inform participants that some products are produced using bio- or nanotechnology, which increases the risk of allergic reactions. The procedure is intended to increase the external validity by mimicking the risk benefit trade-offs people make in their daily lives (Kahan, Braman, Slovic, Gastil & Cohen, 2009; Siegrist, 2000). If low blood glucose levels increase (decrease) risk seeking behavior, we should expect participants in the placebo condition to have a higher (lower) willingness to pay for the risky products compared to participants in the glucose condition.

3.1 Method

Participants. One hundred and seven participants were recruited through a consumer panel provider, M_{age} = 46.30, SD_{age} = 14.80, 54.3% women. The sample size was determined by maximization of laboratory time and budget constraints. Participants received DKK 150 for completing the study and were informed about possible risks and harms prior to the experiment. Participants provided a written informed consent. Participants who suffered from diabetes, metabolic disorders, or food allergies were excluded prior to the study. Participants were asked to refrain from eating or drinking anything containing calories four hours prior to the study.

Experimental design. The study was a 2 x 2 x 2 mixed within-between subjects design manipulating blood glucose levels (high vs low) between subjects, risk (risk vs no risk) within subjects, and product category (food vs non food) within subjects. Each product category contained 12 individual products which were randomly presented to each participant as either a risk or no risk product yielding a total of 24 observations per participant.

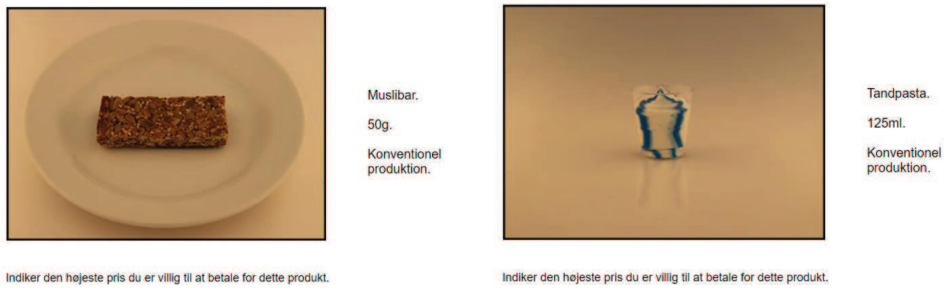

FIGURE 1: Examples of product images and descriptions used in Study 1 for food (left) and non food (right).

Materials and measures. Blood glucose levels were manipulated using 33 cl of Sprite or Sprite Zero, the former contains 33.3 g of sugar while the latter contains no sugar or calories. This manipulation has been used successfully in prior studies and the two types of soda are nearly indistinguishable in terms of flavor and mouth feeling.

Participants provided their willingness to pay for 24 products following the rules of the BDM approach, see Figure 1 for a stimulus example. Participants were given DKK 20 and asked to state their willingness to pay (WTP) for each of the 24 products. The participants were informed that one of the trials would be drawn at random to count and that a random number would be generated ranging between 0 and 20 DKK. The random number was drawn from a uniform distribution. If the participant's stated WTP was equal to or above the randomly drawn price then the participant payed the random price and kept the remaining money. If the participant's stated WTP was below the random price the participant did not purchase the product and kept the 20 DKK. The instructions read: "In the following part of the study you will be presented with 12 different products. Your task is to state the highest amount of money that you would be willing to pay for each of these products. Besides the payment you receive for participating in this study, we have given you 20 DKK that you may use to buy one of these products. At the end of the study, a computer chooses one of the 12 products at random and creates a random price between 0 and 20 DKK. If your buying price is equal to or above the random price, then you have to buy that product. In this case you only pay the randomly drawn price and keep the rest of the money. If your price is below the random price then you cannot buy the product but you get to keep the 20 DKK. If you have any questions at this point, please contact the experimenter."

The 12 food and 12 non-food products were presented separately with images of each product. The images depicted food and non-food products without their packaging to avoid brand-related preferences. The food products were biscuits, muesli bars, and chocolate, and the non-food products were toothpaste, mouthwash, and soap.

To manipulate the riskiness of the products, participants were informed that some products were produced using biotechnology and that these products were engineered to enhance satiety albeit with a small risk of causing allergic reactions. Similarly for the non-food products, participants were informed that some products were produced using nanotechnology to enhance performance albeit with a small risk of causing allergic reactions. Risky and non-risky products were marked with a corresponding text naming them as either conventional products or product produced using bio or nanotechnology (see SI).

Procedure. On entering the laboratory, participants read and signed the consent form. Participants were then seated in front of a laboratory computer and were randomly assigned to either the glucose or placebo condition and received either 33 cl of Sprite or Sprite Zero in a neutral plastic cup. Participants were blind to the experimental condition. Participants were instructed to drink the entire content of the cup and communicate to the experimenter when the cup was empty. When the experimenter had checked that the cup was empty, the participant was given access to the study. The participants completed a short questionnaire on demographics, hunger, satiety and other control questions. Following the questionnaire, participants were randomly assigned to begin with the food or the non-food condition. The participants had two envelopes each containing DKK 20 in front of them on the table and they were instructed to open one envelope. Each condition consisted of 12 products for which the participant provided buying prices within the limit of 20 DKK. After the experiment, participants received the products they had bought. In case the participant bid under the randomly drawn price, they kept the 20 DKK.

4 Results

Analysis of hunger, satiety and exclusions. We measured hunger and satiety for the two experimental groups after receiving the glucose-placebo solution. Our paradigm did not influence hunger or satiety in the glucose group compared to

TABLE 1: Effects of glucose-placebo solution on hunger and satiety measures. Hunger and satiety were rated on a Likert scale rangering from one to seven.

		Hunger		Satiety	
Group	n	M	95% CI	M	95% CI
Glucose	52	3.423	[2.932, 3.914]	3.615	[3.158, 4.073]
Placebo	50	3.280	[2.790, 3.770]	3.440	[2.970, 3.910]

TABLE 2: Mean WTP split by glucose, food vs non-food and riskconditions. Confidence intervals aremade using non-parametric bootstrapping.

	Food				Non-food			
	No risk		Risk		No risk		Risk	
	M	95% CI	M	95% CI	M	95% CI	M	95% CI
Glucose	7.018	[6.202,7.888]	6.221	[5.226,7.203]	8.202	[7.152,9.274]	7.582	[6.273,8.874]
Placebo	6.387	[5.709,7.064]	5.583	[4.727,6.433]	7.200	[6.152,8.250]	6.728	[5.578,7.883]

the placebo group (see Table 1) suggesting that any effects of the manipulation were due to changes in blood glucose levels only. Three participants were excluded for failing to consume the entire content of the glucose-placebo solution (placebo condition), one for having a metabolic-related disease (glucose condition), and one for bidding zero in the entire BDM approach (placebo condition).

Main analysis. We analyzed the effects of the blood glucose manipulation, risk, and food, non-food on willingness to pay with a linear mixed model using the lme4 package in R (Bates, Mächler, Bolker & Walker, 2015). The most predictive model was identified using a hold one person out cross validation based on RMSE (see SI). The cross validation approach reduces the risk of overfitting and is an alternative to null hypothesis significance testing which is subject to several limitations (Cumming, 2014).

For each model, we first estimated its parameters on a training dataset set including data from all but one participant. We then applied the estimated parameters to the test dataset by predicting the responses of the left out participant. We then computed the RMSE for that person and the procedure was repeated for each person in the data set. The average RMSE for the training and test datasets is shown in the SI. We selected the model with the lowest average RMSE in the test dataset. The most predictive model had a fixed effect for blood glucose and random intercepts grouped by participant and product. However, it should be mentioned that there was only a marginal difference between the best performing models, where one of these models was the univariate model. The most predictive model retains a parameter for the glucose condition although the effect does not reach significance, $\beta_{intercept} = 7.256$, $SE = 0.457$, $p < .01$, $\beta_{\text{glucose}} = 0.781$, $SE = 0.541$, $p = .152$, $d = 0.20$. Although not significant, the effect can easily be seen when splitting the mean WTP by glucose conditions (Table 2).

5 Discussion

In Study 1, we examined the effect of blood glucose levels on risk preferences using a BDM auction approach for risky and non-risky food and non-food products. The most predictive model had a fixed effect of blood glucose manipulation. The two next most predictive models in the cross validation both contained risk (see Table SI Table1), and that the effect of risk was in the expected direction, $d = -0.15$, meaning that participants had a lower willingness to pay for risky products. Neither the cross validation nor the significance levels in the fully specified model (see SI Table 2) showed any indications of an interaction between glucose condition and risk. Our findings suggest that changes in blood glucose levels do not affect participant's risk benefit trade-offs to use or consume riskier products as identified from their willingness to pay.

6 Study 2

In Study 2, we manipulated risk using gambles (Levy, Thavikulwat & Glimcher, 2013; Symmonds et al., 2010). We used the same glucose-placebo manipulation as in Study 1, but included a measure of blood glucose levels using a handheld glucometer. Furthermore, we included more trials and more participants to increase the power of the design. As a manipulation of food and non-food, we incentivized

FIGURE 2: Examples of the food (left) and non food gambles (right).

the gambles with M& Ms and a voucher for an online electronics store. All gambles had an expected value of zero but differed in variance. If low levels of blood glucose increases (decreases) risk seeking, we should expect participants in the placebo condition to have a higher (lower) preference for high variance gambles compared to participants in the glucose condition. As a secondary measure of risk preferences, we included the domain risk scale by Wilke and colleagues (Wilke et al., 2014). The scale measures risk attitudes in different domains such as food selection, mate retention, between-group competition, etc.

6.1 Method

Participants. One hundred and sixty-two participants were recruited through the local university participant pool, M_{age} = 25.45, SD_{age} = 5.45,, 59.33% women. The sample size was determined by maximizing within budget constraints. Participants received DKK 150 for completing the study and were informed about possible risks and harms prior to the experiment. Participants provided a written informed consent. Participants who suffered from diabetes, metabolic disorders, or food allergies were excluded prior to the study. Participants were asked to refrain from eating or drinking anything containing calories four hours prior to the study.

Experimental design. The study was a 2 x 2 x 2 mixed within-between subjects design manipulating blood glucose levels (high vs low) between subjects, risk (high risk vs low risk) within subjects, and category (food vs non food) within subjects. Each food and non food category contained 41 gambles and each gamble presented a high risk and a low risk option yielding a total of 82 observations per participant.

Materials and measures. Blood glucose levels were manipulated using 33 cl of Sprite or Sprite Zero. Blood glucose levels were measured before and after the administration of the glucose drink using a Bayer Contour glucometer.

Participants completed 41 risky gambles for each reward type; the gambles consisted of two options with two outcomes each. Examples of the two gamble types are shown in Figure 2 and a complete overview of the gambles is shown in SI Table 6. The food reward was M& Ms and the non-food reward was a voucher for an online electronics store. Participants were informed that gambles were displayed in DKK, that each gamble contributed to their earnings, that the gambles pertaining to the food reward would be remunerated in the equivalent amount of M& M's, and that non-food gambles would be remunerated with a voucher to an online electronics store.

As an additional measure, participants also completed a psychometric test measuring risk attitudes across different domains (Wilke et al., 2014). The items were translated and back translated into Danish. Some items were considered culturally specific to the US and were replaced with items more meaningful to the current context. For a list of items see SI Table 6. The results from this secondary measure are reported on: https://osf.io/mtb5z/

Procedure. On entering the laboratory, participants read and signed the consent form. Participants were then seated in front of a laboratory computer and their blood glucose levels were measured using a handheld glucometer. After the glucose measurement, participants were randomly assigned to the glucose or placebo condition and were given either 33 cl of Sprite or Sprite Zero in a neutral plastic cup. Participants were blind to the experimental condition. Participants were instructed to drink the entire content of the cup and communicate to the experimenter when the cup was empty. When the experimenter had checked that the cup was empty, the participants were given access to the study.

The participants completed a short questionnaire on demographics, hunger, satiety and other control questions. To ensure that participants understood the risk manipulation, they completed 20 practice trials with feedback after each gamble, and 20 practice trails with feedback at the end of the 20 gambles. The demographics and practice trials lasted between five and ten minutes. After the practice trials, participants were instructed to communicate to the experimenter who then measured the their blood glucose levels a second time. When the second glucose measurement was completed, participants were given access to continue the study. In the second part of the study, participants were randomly assigned to begin with either the food or the non-food

TABLE 3: Effects of glucose-placebo solution on hunger, satiety, and blood glucose measures.

	Glucose		Placebo	
Product	M	95% CI	M	95% CI
Baseline blood glucose	4.919	[4.790, 5.047]	4.777	[4.693 ,4.860]
Post ingestion blood glucose	6.447	[6.203, 6.691]	4.726	[4.605, 4.847]
Hunger	3.494	[3.127, 3.861]	3.884	[3.486, 4.283]
Satiety	3.074	[2.704, 3.444]	3.058	[2.709, 3.407]

TABLE 4: Mean risky choice split into conditions. Confidence intervals aremade using non-parametric bootstrapping.

	Food		Non-food	
	M	95% CI	M	95% CI
Glucose	0.495	[0.457,0.534]	0.507	[0.468,0.544]
Placebo	0.556	[0.514,0.598]	0.537	[0.494,0.578]

condition. Each condition consisted of 41 gambles without feedback. Having completed the 41 food and 41 non-food gambles, the participants were instructed to answer a short questionnaire measuring risk attitudes. After completing the questionnaire, participants were instructed to contact the experimenter, who remunerated the participant according to the earnings in the critical gambles.

Earnings in the food-related gambles were paid in M&M's, and earnings in the non-food gambles were paid out as a voucher for an online electronics store. The DKK 150 reward was divided unevenly with DKK 100 for the electronics store and DKK 50 for M& Ms. Because the expected value was zero, participants earned on average DKK 100 vouchers and received DKK 50 worth of M&Ms. To avoid influencing risk preferences, participants were not informed about the division of the reward. If participants achieved losses in one domain, no reward was paid out.

7 Results

Blood glucose, hunger, satiety, and exclusions. We measured blood glucose, hunger, and satiety for the two experimental groups. As in Study 1, our paradigm did not influence hunger or satiety in the glucose group compared to the placebo group, but effectively increased the blood glucose level for the glucose group (Table 3). Twelve participants from the placebo condition were excluded for having a blood glucose level above 5.5 mmol/l (SI Table 3). The analysis was also made with these included in the glucose condition (SI Table 4).

Main analysis. We analyzed the effects of the blood glucose manipulation and food vs non-food domain on the probability of choosing the high risk gamble using a generalized linear mixed model. The most predictive model was identified in a manner similar to Study 1 using a hold one person out cross validation based on Brier Scores which is more appropriate for binomial responses (see SI). The most predictive model had a logit link function, a fixed effect for blood glucose, and random intercepts grouped by participant and gambles, i.e., each gamble is unique in terms of the variance of the options, the levels of rewards and probabilities. These gamble parameters contribute to the participant response, which is captured in the random intercept for each of the 41 gambles. The model suggests an effect of glucose on risk aversion here reported as odds ratios, $\beta_{\text{intercept}} = 1.24$, $SE = 0.099$, $p = .032$, $\beta_{\text{glucose}} = 0.81$, $SE = 0.126$, $p = .093$. Table 4 shows the mean number of risky options chosen by the participants split by the different conditions. Figure 3 illustrates the percentage of participants choosing the risky gamble split by conditions and variance. The placebo condition increases the likelihood of choosing the riskier gamble for both the food and non food rewards, but seems to have a larger effect on the former. We performed a robustness check with different models, including models with continuous measures of blood glucose levels and models where excluded participants were assigned to the treatment group. The robustness check corroborates the reported findings and can be found on https://osf.io/mtb5z/.

7.1 Discussion

In Study 2 we operationalized risk using gambles. Blood glucose levels were manipulated as in Study 1, but we additionally measured blood glucose levels before and after the glucose-placebo solution using a handheld glucometer. The analyses suggest that lower blood glucose increased risk seeking so participants were on average risk neutral with high levels of blood glucose (50.2% risky choices) and risk seeking with low levels of blood glucose (54.11% risky choices). The largest difference between glucose and placebo conditions was in the food domain.

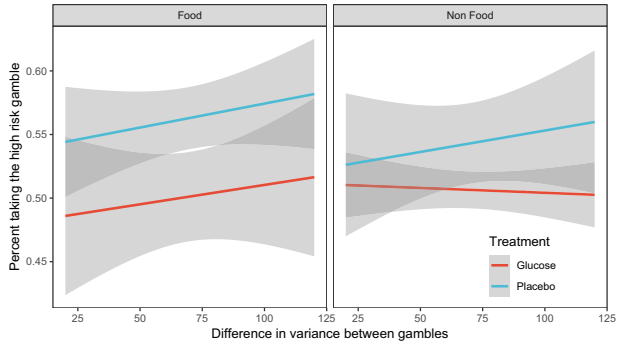

FIGURE 3: Percent of participants choosing the high risk gamble split by glucose vs. placebo and food vs. non food conditions. The x-axis indicates the difference in variance between the gambles and the grey areas indicate the95% confidence interval.

8 Meta-analysis

To further advance our understanding of blood glucose effects on decision making under risk, we synthesize our findings and those of previous studies using a meta-analysis. Because the identified studies vary in their operationalization of blood glucose, we apply a psychometric meta-analysis. The procedure takes into account the construct validity of the specific blood glucose operationalization since low validity attenuate effect sizes. The procedure corrects the attenuated effect sizes and adjusts the influence of each study according to its validity (Hunter & Schmidt, 2004).

8.1 Method

Literature search. Eleven articles were included in the meta-analysis. The articles were identified using Web of Science with the following keywords: "blood glucose" OR hunger OR "food deprivation" OR "blood sugar" OR "metabolic∗ " OR "energy budget" OR "food insuff∗ " OR "food insecur∗ " AND "risk attitude" OR "risk pref∗ " OR "risk seek∗ " OR "risk aver∗ " OR "risk behavi∗ " OR "risk percep∗ " OR "decision making under risk" OR "risky choice" OR "risky decision". Google Scholar was used to identify grey literature as it indexes conference proceedings, university websites, personal websites and other sources of unpublished materials. Previous meta-analyses on blood glucose effects and decision making were searched for relevant articles (Dang, 2016; Hagger, Wood, Stiff & Chatzisarantis, 2010; Orquin & Kurzban, 2016; Vadillo, Gold & Osman, 2016). Finally, all articles included were searched using forward and backward citation analysis. The meta-analysis included experimental and quasi-experimental studies on humans in which the independent variable manipulated or measured blood glucose, or in other ways operationalized blood glucose levels, such as through measurement of hunger, food intake, food deprivation, or cephalic phase responses. Only studies in which the dependent variable was related to decision making under risk were included. Studies in which participants were selected based on a clinical diagnosis, psychographic, or specific sociodemographic traits (e.g., eating disorders, diabetic symptoms, etc.) were excluded because these subgroups are likely to respond differently to fluctuations in blood glucose. The search process yielded 64 full text records that were screened for eligibility. Study eligibility was established using the following inclusion criteria: 1) The independent variable operationalized blood glucose through glucose administration, glucose measurement, cephalic phase reaction, food deprivation, or via a hunger score. Studies on hormonal effects or glucose tolerance were excluded from our analyses ($k = 2$). 2) The dependent variable was related to decision making under risk, i.e., the study operationalized the variance of the outcomes of choice options. The excluded studies mostly concerned time discounting, willingness to pay, willingness to work, or decision style ($k = 37$). 3) Studies analyzing data at aggregated levels of behavior, i.e., econometric studies, were excluded ($k = 11$). 4) Participants were selected without regard for clinical diagnosis, psychographic, or specific sociodemographic traits. Studies on clinical subgroups were excluded from analysis ($k = 2$). 5) The study provided sufficient information for a quantitative synthesis. Studies with insufficient information were excluded from analysis ($k = 2$).

Extraction of effect sizes and coding of studies. Effect sizes were extracted from descriptive statistics (e.g., M, SD, SE), test statistics (e.g.,F, t, χ^2, p), coefficients and effect sizes (e.g., d, η^2 OR) to produce a Pearson correlation coefficient for each study. Each study was coded on the operationalization of the independent variable and its domain (food vs. non-food). We identified four different operationalizations of blood glucose levels: i) studies

in which blood glucose was manipulated by administrating either a glucose-placebo solution or a meal to participants (glucose administration); ii) studies in which blood glucose levels were measured with handheld glucometers (glucose measurement); iii) studies measuring self-reported hunger and satiety scores (hunger score); and iv) studies manipulating a cephalic phase reaction by exposing participants to, for instance, food stimuli and food smells (cephalic phase). Studies were coded as belonging to the food domain if participants made decisions concerning food stimuli or were rewarded with food stimuli. All other studies were coded as belonging to the non-food domain. We identified six different operationalizations of risk preferences. Most studies used risky lotteries, the Iowa Gambling Task (IGT), or the Balloon Analogue Risk Task (BART). One study reported the effect of blood glucose on the propensity to cheat in an experiment, i.e., participants could choose to report having earned a higher reward than they actually did and run the risk of being caught cheating or truthfully report a lower reward (Cheating). One study reported the effect of blood glucose on risk taking on multiple measures such as leaving personal belongings alone and transferring money to trustees in economic experiments (Multiple). For this study, we computed an average effect size across the different measures. Finally, our own Study 1 operationalized risk preferences using willingness to pay for risky products (WTP).

Effect size synthesis. We analyzed the effect sizes using a psychometric meta-analysis. The method takes the varying construct validity of the different operationalizations of blood glucose levels into account. Imperfect construct validity attenuates the observed effect size r relative to the true effect size ρ proportional to the square root of the reliability $\mathrm{r}_{xx} : \mathrm{r} = \rho\sqrt{\mathrm{r}_{\mathrm{xx}}}$. This attenuation introduces a bias in the final estimate of the population effect size unless corrected for taking a psychometric approach (Hunter & Schmidt, 2004). The psychometric meta-analysis computes the true average effect size ρ based on the unattenuated correlation coefficients $\mathrm{r}_{\mathrm{i}}^{\mathrm{u}}$, the sample size n_i, and the artifact multiplier a_i:

$$\rho = \frac{\sum_{\mathrm{i}=1}^{\mathrm{k}} \left(\mathrm{n_i a_i^2 r_i^u}\right)}{\sum_{\mathrm{i}=1}^{\mathrm{k}} \left(\mathrm{n_i a_i^2}\right)}$$

The artifact multiplier is the square root of the reliability r_xx. We used the same artifact multipliers as reported in (Orquin & Kurzban, 2016): glucose administration, $a = 1.0$, glucose measurement, $a = .96$, cephalic phase, $a = .67$, food deprivation, $a = .503$, hunger score, $a = .4$. Artefact corrections are performed on the Fisher z transformed correlation coefficients.

9 Results

We analyze the effect sizes with a psychometric meta-analysis using the metafor package in R (Viechtbauer, 2010) using a break down strategy to test the effect of the food vs the non-food moderator. Table 4 shows corrected and uncorrected effect sizes for each study. The main analysis of the complete data set revealed no general effect of blood glucose on risk taking, $\beta = -0.017, SE = 0.041, Z = 0.417, CI\_95 = [-0.063, 0.097]$, $I^2 = 49.78\%$. Analyzing the food and non-food studies separately reduced study heterogeneity and revealed an effect of blood glucose on risk seeking in the food domain, $\beta = 0.135, SE = 0.044, Z = 3.043, CI\_95 = [0.048, 0.222]$, $I^2 = 0\%$. There was only a minor improvement in heterogeneity, but no effect in the non-food domain, $\beta = -0.049, SE = 0.048, Z = -1.027, CI_{95} = [-0.142, 0.044]$, $I^2 = 42.17\%$.

Figure 4 shows a forest plot of the unattenuated effect sizes. We conduct an Egger's regression to test for potential publication bias in our results. We perform the test on the entire data set, $z = 0.569$, $p = .569$, and on the food moderator group, $z = 1.468$, $p = .142$, and the non-food moderator group, $z = 0.068$, $p = .946$. All tests suggest the absence of publication bias which is further corroborated by inspecting the funnel plots in Figure 4. Table 5 shows the included effects.

9.1 Discussion

The meta-analysis shows that low levels of blood glucose have a small effect on risk taking for food rewards, but there is no effect on risk taking for non-food rewards. Effect sizes in the non food domain are subject to some heterogeneity, $I^2 = 42.17\%$, which could be due to unobserved moderators. Except for the effect size in Study 1 food condition, which falls short by a small margin, the effect sizes from our own studies lie within the confidence intervals of the meta-analytic estimates.

10 General discussion

Do changes in blood glucose levels influence decision making under risk? Previous research has provided mixed evidence, but theoretically the answer is that is does. We review two theories that differ in their predictions about how risk preferences change as a function of blood glucose levels. The dual systems model (Mukherjee, 2010) predicts that low levels of blood glucose change the balance between two mental systems in favor of a more intuitive and risk averse system, and hence that low blood glucose increases risk aversion (we note that there are exceptions to this prediction, Mukherjee, 2010, p. 248–249). The budget rule (Stephens, 1981) predicts that a negative energy budget, which we operationalize as low or decreasing blood glucose levels, changes decision makers from risk averse to risk seeking regarding food rewards.

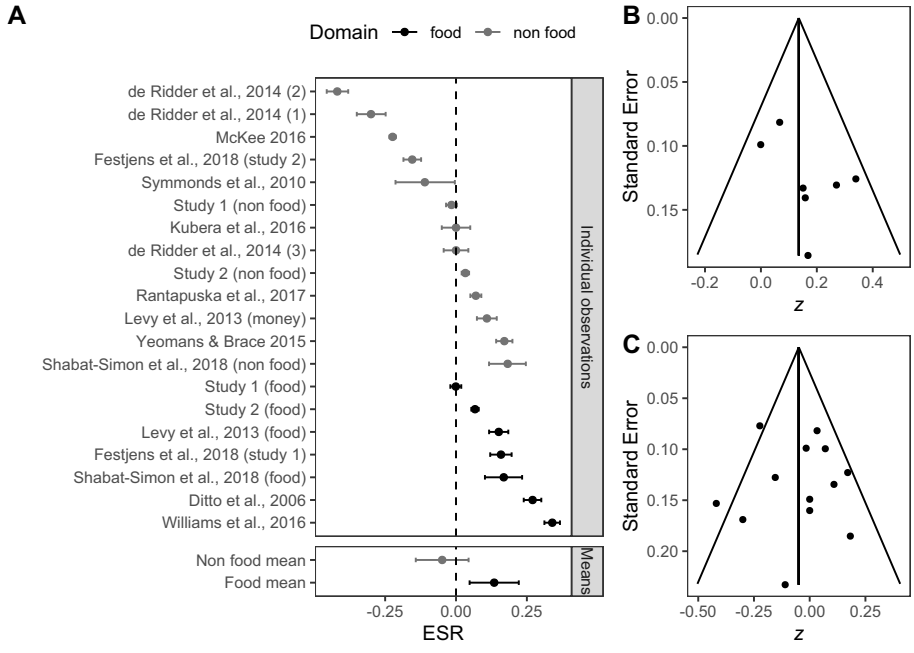

FIGURE 4: Panel A: Forest plot of the observed and synthesized effect sizes in the meta-analysis. Error bars indicate 95% confidence intervals. Effect sizes from our own studies are named Study 1 and Study 2. Panel B: Funnel plot for food data. Panel C: Funnel plot for non food data.

We investigate the role of blood glucose on decision making under risk by performing two experimental studies and a meta-analysis. In Study 1, we manipulated participants' blood glucose levels and measured their willingness to pay with a BDM auction approach for risky and safe consumer products. We did not find any effect of blood glucose on participants' willingness to pay for the risky vs safe products. In Study 2, we operationalize risk using gambles. In this study, participants with low levels of blood glucose were more willing to choose high variance gambles. This effect was more pronounced in the food compared to the non-food domain. In the meta-analysis which includes our own and previous studies, we found that the data was best explained by including the food vs non-food domain as a moderator and that low blood glucose increase risk seeking in the food domain, but not in the non-food domain.

Overall, the results of the meta-analysis, which bears the greatest weight, align well with the predictions of the budget rule which predicts that negative energy budgets, here operationalized through low blood glucose levels, increase risk seeking for food rewards. The budget rule makes no predictions concerning non food rewards, nor do we observe any effect in the non food domain in the meta-analysis. The finding dovetails with other studies showing that human decision makers sometimes apply foraging principles. Prior studies have, for instance, shown that hunter-gatherers follow foraging principles (Raichlen et al., 2014) and similar findings have been demonstrated with visual search in laboratory studies (Wolfe, 2013), search in memory (Hills, Jones & Todd, 2012) and when people search for information on websites (Pirolli & Card, 1999). Other studies have shown that decision makers respond to monetary budgets in manner consistent with our findings (Pietras & Hackenberg, 2001; Pietras, Searcy, Huitema & Brandt, 2008). We add to this literature by demonstrating that the effect of blood glucose levels on human decision making may best be explained by the energy budget rule or a similar need-based model of risk taking (Barclay, Mishra & Sparks, 2018).

Our findings corroborate a previous meta-analysis (Orquin & Kurzban, 2016) in demonstrating that dual systems theory cannot account for the effects of blood glucose on decision making. Although dual systems theory is developed specifically to explain the influence of emotional and physiological states on decision making, it seems unable to account for the domain specific effect observed in this meta-analysis. The Mukherjee model furthermore predicts an effect in the op-

TABLE 5: Included effect sizes and their operationalizations of risk and blood glucose.

Author	r	N	A	vi	ric	vic	Domain	Dependent var.	Independent var.
Ditto et al., 2006	0.223	80	0.67	0.223	0.013	0.272	0.019	food	Gambles
Festjens et al., 2018 (study 1)	0.113	99	0.50	0.113	0.010	0.160	0.020	food	Gambles
Levy et al., 2013 (F)	0.151	55	1.00	0.151	0.019	0.151	0.019	food	Gambles
Shahat-Simon et al., 2018 (F)	0.120	57	0.50	0.120	0.018	0.170	0.036	food	Gambles
Study 1 (F)	−0.001	103	1.00	−0.001	0.010	−0.001	0.010	food	WTP
Study 2 (F)	0.067	150	1.00	0.067	0.007	0.067	0.007	food	Gambles
Williams et al., 2016	0.220	144	0.40	0.220	0.007	0.348	0.017	food	Cheating
de Ridder et al., 2014 (1)	−0.300	30	1.00	−0.300	0.034	−0.300	0.034	non food	IGT
de Ridder et al., 2014 (2)	−0.350	50	1.00	−0.350	0.020	−0.350	0.020	non food	IGT
de Ridder et al., 2014 (3)	0.000	46	1.00	0.000	0.022	0.000	0.022	non food	BART
Festjens et al., 2018 (study 2)	−0.110	120	0.50	−0.110	0.008	−0.156	0.017	non food	Gambles
Kubera et al., 2016	0.000	40	1.00	0.000	0.026	0.000	0.026	non food	Gambles
Levy et al., 2013 (money)	0.109	55	1.00	0.109	0.019	0.109	0.019	non food	Gambles
McKee 2016	−0.160	319	0.50	−0.160	0.003	−0.226	0.006	non food	Gambles
Rantapuska et al., 2017	0.070	101	1.00	0.070	0.010	0.070	0.010	non food	Multiple
Shahat-Simon et al., 2018 (NF)	0.130	57	0.50	0.130	0.018	0.184	0.036	non food	Gambles
Study 1 (NF)	−0.016	103	1.00	−0.016	0.010	−0.016	0.010	non food	WTP
Study 2 (NF)	0.033	150	1.00	0.033	0.007	0.033	0.007	non food	Gambles
Symmonds et al., 2010	−0.110	19	1.00	−0.110	0.056	−0.110	0.056	non food	Gambles
Yeomans & Brace 2015	0.140	96	0.67	0.140	0.011	0.171	0.016	non food	BART

posite direction of what we observe, i.e., it predicts that low blood glucose levels increase risk aversion, but we observe that it decreases risk aversion in the food domain.

Finally, it is relevant to mention that further research is needed on the role of blood glucose and risk taking for non-food rewards. While there is no effect on average in the non-food domain, the studies were subject to some heterogeneity beyond what can be explained by sampling error. This could indicate a missing moderator at work influencing when low blood glucose increases or decreases risk seeking for non-food. Concerning risk taking for food rewards, there should be little cause for public concern. While decision makers become more variance seeking it does not seem to change their risk benefit trade-offs. In plainer words, hunger makes us more likely to gamble on getting a bigger meal, but presumably we do not become willing to eat unsafe foods.

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Supplementary Information

Manipulation of food related risk in Study 1

Figure SI 1: Translation: "You will now be shown 12 food items, including chocolate bars, muesli bars and crackers. Some of these food items are produced using biotechnology, while others are produced using conventional methods. Each product is shown without packaging. Biotechnology foods differ from conventional foods in several respects. The table below lists the most important benefits and disadvantages of biotechnology foods. Upper left: Benefits: A higher level of satiety is achieved than from equivalent conventional foods. Lower left: Disadvantages: 1 out of 500 may be subjected to a temporary allergic reaction. Upper right: Some degree of satiety is achieved. Lower right: No risk of allergic reactions.

Manipulation of non -food related risk in Study 1

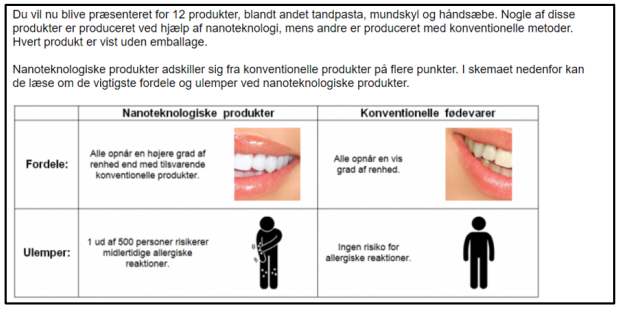

Figure SI 2: Translation: "You will now be shown 12 products, including toothpaste, mouthwash and hand soap. Some of these products are produced using nanotechnology, while others are produced using conventional methods. Each product is shown without packaging. Products manufactured using nanotechnology differ from conventional products in several respects. The table below lists the most important benefits and disadvantages of nanotech products. Upper left: Benefits: A higher level of cleanness is achieved than with the similar conventional products. Lower left: Disadvantages: 1 out of 500 may be subjected to a temporary allergic reaction. Upper right: Some degree of cleanness is achieved. Lower right: No risk of allergic reactions.

Table SI 1

Cross Validation Study 1

Models	Root Mean Square Error	
	Training	Test
WTP = Glucose + (1|ID) + (1|prodID)	3.387036	4.091270
WTP = Glucose + Risk + (1|ID) + (1|prodID)	3.369168	4.091486
WTP = Risk + (1|ID) + (1|prodID)	3.369165	4.091726
WTP = (1|ID) + (1|prodID)	3.387033	4.092173
WTP = Glucose + Food + (1|ID) + (1|prodID)	3.387200	4.092909
WTP = Glucose+Risk+Food+ (1|ID)+(1|prodID)	3.369328	4.093077
WTP = Risk + Food + (1|ID) + (1|prodID)	3.369325	4.093328
WTP = Food + (1|ID) + (1|prodID)	3.387197	4.093824
WTP = Glucose*Risk + (1|ID) + (1|prodID)	3.369135	4.095623
WTP = Glucose*Food + (1|ID) + (1|prodID)	3.386356	4.099073
WTP = Glucose*Risk*Food+ (1|ID) + (1|prodID)	3.367640	4.105291
WTP = Glucose + Food + (1|ID)	3.574428	4.241667
WTP = Food + (1|ID)	3.574424	4.241960
WTP = Risk + Food + (1|ID)	3.558398	4.242685
WTP = Glucose + Risk + Food + (1|ID)	3.558401	4.242911
WTP = Glucose*Food + (1|ID)	3.573629	4.248194
WTP = Glucose + (1|ID)	3.619023	4.251798
WTP = (1|ID)	3.619019	4.252021
WTP = Risk + (1|ID)	3.603189	4.253281
WTP = Glucose + Risk + (1|ID)	3.603193	4.253650
WTP = Glucose*Risk*Food + (1|ID)	3.556905	4.256297
WTP = Glucose*Risk + (1|ID)	3.603125	4.258555

Table SI 2
Full model of treatment and conditions effect on Willingness to pay

		WTP	
Predictors	*Estimates*	*CI*	*p*
(Intercept)	7.60	6.56 – 8.64	**<0.001**
Glucose	-0.89	-2.06 – 0.27	0.131
Risk	0.59	0.04 – 1.13	**0.035**
Food	-1.37	-2.43 – -0.30	**0.012**
Glucose * Risk	-0.07	-0.84 – 0.71	0.867
Glucose * Food	0.20	-0.57 – 0.98	0.608
Risk * Food	0.19	-0.58 – 0.96	0.633
Glucose * Risk * Food	0.18	-0.92 – 1.28	0.748
Random Effects			
σ^2	11.94		
$\tau_{00\ ID}$	6.95		
$\tau_{00\ prodID}$	1.31		
ICC	0.41		
$N_{\ ID}$	102		
$N_{\ prodID}$	24		
Observations	2448		
Marginal R^2 / Conditional R^2	0.029 / 0.426		

Table SI2 reports the full model of the different conditions effect on willingness to pay.

Table SI 3
Cross Validation for study 2 with participants with high blood glucose for placebo excluded

	Brier Score	
Models	Training	Test
Risk = GlucoGroup + (1|ID) + (1|GambleNr)	0.21821	0.24829
Risk = GlucoGroup*Food+ (1|ID) + (1|GambleNr)	0.21814	0.24833
Risk = GlucoGroup+Food+ (1|ID) + (1|GambleNr)	0.21821	0.24834
Risk = (1|ID)+(1|GambleNr)	0.21821	0.24836
Risk = Food+(1|ID)+(1|GambleNr)	0.21821	0.24841
Risk = GlucoMeasure + (1|ID)+ (1|GambleNr)	0.21821	0.24849
Risk = GlucoMeasure +Food+(1|ID)+(1|GambleNr)	0.21821	0.24854
Risk = GlucoMeasure *Food+(1|ID)+(1|GambleNr)	0.21821	0.24861
Risk = GlucoDiff + (1|ID)+ (1|GambleNr)	0.21821	0.24862
Risk = GlucoDiff +Food+(1|ID)+(1|GambleNr)	0.21821	0.24867
Risk = GlucoDiff *Food+(1|ID)+(1|GambleNr)	0.21817	0.24871
Risk = GlucoGroup + (1|ID)	0.22147	0.24986
Risk = GlucoGroup*Food+ (1|ID)	0.22141	0.24991
Risk = GlucoGroup+Food+ (1|ID)	0.22147	0.24991
Risk = (1|ID)	0.22147	0.24994
Risk = Food+(1|ID)	0.22147	0.24999
Risk = GlucoMeasure + (1|ID)	0.22147	0.25007
Risk = GlucoMeasure +Food+(1|ID)	0.22147	0.25012
Risk = GlucoMeasure *Food+(1|ID)	0.22146	0.25019
Risk = GlucoDiff + (1|ID)	0.22147	0.25020
Risk = GlucoDiff +Food+(1|ID)	0.22147	0.25025
Risk = GlucoDiff *Food +(1|ID)	0.22143	0.25029

Table SI 4

Cross Validation for study 2 with participants with high blood glucose for placebo included in glucose group

	Brier Score	
Models	Training	Test
Risk = GlucoMeasure + (1|ID)+ (1|GambleNr)	0.21868	0.24828
Risk = GlucoMeasure +Food +(1|ID)+(1|GambleNr)	0.21868	0.24832
Risk = GlucoGroup+ (1|ID) + (1|GambleNr)	0.21868	0.24833
Risk = GlucoGroup+Food + (1|ID) + (1|GambleNr)	0.21868	0.24837
Risk = GlucoMeasure *Food +(1|ID)+(1|GambleNr)	0.21868	0.24838
Risk = GlucoGroup*Food + (1|ID) + (1|GambleNr)	0.21865	0.24839
Risk = (1|ID)+(1|GambleNr)	0.21868	0.24840
Risk = Food+(1|ID)+(1|GambleNr)	0.21867	0.24844
Risk = GlucoDiff+ (1|ID)+ (1|GambleNr)	0.21868	0.24863
Risk = GlucoDiff+Food+(1|ID)+(1|GambleNr)	0.21867	0.24867
Risk = GlucoDiff*Food +(1|ID)+(1|GambleNr)	0.21863	0.24869
Risk = GlucoMeasure + (1|ID)	0.22197	0.24996
Risk = GlucoMeasure +Food+(1|ID)	0.22196	0.25000
Risk = GlucoGroup + (1|ID)	0.22197	0.25001
Risk = GlucoGroup+Food + (1|ID)	0.22196	0.25005
Risk = GlucoMeasure *Food +(1|ID)	0.22196	0.25006
Risk = GlucoGroup*Food + (1|ID)	0.22193	0.25007
Risk = (1|ID)	0.22196	0.25008
Risk = Food+(1|ID)	0.22196	0.25012
Risk = GlucoDiff + (1|ID)	0.22196	0.25031
Risk = GlucoDiff+Food+(1|ID)	0.22196	0.25035
Risk = GlucoDiff*Food +(1|ID)	0.22191	0.25037

Table SI 5

Full model of treatment and conditions effect on risky choice. First model is with the cleaned data. Second model is with participants with a blood glucose level higher than 5.5 mmol/l included in the treatment condition

	risk			**risk**		
Predictors	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*
(Intercept)	1.18	0.97 – 1.45	0.101	1.18	0.97 – 1.45	0.099
GlucoGroup	0.87	0.67 – 1.12	0.282	0.84	0.65 – 1.07	0.155
Food	1.09	0.98 – 1.22	0.125	1.09	0.98 – 1.22	0.125
GlucoGroup * Food	0.87	0.75 – 1.01	0.069	0.90	0.77 – 1.04	0.142
Random Effects						
σ^2	3.29			3.29		
τ_{00}	0.53 $_{ID}$			0.52 $_{ID}$		
	0.05 $_{GambleNr}$			0.05 $_{GambleNr}$		
ICC	0.15			0.15		
N	150 $_{ID}$			162 $_{ID}$		
	41 $_{GambleNr}$			41 $_{GambleNr}$		
Observations	12300			13284		
Marginal R^2 / Conditional R^2	0.003 / 0.154			0.004 / 0.152		

Table SI5 shows the full model for Study 2. The first column of effects are with the cleaned data whereas the last one is the robustness check where high level blood glucose individuals are moved to the treatment condition. This inclusion of the 12 individuals that were deleted from the first analysis does not change the result in any major way.

Table SI 6
Wilke questionnaire factor loadings

Latent Factor	*B*	*SE*	*ρ*	*β*
Betweengroup competition				
Sitting in the section for fans of the opposing team with a group of friends while wearing your team's colors.	0.429	0.167	0.010	0.224
Adamantly defending the honor of your local team against a fan from a different sporting team, even if it may cause a fight.	0.618	0.175	0.000	0.350
Starting a rivalry with students from another school in one of your extracurricular activities	0.691	0.177	0.000	0.413
Withingroup competition				
Trying to take a leadership role in any peer group you join.	0.799	0.161	0.000	0.498
Arguing with members of a group project over what should be done.	0.373	0.148	0.012	0.248
Attempting to influence people in your social group to advance your own agenda.	0.976	0.186	0.000	0.540
Status power				
Blackmailing your opponent to win an election.	0.984	0.134	0.000	0.652
Driving too fast to appear strong and in control to your peers.	0.470	0.137	0.001	0.306
Telling lies to the leader about a teammate to appear more trustworthy than the other person (i.e., to get ahead).	0.628	0.103	0.000	0.528
Environmental exploration				
Swimming far out from shore to reach a diving platform.	1.171	0.179	0.000	0.568
Hiking on a mountain trail with a beautiful view but with a high chance of a landslide.	1.293	0.164	0.000	0.693
Going on an expedition into a deep forest where there will be no one else around.	1.407	0.174	0.000	0.711
Food selection				
Planting your own garden to grow your own fruit and vegetables.	0.770	0.152	0.000	0.448
Only eating meat from a local organic farm.	1.113	0.180	0.000	0.566
Significantly increasing your weekly food bill to buy healthy organic food.	1.534	0.183	0.000	0.876
Food acquisition				
Not boiling or filtering water from a questionable source before drinking it.	0.540	0.220	0.014	0.309
Eating at a restaurant where your friend got food poisoning.	0.444	0.207	0.032	0.244
Eating a piece of food that has fallen on the floor	1.428	0.459	0.002	0.810
Parent offspring conflict				
Talking your parents into giving you weekly allowance money.	1.263	0.163	0.000	0.721
Bugging your parents for money to go out with friends until they finally give in.	0.826	0.134	0.000	0.558
Asking your parents to get their old car when they get a new one (instead of giving it to your siblings).	0.977	0.173	0.000	0.511
Kinship				
Risking your life to drag your parents from a burning building.	0.450	0.127	0.000	0.365
Staying up all night to help your sibling with a difficult school project.	0.304	0.131	0.020	0.233
Donating a kidney to your sibling.	1.118	0.221	0.000	0.731
Mate attraction				
Taking part in sexual acts that you may not usually do to look more sexually appealing to the opposite sex.	0.621	0.165	0.000	0.342
Casually dating more than one person at a time.	1.324	0.179	0.000	0.654

Having a consistent sexual partner with whom you are not romantically involved.	1.446	0.182	0.000	0.712
Mate retention				
Not putting in the effort to fulfil the requests of your significant other, such as remembering to call them when they ask you to.	0.621	0.149	0.000	0.376
Dumping the person you have been seeing when they mention commitment.	0.862	0.135	0.000	0.577
Spending the night with an attractive person while vacationing without your significant other.	0.856	0.145	0.000	0.530

Note: B = *Unstandardized coefficients, SE = standard error,*ρ = *p-value,* β = *standardized coefficients*

Acta Universitatis Agriculturae Sueciae

Doctoral Thesis No. 2023:2

This thesis investigates consumer behavior and how theories from evolutionary biology might help understand the motives behind different consumption patterns. Paper I is the backbone of the methodological decisions for the three empirical papers presented in the thesis. Paper II investigates what happens with choices when humans have low blood glucose. Paper III and IV studies conspicuous consumption and the link between this consumption and relationship status and increasing uncertainty, respectively.

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