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by

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ESSAYS IN RISK AND EXPERIMENTAL FINANCE

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Contents

Ευχαριστίες

Allow me to first express in Greek my gratitude to those that contributed to my success in this marvellous journey. First of all because I want to have the chance to express my inner thoughts and feelings, and second, for a reason that I would like to share with as many people as I can. No matter how much and how far I have seeked and tried, I have not found any other language that can express human experience, cosmos, truth, freedom and love better than Greek.

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I intentionally left for the end those to which I want to speak, here, in first person.

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Introduction

My thesis comprises three chapters, and thus, papers, that initiate from a broad common quest: to explore how does risky choice and behaviour in various settings impact individual and group decision-making and financial performance. This question intersects with the fields or corporate finance and asset management, behavioural finance and risk elicitation, and market extreme events prediction. However, it does not exhaust the more domain-specific research motivation that encompasses each study. It does not either exhaust the entire set of research questions that each chapter addresses. It is, however, the basic conceptual link, that allows for a coherent examination of all the primary and secondary research questions and objectives, included in each particular study (chapter).

The three chapters deal mostly with the notion of *measurable uncertainty* Knight (1921), known as *risk*, and less with immeasurable uncertainty, which is mostly known as *uncertainty* (Knight, 1921). In each paper we are motivated by discrete research objectives, and we approach and analyse empirical evidence of risky choice and behaviour from a different standpoint. In the first chapter, we examine the relevance and impact of prominent financial and macroeconomic indicators, to the probability of observing an *extreme event* in the stock market. The latter extreme events include a stock market downfall, namely crash. In the second chapter, we investigate risky choices and risk preferences across two mathematically isomorphic decision environments. In particular, we show that the private-value sealed bid first-price auction (Selten and Neugebauer, 2006), and the bomb risk elicitation task (Crosetto and Filippin, 2016) are isomorphic in a mathematical sense, and thus, predict identical choices and preferences. We develop a set of testable hypotheses that relate to potential behavioural biases and risky choice context dependence, and challenge the latter prediction. In the third chapter, we extend, propose and empirically test a fair bidding mechanism in asset management and corporate finance group decision-making. We formulate a set of hypotheses based on the main properties of the mechanism, and test the mechanism implications in agency problems (opportunism), funding (investment) decisions and efficiency (funding decisions and knowledge based honest decision-making).

Chapter 1

In the first chapter we conduct an empirical exercise that attempts to address the following question: which, and to what extent, prominent indicators, relate to the probability of observing stock market movements, that are largely beyond the average stock market performance. The indicators are prominent factors in the existing literature on tail risk (extreme events). They proxy both financial performance and prevailing macroeconomic conditions. The measure of probability we deploy, reflects the imminence of such events.

We chose to address this question by applying a sophisticated methodology that has been, to our knowledge, slightly used in modelling stock market crashes (as part of stock market extreme events). The latter methodology is *duration analysis* (Kiefer, 1988). Classic applications of duration data analysis root back in economics, and in particular, in unemployment duration and in job-search theories' assessment. Those theories provide the setting for the first empirical dynamic programming models in economics (Burdett et al. (1984), Bowlus, Kiefer, and Neumann (1995), Bowlus, Kiefer, and Neumann (1996), Bowlus, Kiefer, and Neumann (1994)). We chose this methodology both for its prominence in the aforementioned economics applications, but also for its implicit relevance to other prominent measures of tail and disaster risk. Among the latter we distinguish, the hallmark work of Barro (2006), Barro and Ursúa (2009) and Wachter (2013). Barro (2006) develops a measure of implied disaster probabilities, that relates to consecutive instants of time. Duration data analysis deals with time spells and their probability of ending (or surviving) at each particular point in time. The latter is methodologically achieved by taking into account the contribution of each observation of the time series data on stock returns. [1]. In that sense, we see an analogy between the first and the second measure, and consequently, a potential for the second (duration data) to unravel the factors that drive a very core part of the probability of stock market crashes (and extreme events in general). In addition, duration analysis is theoretically adequate for investigating the time to bank failure and the length of business cycles. The latter phenomena share several common (theoretical) characteristics to stock market extreme events. Moreover, duration data and intensity (hazard) functions are a measure of conditional probability similar to the work of Barro and Ursúa (2009) and Wachter (2013). This empirical study, though, departs from the way the latter studies deal with probabilities in

[1] The latter holds true only for our section of Cox regressions with time-varying co-variates.

the following way: by deploying a given measure of conditional probabilities, this study attempts to identify which indicators significantly explain the probability measure deployed with duration data.

This study shows that the non-parametric estimation of extreme events differs substantially for upward and downward extreme market events. The probability of observing a stock market crash (3σ event), is significantly lower than the probability of extremely high stock events. Our estimates indicate that a firm's share and book value, investors' expectations, real output and federal funds rate impact the frequency (intensity) of extreme stock market realisations. We elaborate on the specific type of effects of each indicator in the probability of such events in our results section in *Chapter 1*. Finally, we find that the differentiation in time to extreme events introduced by those indicators, does not solely relate to the industry sector.

Chapter 2

In the second chapter, we introduce, develop and experimentally test a set of testable hypotheses in individual risk decision-making, across two isomorphic tasks. We explore the potential for context dependence and framing effects (Kahneman and Tversky (1981), Kahneman and Tversky (1986), Hershey and Schoemaker (1980), Hershey, Kunreuther, and Schoemaker (1982)), preference reversals (Lichtenstein and Slovic (1971), Lichtenstein and Slovic (1983), Isaac and James (2000),Lindman (1971),Grether and Plott (1979)), and other distortions in risky choice (Kahneman, Knetsch, and Thaler (1990)). As already mentioned, the tasks consist of the sealed-bid first-price auction Selten and Neugebauer (2006), and the bomb risk elicitation task (Crosetto and Filippin, 2016).

We compare choices and constant relative risk aversion measures per task (Cox, Smith, and Walker (1982)). We basically challenge whether we indeed observe a one-to-one mapping between choices and the constant relative risk aversion measures of the theoretically isomorphic tasks. We choose an experiment to attain our research objectives, and thereby test our hypotheses, for two reasons. First, because experiments are a frequently employed and valid method of eliciting and assessing risk attitudes within subjects. Second, because experiments allows us to induce incentives in risky choice and financial decision-making, that is, with real monetary payoffs. We test our hypotheses by designing and experimentally applying eight (8) different market sizes in the first-price auction, within cohorts. We provide evidence of non-isomorphic choices across the two tasks, and of preference reversals, with a significant magnitude in 50% of the markets. We also find that a **loss** frame in the bomb risk elicitation task indeed applies, the level of choices. Our results relatively to the constant relative risk measures, also favour a **gain** framing effect for the auction, and a loss framing effect attached to the bomb risk elicitation task. Higher risk aversion in the first-price auction correspond to lower risk aversion in the BRET, in the most theoretically relevant case ($N = 2$).

Chapter 3

In the third chapter we extend and experimentally test a fair private bidding mechanism, with value ambiguity and private investment in information search (knowledge), in corporate governance. The mechanism introduces an innovative approach for corporate finance structural decisions, and asset management. The mechanism ensures equal treatment, veto power and private information search. Our study introduces the novelty of a realistic essential aspect in financial group decision-making: ambiguous investment values. It incorporates the latter function in a fair institutional setup, where decisions are substituted by private bids, and allows for comparability of investment decisions in the management level.

We mainly explore how such a bidding mechanism may tackle agency problems (opportunism), how it may improve decision outcomes, and whether it induces knowledge-based honesty in the decision-making process. The proposed mechanism is proved to satisfy the theoretical requirements of the first-price auction. It thus, allows us to examine partners' bidding behaviour through the prism of underbidding (opportunism), and overbidding (running the risk of not recovering from potential losses). It also allow us to investigate truthful bidding conditional to investment in information search. We attain this goal by designing and applying an experiment with two treatments. The first treatment relates to free-choice of information search, and the second one to randomly assigned information search. For the same purpose, we experimentally design the potential for negative value assignment, repeatedly, in a randomly determined group member, among partners that co-decide. Via examining bidding behaviour, we attach our study to the notion of risk-taking, and test our hypotheses on how such a decision mechanism may impact opportunism and investment outcomes.

We find that a private value sealed-bid fair mechanism with value ambiguity, limits opportunism and boosts desirable investment outcomes and truthful bidding. Corporate partners undertake the risk of not recovering from potential losses to a significant extent, in order not to prevent overall profitable investments from being implemented. Overall, the proposed bidding mechanism leads to improved (desirable) corporate decision outcomes, and limits opportunism significantly.

Chapter 1

An empirical duration analysis of extreme stock market events

1.1 Introduction

A key principle of financial theory is that, stock returns, are the main signals of principal economic activity. The rationale of this relationship has its roots to household and investment spending. In particular, increases in stock prices raise household wealth levels, resulting to higher consumption, and lower debt and equity financing. Increased consumption spending accelerates GDP growth, and reduced cost of capital lowers the return required for capital investment to be worthwhile, increasing the latter's profitability. By consequence, stock returns' distribution over time maps major rises and falls, in the core of economic action. It, thus, provides the empirical ground that best reflects the time intervals, at which an extreme event state of the world is historically reached.

In existing literature, the focus on extreme events (extreme stock market prices, and thus, returns) is not new. However, it is overwhelmingly focused on negative extreme events and especially, financial crises, such as banking, currency or debt crises. The latter have been the subject of extensive research. Several studies, since late 1990's, focused on developing a methodological framework with the objective to foresee financial crises. The most ambitious among these techniques involves the combination of several crisis predictors, that constitute the so-called *Early Warning Systems* (hereafter EWS).

[0] This chapter refers to a joint paper with Michail Karoglou and Christian Wolff.

Although there exist various statistical and econometric models in crisis prediction, their performance is not sufficiently satisfactory, especially in terms of prediction of the out of sample crisis incidents (Berg, Borensztein, and Pattillo, 2005). For instance, predictors developed after the European currency crisis of $1992 - 1993$, failed to predict the events of the Mexican financial crisis of $1994 - 1995$. Likewise, predictors developed after the Mexican crisis, failed to predict the Asian financial crisis of $1997 - 1998$. And predictors developed thereafter, failed to predict the 2001 Turkish crisis. The challenge of designing an effective EWS was further intensified when the existing models failed to foresee the recent global financial crisis. As a result, several new or modified approaches towards forecasting a specific type of financial crisis, or a crisis in a specific type of economy, have been introduced.

Dastkhan (2019) splits the existing EWS literature into two categories based on the employed methodology [1]. The category based on the recent advances in computation power, includes studies that deploy alternative statistical methods, such as machine-learning algorithms (artificial intelligence). The primary issue with research in this category is that the EWS is effectively treated a *black box*. The other category bypasses this issue, by being founded upon the more established literature. The latter consists of studies that uses either the so-called *signal approach*, or the limited dependent probit-logit modelling [2]. This category also includes EWS that are based on particular econometric techniques. Hence, this is where this study is basically positioned.

Within the first category of EWS research, there is the rapidly growing strand of the modern literature. As mentioned, the latter relates to the prediction of financial crises, based on artificial intelligence approaches. For example, Yoon and Park (2014) applied pattern recognition techniques to introduce a market instability index in the stock markets. This index classifies the unstable period of a stock market into different levels of instability. The criterion of this classification is the strength of the signal of instability. This allows the current instability of a stock market, to be used in predicting how the instability will proceed, and to prepare the market for an upcoming financial crisis. The latter crisis, is, thus contingent upon the levels of instability warning. Döpke, Fritsche, and Pierdzioch (2017) used a machine-learning approach, known as *boosted regression trees*, to re-examine the usefulness of selected leading indicators in predicting recessions. Their findings suggested that, measures of the short-term interest rate and the term spread, are important leading indicators of recession in Germany. We are basically deploying

[1] Other forms of clustering the respective research also exists. For instance Sevim et al. (2014) suggested three categories. One for regression modelling, one for the signal approach, and one for machine-learning applications. Chatzis et al. (2016) add one more category, that includes approaches that split the sample into researcher-selected crisis, and non-crisis countries.

[2] Signals approaches and binary choice models are mostly used in predicting banking and currency crises.

a specific technique to assess the usefulness of well-established in existing literature indicators, in extreme stock market events prediction. Among others, we consider Döpke, Fritsche, and Pierdzioch (2017) findings, and we incorporate the U.S. federal funds (interest) rate in our model. Chatzis et al. (2018) used extensive variations of machine-learning and deep learning algorithms. They investigated the latter algorithms' performance in forecasting tail events in the global stock markets. Their approach seems to offer a more efficient and risk sensitive global systemic early warning tool, compared to the others.

Dastkhan (2019) used a network representation of assets, based on the values of the forward-looking conditional value-at-risk (CoVaR) model. These values are applied as indicators for the proposed EWS to predict downturns and crises in the firm-level, and the aggregate level (the entire market). They found that the suggested indicators have a good ability to predict the crises in the market. We incorporate in our model three basic and established in existing literature financial ratios: price-to-book value, dividend-yield and price-to-earnings. In a similar context, Samitas, Kampouris, and Kenourgios (2020) combined network analysis and machine-learning algorithms. They attempt to create an accurate model for predicting the possibility of contagion risk, during shock events and crisis periods in stock exchange markets. They model the global financial system as a network. They deploy financial contagion risk measures as an early warning indicator, so as to improve the performance of standard prediction models for crises.

Within the more established literature of EWS research, there is the so-called *signals approach*, introduced by the seminal papers by Kaminsky, Lizondo, and Reinhart (1998) and Kaminsky and Reinhart (1999). The *signals approach* is a non-parametric threshold approach. It entails the identification and monitoring of certain variables, that tend to behave in an unusual manner during financial or economic distress. Their studies identifies thresholds beyond which, each of the leading indicators signals a crisis. Various indicators can be summarised to form a composite indicator (Kaminsky, 1999). Our model examines time data (duration) analysis (regressions), as an approach for predicting tail events in the stock market. Duration analysis introduces the imminence of tail events as a measure, that relates to each observation-realisation of the time series of prices (returns). Tail events are defined as 3σ events. The rate at which a time spell (that started at a previous event) is completed, signals, thus, a threshold, beyond which extreme events will proceed. In that sense, an extreme event is contingent upon the occurrence of past market crashes, and prepares the market for another upcoming extreme event. Our study identifies thresholds of extreme stock returns realisations, that is, 3σ events, and examines whether imminence towards these thresholds can be explained by certain leading indicators.

Applications and extensions of *signals approach* in the literature include Berg and Pattillo (1999); Brüggemann and Linne (2002); Edison (2003) and El-Shagi et al. (2013). Alessi and Detken (2011) used a quasi-real time signalling approach to predict asset price booms. They consider asset price booms that have serious real economy consequences, by considering important indicators from the policy maker's perspective. According to their results, global measures of liquidity are the best performing indicators in forecasting crises. Similar to the *signals approach*, binary choice models aim to predict a binary crisis variable (see e.g. Frankel and Rose (1996); Berg and Pattillo (1999); Kumar, Moorthy, and Perraudin (2003)). Binary choice models fit a specific stable relation between indicators and the crisis variable, that takes the value of one, for the periods a country is hit by a crisis, and zero, otherwise. In order to establish a stable relation between indicators and crises, quite rigid modelling assumptions are required. Otherwise, the respective analysis suffers from an inherent endogeneity problem, as the behaviour of the indicator variables is affected both by the crisis itself, and the policies undertaken so as to mitigate it. Bussière and Fratzscher (2006) extend the discrete choice from two (yes/no) to more states, namely crisis, post-crisis, and tranquil periods. Their extension targets at enhancing the efficiency of the EWS, using the multinomial logit model instead of the binomial logit model. In another study, Li, Chen, and French (2015) considered the data index futures and option markets to built up a multinomial logit model, as an EWS for equity market crises. Their results suggest that models estimated with futures and put options, significantly improve the medium-term predictability of equity market crises. Duca and Peltonen (2013) developed a framework for predicting periods of financial instability. They use a Financial Stress Index to identify the starting date of systemic financial crises, and a discrete choice model that combines both, domestic, and global indicators. The results showed that factors of domestic and global macro-financial vulnerabilities have positive impact in predicting financial crises.

EWS studies that are based on econometric models lie within the same category. For instance, Abiad (2003) proposed an EWS to predict a crisis, based on Markov-switching models, with time-varying transition probabilities. This approach does not require to date the crisis episodes in advance, as the crisis periods are estimated simultaneously to the crisis forecasting probabilities. As a result, such an EWS avoids the issue of dating a crash, that relates to the probit-logit models, and the *signal approach*. Faranda et al. (2015) analysed U.S. and Europe stock indices by means of ARMA models, in order to identify early warning indicators of financial crises. In this procedure, the early warning indicator represents the deviation, in the ARMA space, from the reference model. Gresnigt, Kole, and Franses (2015) model the extreme returns of a market by using a model for earthquake sequences, the so-called Epidemic-Type Aftershock Sequence model (ETAS). The approach is built upon the self-exciting behaviour of stock returns, around a financial market crash, which is similar to the seismic activity around earthquakes. By considering that a shock tends to be followed by another shock, they developed an EWS for events in the financial market, based on the probability of the occurrence of an event, within a certain time period.

In this setup, this study proposes two very important departures from the existing literature. The first, involves the focus on extreme events, that are commonly viewed as either positive or negative. We revise the notion of what constitutes an adverse extreme event, in order to account for portfolios that include short positions. The second departure, involves the use of *survival analysis* methods. Instead of modelling whether another extreme event will take place, we consider the generation of extreme events, as part of the normal operation of the underlying market (here stock market). Therefore we model the time until the next extreme event.

With regards to the first proposed innovation, we examine both positive and negative extreme events as a more pragmatic approach, when examining stock markets of developed economies. The primary reason, is that in such markets, it is both institutionally possible and common practice for individual investors, to hold, not only a long position in an underlying share, but also a short position. The latter short position is hold either directly, or through some derivatives market, that is typically available in developed economies. This rationale suggests that, for individual portfolios, the distinction between negative and positive extreme events is uncertain. Indeed, adverse extreme events may well be attributed to positive extreme events, as well. Therefore, by focusing only on the negative extreme events, we would effectively be ignoring a vast set of portfolios that include short positions. Consequently, we view this innovation as one that distinguishes our work from any other in the EWS literature.

With regards to the second proposed innovation, we build our EWS based on *survival analysis* methods, and particularly, based on *Counting Processes*. *Counting Processes* generalise the typical Cox semi-parametric approach, to account for time-varying co-variates. This means that, our study is based on the EWS literature, that is founded upon regression analysis. At the same time, it constitutes a substantial departure from the latter, due to the adopted methods. It also implies a perceptual shift from thinking of extreme events as isolated events. Our study, rather thinks of extreme events as parts of an ongoing "normal" operation of the underlying market. The ongoing "normal" operation is nevertheless well justified, given the high frequency of such events, and the fact that it is commonly assumed that they will not simply disappear. This rationale is clearly demonstrated in the recent growth of the so-called Black-swan funds, which are literally developed with this perception in mind.

Beyond the scope of the EWS literature, we also view our study as one that relates to a series of seminal studies in *disaster risk*. In his seminal work on *Rare disasters and asset markets*, Barro (2006) models economic disasters as downward jumps in per capita gross domestic product (GDP). In particular, Barro (2006) characterises economic disasters by steep declines of at least 15% in real per capita GDP for twenty O.E.C.D. countries [1]. We are inspired by the work of Barro (2006) from the perspective of his approach towards the probability distribution of rare events (disasters). The measure by which he implies observed probabilities of economic disasters basically renders instants of time of observed disasters consecutive, rather than fixed. As his concise methodology addresses GDP declines based on the greater war periods in the 20th century, Barro (2006) shifts disaster's modelling attention to the notion of probabilities of entering a particular state of the world, relative to the variable of interest (GDP sharp declines). Our duration modelling approach over sharp declines on market returns (market crashes), focuses respectively on assessing the factors that drive the probability of entering an extreme event state of the world. The latter state is defined by extreme values belonging to the tails of the distribution of stock returns. Entrance to such a state state of the world stems from survivor and hazard rate functions. By analogy, the time spells of duration analysis are the main object, by which we observe the predicted time to surviving a current state of the world, and consequently, entering another. The main interpretation of the time spells of duration is, actually, the time to failure (default). Also, Barro (2006) calibration of the disaster parameter, that relates to the probability of a default, is contingent upon the occurrence of a disaster. Similarly, our model is one that assumes that, the probability of observing a market crash is contingent upon the rate at which a time spell is completed. In other words, that the probability of observing a market crash is contingent to the occurrence of past market crashes.

In further work, Barro and Ursúa (2009) examine conditional probabilities of large consumption declines given the historical information set of past stock market crashes. Their predictions are based on cumulative return drops of 25% and average declines in consumption, through the lens of 100 macroeconomic contractions. What they highlight, is the change in the conditional probability of a transition to a state, that satisfies particular conditions of a macroeconomic contraction, given past stock market extreme events. Our duration data approach directly targets

[1]O.E.C.D.: Organization for Economic Cooperation and Development

at future market crashes prediction, by looking at conditional probabilities of at each (time unit) observation. Thus, we assume the relative importance of the macro economy critical for our model. Among others, we motivate our work also in the spirit of Barro and Ursúa (2009), by incorporating in our model the most prominent in existing literature macroeconomic environment indicators: industrial production, GDP and the U.S. federal funds (overnight) rate.

Moreover, Wachter (2013) extends Barro's constant disaster probability and power utility model, by introducing rather stochastic probability, and recursive preferences. The model allows for the intensity of jumps to follow a square root process (Cox, Ingersoll, and Ross, 1985), and, while accommodating reasonable risk aversion levels, it explains the quantitative puzzle on equities returns (Mehra and Prescott, 1985). Implied disaster probabilities of the model, as well as the matching of stock returns volatility to excess stock returns volatility, is based on a variation of the price-dividend ratio (dividend yield). Our work can be seen as part of an empirical counter-exercise of the work of Wachter (2013) in the following way: we address the question of how well do prominent in existing literature financial and macroeconomic indicators perform in predicting the intensity (probability) of negative and positive stock market extreme events. The latter are widely known as *Black Swans* [1]. While we rely on conditional probabilities of entering a market crash state of the world based on past observations, we shift attention to identifying the factors that impact those conditional probabilities, such that they fit historical data. Our dependent variable is the intensity function, and thus the probability of a market extreme event [2]. Our independent variables, financial and macroeconomic, consist of the explanatory variables assigned to the model. In other words, our study is an empirical exercise on which, financial indicators and proxies of the macroeconomic environment, can adequately predict a measure of rare disasters. The latter measure is by default constructed to address empirical data over consecutive time intervals.

Further recent work on the link between rare disaster risk and market performance, also accounts for the disaster probability, through the scope of transition probabilities from one state of the world, to another. Berkman, Jacobsen, and Lee (2011) show that a conditional measure of rare disaster probability correlates with the stock market, and drives stock returns. The financial indicators that are shown by Berkman, Jacobsen, and Lee (2011) to govern disaster risk, relate to stock market performance, and are summarised to the earnings-price ratio and the dividend

[1] In his book "The *Black Swans*: the impact of the highly improbable", Taleb (2008) discusses that *Black Swans* are mainly characterised by three elements: their probability of occurring is unknown, their impact is largely significant and, by consequence devastating, and they can be foreseen in hindsight

[2] Details on the dependent variable of our duration model follow in *Sections 1.2.1* and *1.2.2*. More precisely, the intensity function reflects the imminence of a market extreme event

yield. In addition, in their "horse race" estimation exercise among prominent financial forecasting variables and their own dynamic tail risk measure, Kelly and Jiang (2014) also find that the (aggregate) dividend-price ratio succeeds on predicting future stock market returns [1].

Relying, thus, on evidence of prominent predictors in existing literature studies, we have selected and incorporated in our model both financial and macroeconomic predictor variables. Our selection is based on the results and correlations of the above-mentioned variables in extreme events prediction. In order to simplify the terminology used in our results and analysis, and following Taleb (2008) terminology, we hereafter refer to positive and negative extreme returns values as *positive Black Swans* and *negative Black Swans*, respectively. Overall, this study conducts an empirical investigation, to determine what factors can be used to explain the duration of the period, measured in number of days, between two consecutive Black Swans. The latter is done for all individual shares of the the SP500 index. Given that several of these factors are time-varying, this study departs from the predominant survival analysis paradigm of the Cox method, and deploys instead methodologies relative to Counting Processes. The latter processes generalise the predominant survival analysis paradigm of the Cox method, and facilitate the use of such explanatory variables.

This empirical investigation is conducted at daily frequency. We collect the periods, that in the context of survival analysis are denoted as 'runs', from every single individual share included in the S&P500. Discussion at sectoral level is based upon the grouping of these constituent shares, according to the industry they belong to.

The rest of this study is organized as follows: In Section 1.2 we present our data and elaborate on the theoretical considerations of our modelling approach, that is the *duration analysis* methodology. In Section 1.3 we report the results relative to our duration modelling estimation. In particular, in Section 1.3.1 we report and discuss the Nelson-Allen non-parametric survival function estimation results. In Section 1.3.2, we report and discuss the Cox estimates with time-varying co-variates, and in Section 1.3.3, we present the graphical testing method of testing the Proportional Hazards (PH) assumption. Section 1.4 summarises and concludes the paper.

[1] Market returns in the study of Kelly and Jiang (2014) refer to CRSP value-weighted market index returns over one-month

1.2 Data and methodology

Our dataset comprises of seven variables one of which, namely, stock returns, is used to generate the durations of spells. The latter duration spells are defined as the time spells until the first next positive, or negative, Black Swan. Table 1.1 overviews some of our variables' statistical features.

Table 1.1: Summary Statistics

This table reports summary statistics of the financial and macroeconomic indicators used in our model. The later consists of a duration model of stock market extreme (3σ) events, known as *B*lack Swans.

	Mean	Std.Dev.	Skewness	Kurtosis	Observations
Stock returns	0.01	0.10	-0.09	37.13	190405
Price-to-book value	2.79	36.91	-33.22	2090.40	177483
Dividend Yield	0.31	0.39	-0.90	4.82	147431
Price-to-earnings	1.28	0.32	1.49	14.79	174160
Industrial Production	0.001	0.003	-1.35	9.53	270805
Federal Funds Rate	4.80	3.91	0.87	3.84	270805
Inflation	-0.001	0.16	0.01	5.64	251125

Our dataset comprises of seven key variables, that are proved to forecast tail risk measures in the existing literature, deployed widely in EWS literature, and selected among 'horse race' studies with respect to their performance. They consist of financial ratios and macroeconomic variables. Those refer to the constituent shares of the S&P500 stock market index and are: the stock returns, the price-to-book value ratios, the dividend yields (price-dividend ratios), the price-to-earnings ratios, the US Industrial Production index, the U.S. federal funds rate and the U.S. trimmed mean PCE inflation measure. The logarithm of stock returns, dividend yields and price-to-earnings ratios are particularly relative to our modelling estimation approach. Equivalently relevant to our duration analysis approach are, respectively, the logarithmic levels for the U.S. Industrial Production (real output). Our data sample ranges from 2/1/1973 until 10/2/2019 and refers to daily observation for all financial ratios and variables, monthly for the U.S. federal funds (interest) rate and the U.S. trimmed mean PCE inflation measure, and quarterly for the U.S. Industrial Production index. Different orders of magnitude among financial ratios and macroeconomic variables, in the setting of *Counting Processes*, is a perfectly legitimate practice. Despite the fact that the indicators' variability is lower, compared to the case where all of them would exhibit higher frequencies, the indicators are actually capturing the actual information set, that is available at each point in time (e.g. the publicly available national statistics). It is also noteworthy, that our sample size renders unnecessary to include observations of each share (stock) from the start of the sample, and until the share's (stock's) first Black Swan. Similarly, our sample size does not require either to include the observations after each share's last Black Swan. This is particularly important in our approach, since we conveniently surpass the impact of left and right censoring, from which various survival analysis studies suffer. Consequently, our analysis is based on 1137 identified Black Swans (positive and negative).

Given that the chief stepping stone in this study is the investigation of the factors that may indicate increases or decreases in the probability of an extreme event, there are two principal issues that need to be addressed. The first is the identification of an extreme event. The second is the determination of increases or decreases in the probability of such extreme events occurring.

With regards to the identification of an extreme event, there are two approaches. The first approach focuses on *extreme values*, typically the 5% percentile of the distribution of stock returns. The second focuses on the so-called Black Swans or 3σ events, that is, the returns that are three standard deviations away from the mean. The *extreme values* approach ensures that a given number of observations is included in the sample size. This fact renders focusing on *extreme values* particularly convenient, for studies with relatively small samples. However, it cannot ensure that the identified observations are sufficiently uncommon, so as to be classified as extreme events. Contrary, the *Black Swan* approach ensures that the observations identified as extreme events will be sufficiently unusual. It cannot ensure, though, that there will be a sufficient number of observations for a meaningful analysis. Nevertheless, if the available samples are sufficiently large then, the *Black Swan* approach is the suggested method of analysing tail risk. Thus, given our large sample size, we adopt this approach in this study. For later reference, it is also worth noting at this point, that by both approaches it is possible to distinguish between positive and negative extreme events. Since a key focus of the traditional tail risk literature has been only the negative outcomes, it should be obvious to the reader why the *extreme values* approach, sometimes also referred to as *extreme value theory*, has become much more pronounced than the *Black Swan* approach.

With regards to the determination of increases or decreases in the probability of extreme events, we adopt a semi-parametric approach, often denoted as the *Cox* model with time-varying co-variates. The remainder of this section is dedicated to elaborating and explaining on the study's main theoretical and methodological features.

The duration data approach is a methodological approach that concentrates on investigating, and estimating, the time (units) to particular events occurring. Time is examined through the lens of *time spells*. Time spells' duration and survival estimation focuses on predicting the survival time of each observation in the dataset. In that sense, survival functions and time spells define the entrance to a particular time "window" of events, i.e. extreme stock returns. Thus, time spells actually consist of the criteria for a particular state of the variable upon examination.

1.2.1 Defining the Survival Function

Klein and Moeschberger (2005) denote the survival function notion in the following way. The distribution of time T, that is the time to the event upon examination is identified by a function. The latter function reflects the probability of a (time series) observation to survive beyond a time point $t \leq T$, or the probability of entering another "state" and, thus, to exhibit the characteristics of the event criteria. Hence, t defines the shift between the two different "states" (in our cases extreme or non-extreme values of stock returns). Such a probability is defined as a function of the following form:

$$S(t) = Pr(T > t) \tag{1.1}$$

A strict inequality governs the probability of surviving, as only part of the time series observations may be eligible for entering a different "state", and, thus not surviving beyond t . The observations that do not survive beyond a particular time point t are called censored observations.

As elaborated in Klein and Moeschberger (2005), the survival function is nothing else than the complement of the cumulative distribution function

$$S(t) = 1 - F(t) \tag{1.2}$$

and, consequently the

$$\int_t^{\infty} f(u)\, du$$

With continuous T, $S(t)$ is also continuous and a strictly decreasing function. The survival probability is 1 in the beginning ($t = 0$) and decreases with time elapse (increasing time towards infinity). In financial practice, and thus, with regards to stock returns, we do, though, deal with discrete time T, as extreme events in stock prices can be observed once per day (our stock prices frequency). The survival function in this case is formulated as follows: let t_i such that $i = 1, 2, 3, ...$ take only discrete values. The probability of observing an extreme event is then:

$$p(t_i) = Pr(T = t_i), i = 1, 2, 3, ... \tag{1.3}$$

such that $t_1 < t_2 < t_3 < ....$ Then,

$$S(t) = Pr(T > t) = \sum_{t_i > x} p(t_i) \tag{1.4}$$

1.2.2 The Hazard Function

Kiefer (1988) shows that the hazard function (hazard rate) expresses, at each time point, the probability of experiencing an event, in the next time unit (day). This probability is conditional to the fact that the event has not occurred up to the time point of reference. The hazard function is, thus, as follows:

$$h(t) = \lim_{Dt \to 0} \frac{P(t \leq T < t + Dt | T \geq t}{Dt} \tag{1.5}$$

where Dt reflects a very small increase in time. Accordingly, in the discrete case of time units (that is our case, days), the cumulative hazard function corresponds to the sum of all discrete time units t_i hazard functions:

$$H(t) = \sum_{t_i \leq T} h(t_i) \tag{1.6}$$

1.2.3 Nelson-Allen non-parametric survival and hazard function estimator

Our selected measure for the non-parametric estimation of the cumulative hazard function is the Nelson-Allen estimator, as presented in Klein and Moeschberger (2005).

$$\hat{S}(t) = \sum_{t_i \leq t}^{\infty} \left(1 - \frac{d_i}{y_i}\right); t_i \leq t \tag{1.7}$$

where d_i corresponds to the extreme event occurrence (if the event occurs, then $d_{=}1$). The variable y_i indicates the number of observations at risk in industry at time t_i, that is, the number of observations that have not yet experienced an extreme event. If $t_1 \leq t$ does not hold, the cumulative hazard before the first observation is 0. Moreover, from the relationship

$$-\ln \hat{S}(t) = \hat{H}(t) \tag{1.8}$$

we derive an equivalence between the survival and hazard function, relative to the Nelson-Allen estimator:

$$\hat{S}(t) = -exp\hat{H}(t) \tag{1.9}$$

Hypothesis 1 : What is of interest in our dataset and approach is to examine whether there are any industry (ICB) sector differences, with respect to the survival and hazard estimations. In other words, we want to test the following hypothesis set:

Null hypothesis: $h_1(t) = h_2(t) = h_2(t) = ... = h_k(t)$ for all $t \leq T$

Alternative hypothesis: At least one $h_j(t)$ differs for one or more $t \leq T$

According to Klein and Moeschberger (2005) the hypothesis above is tested by the test function

$$Z_j(t) = \sum_{i=1}^{D} W_j(t_i) \left(\frac{d_{i,j}}{Y_{i,j}} - \frac{d_i}{Y_i} \right); j = 1, ...K \tag{1.10}$$

where $W_j(t_i)$ is the corresponding weight per industry j (ICB) sector. A simpler, though, test function is used, indicating that weights are identical across sectors: $W_j(t_i) = W(t_i) \cdot Y_{i,j}$. The variable $Y_{i,j}$ indicates the number of observations at risk in industry j at the time t_i. Thus (1.11) is reformulated as:

$$Z_j(t) = \sum_{i=1}^{D} W(t_i) \left(d_{i,j} - Y_{i,j} \left(\frac{d_i}{Y_i} \right) \right); J = 1, ...K \tag{1.11}$$

Hypothesis 2: We rely on the log-rank test of function 1.11 for inference. The log-rank test simple *hypothesis*, assumes that all time units exhibit equal weights, that is $W(t) = 1$. The latter hypothesis is a main starting point that renders the test ideal when rates in all industry sectors are proportional.

1.2.4 The Cox Proportional Hazards (PH) model

The Cox Proportional Hazards model (Cox, 1972) accounts for the case where the differentiation variable, relative to survival rates, does not solely relate to the industry sector. Sticking with the notations of Klein and Moeschberger (2005), the time t_j, denotes the time during which an observation has been inside a time spell. Also, as already mentioned, d_j reflects extreme event occurrence ($d_j = 1$), and $Z_j(t)$ is a vector of the $k = 1, ..., p$ observed co-variates for observation j, at time t [1]. We then derive the hazard rate

$$h(t|Z) = h_0(t)c(b^t Z) \tag{1.12}$$

at time t, and, Z the co-variate vector ($h_0(t)$ is the baseline hazard). What renders the Proportional Hazard (PH) model semi-parametric, is actually the fact that it allows for ignorance of the actual distribution of the survival (Kiefer, 1988) [2].

A commonly chosen function for $c(b^t Z)$ is the exponential

$$c(b^t Z) = exp(b^t Z) \tag{1.13}$$

where b^t denotes the coefficient of the co-variates Z. The function above (1.13), actually consists of

$$b_t(Z) = b_1(Z_1) + b_2(Z_2) + b_3(Z_3) + ... + b_p(Z_p) = \sum_{k=1}^{p} b_k(Z_k) \tag{1.14}$$

and can be rewritten as

$$h(t|Z) = h_0(t)exp(b^t Z) = h_0(t)exp\left(\sum_{k=1}^{p} b_k(Z_k)\right) \tag{1.15}$$

According to Klein and Moeschberger (2005), the so-called *hazard rate* reflects the differences in hazards (of experiencing an extreme event occurring), between two observations with different co-variate values, and is defined as

$$\frac{h(t|Z)}{h(t|Z^*)} = \frac{h_0(t)exp\left(\sum_{k=1}^{p} b_k(Z_k)\right)}{h_0(t)exp\left(\sum_{k=1}^{p} b_k(Z_k^*)\right)} = exp\left(\sum_{k=1}^{p}(Z_k - Z_k^*)\right) \tag{1.16}$$

[1] We let $Z_j(t) = Zj$

[2] By formulating different baseline hazard specifications $h_0(t)$ one derives various other models, eg. exponential or Weibull models

$$\frac{h(t|Z)}{h(t|Z^{*})} = exp(b_1) \tag{1.17}$$

Hypothesis 3: The Proportional Hazard, thus, expresses the ratio of the two differing hazards, where Z and Z^{*} are the sets of co-variates for the first and second observations, respectively. The key *hypothesis* of the Cox Proportional Hazards model, that we also test in our study, is exactly the proportionality of the hazards. That is, the main *hypothesis* of the Cox Proportional Hazards model assumes *constant hazard rate.* The simplest case of proportional hazards is of the form:

$$exp(b_1) = \frac{h(t|Z)}{h(t|Z*)} \tag{1.18}$$

where $exp(b_1)$ reflects the risk of an extreme event occurring, conditional upon one observation having experienced an extreme event.

Regressors whose values change over the course of spells are conceptually straightforward to handle in the hazard function framework. Suppose the co-variates z_j is a function of time, $z_j(t)$, where t is measured from the beginning of the spell. The integrated hazard, survivor, and density functions will depend on the entire time path (up to t) of the co-variate. With hazard $h(t, z_j(t), Z)$,

$$H(t, Z) = \int_0^t h\,(u, z(u), Z)\, \mathrm{d}u \tag{1.19}$$

The values of b (coefficients), are then estimated in the absence of ties in the time to event, by partial maximum likelihood estimation. The log likelihood function is

$$L(Z) = \sum_{j=1}^{n} d_j(h(t_j, z_j(t_j), Z)) - \sum_{j=1}^{n} \int_0^{t_j} h(u, z_j(u), Z)\mathrm{d}u \tag{1.20}$$

Most frequently co-variates change over a few times over the spell, and thus the integral is usually the sum of small number of terms.

1.3 Results

The structure of the results follows the standard paradigm. First, we discuss the estimates based on the Nelson-Allen (or Allen) method. Then, we examine the results from fitting the Cox model with time-varying co-variates. Finally, we present the Schoenfeld residuals diagnostics (Schoenfeld, 1982) and test proportional hazards (PH) assumption, namely *Hypothesis 3*.

1.3.1 Nelson-Allen estimates

Figure 1.1 depicts the results from applying the Nelson-Allen non-parametric method, and estimating the survival function of the durations of time spells, without a Black Swan (positive or negative). As it can be seen in Figure 1.1, the survival curve declines smoothly, as time elapses. However, the Nelson-Allen estimated survival function is not by itself entirely informative. Survival curves actually become much more informative when contrasted against one another. Since we examine the S&P500 stock index with all its constituents, in our setup such a comparison is reasonable across industries and sectors. The latter rationale is the rationale behind our *Hypothesis 1*. We partly test *Hypothesis 1* by comparing the survival curves of each industry against all other industries. Figure 1.2 provides preliminary support to confirm our *Hypothesis 1*, as it cites the aforementioned Nelson-Allen survival curves comparison. Each industry is identified by the globally utilised standard for categorising and comparing companies by industry and sector, namely the Industry Classification Benchmark (ICB). The result of the Nelson-Allen survival functions graphical comparison is of particular interest. Graphs show that, with the exception of only a few industries, the survival curves seem identical. Even for those industries that, at first sight seem graphically different, the confidence intervals overlap substantially. We do not depict in detail confidence intervals, in order not to clutter our graphical depictions. The Nelson-Allen non-parametric estimation results, thus, implies that an analysis on the aggregate level is highly likely to hold for each component, as well.

In our study we are interested to tract and report modelling results for all types of extreme events, that is for both negative and positive Black Swans. Thus, we also conduct a comparison in the non-parametric level that distinguishes between the latter two types of extreme events. An interesting pattern emerges from such a comparison as illustrated in Figure 1.3. Indeed, it is noticeable that the survival curve of positive Black Swans is much lower than that of the negative ones. This result seems to be in perfect alignment with the fact that the overall number of negative Black Swans, in the raw stock returns, is three times as large as that of positive

Black Swans, in particular 690 out of a total of 2022. The difference seems to be rather striking, especially for Black Swans that take place within a 10-year period since the last extreme event.

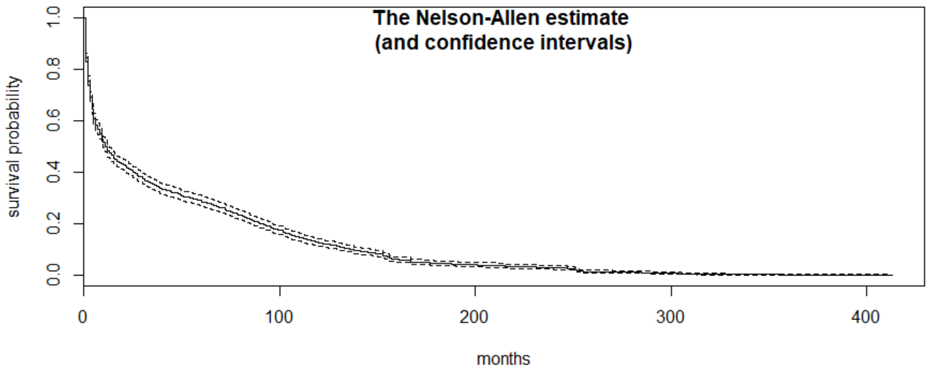


Figure 1.1: The survival curve for all Black Swan events

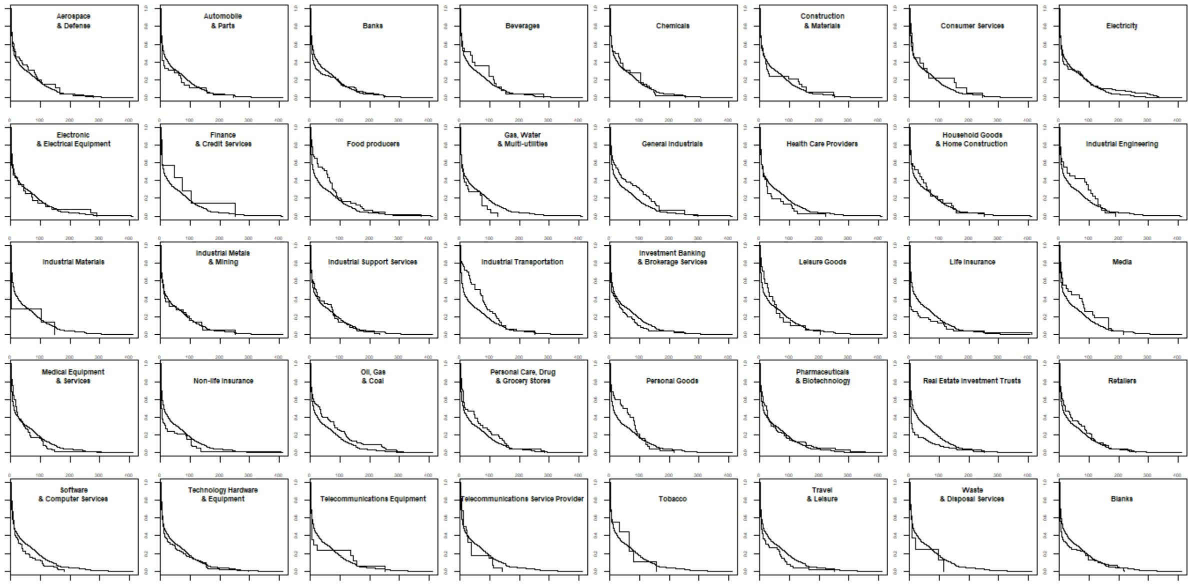


Figure 1.2: The Nelson—Allen survival curves of each industry against that of all other industries

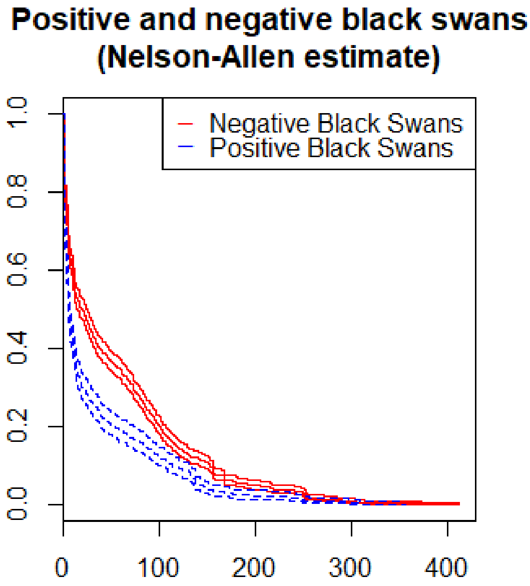


Figure 1.3: The survival curves of positive and negative Black Swans

1.3.2 Cox estimates with time-varying co-variates

This study formulates a single main model specification, that applies to all firms and sectors. Auxiliary regressions, that also include a frailty factor (one for each variable of the specification), are also conducted. The objective of running the latter regressions is to show that the results of the main model are robust. Moreover, further in the analysis, we control for firm specific effects. We find this important for two reasons. First, for the purpose of ensuring a large number of events. Second, because it is practically impossible to account for all the Black Swans in all possible portfolios. Moreover, it enables us to aggregate our results in order to talk about the sectoral properties of Black Swan runs.

Table 1.2 contains the Cox estimates for the benchmark model with the seven co-variates.

As already defined and presented in equation (1.15), our semi-parametric Cox model comprises of a linear regression of the logarithm of the hazard, on the set of financial and macroeconomic co-variates, that we choose for modelling time spells durations. The baseline hazard in this case works as the time-varying intercept term, and the specification for the benchmark model is:

Table 1.2: Cox coefficient estimates and test statistics of fitting the benchmark model

Based on 1137 events (63475 observations after removing missing observations), with Concordance 0.724 (Std.Error 0.009), Likelihood Ratio Test 787.9 (p-value ≤ 0.001), Wald test 804.3 (p-value ≤ 0.001), Score (logrank) test 853.5 (p-value ≤ 0.001). Standard errors are reported in parentheses and statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Cox Estimation Results					
	Coeff.	Expected Coef.	Std.Err.(Coef.)	z	$Pr(>\|z\|)$
Stock Returns	-3.10^{***}	0.05	0.24	-13	< 0.0001
Price-to-book value	0.002^{*}	1.002	0.001	1.72	0.085
Dividend Yield	0.17^{**}	1.19	0.08	2.14	0.033
Price-to-earnings	-0.19^{*}	0.83	0.11	-1.65	0.098
Industrial Production	-83.32^{***}	< 0.0001	6.43	-12.95	< 0.0001
Federal Funds Rate	-0.16^{***}	0.86	0.01	-14.1	< 0.0001
Inflation	0.85^{***}	2.35	0.16	5.3	< 0.0001

$$\begin{aligned} h(t|Z) = h_0(t) \cdot exp(b_1 \cdot \text{STOCK RETURNS}_{i,t} + b_2 \cdot \text{PRICE-TO-BOOK VALUE}_{i,t} \\ + b_3 \cdot \text{DIV YIELD}_{i,t} + b_4 \cdot \text{PRICE-TO-EARNINGS}_{i,t} \\ + b_5 \cdot \text{IND PROD}_{i,t} + b_6 \cdot \text{FED FUNDS RATE}_{i,t} + b_7 \cdot \text{INFLATION}_{i,t} \end{aligned} \tag{1.21}$$

where, i corresponds to each constituent share in the $S\&P500$ and t in the consecutive time points of each co-variate series.

Cox estimates for the benchmark model show that all variables are statistically significant, although, the price-equity ratio and price-earnings ratio are significant at the 10% significance level, and the dividend yield at 5%. What is particularly interesting is that the higher a firm's share value (price-earnings ratio) the less imminent becomes the appearance of a Black Swan. We interpret this result as a concrete indication that, overvaluation of stocks or an revision of investors' expectations of high growth rates in the future, reflected into rising price-earnings ratios, decrease the probability of extreme events. Moreover, real output and federal funds overnight rate (US Industrial Production and US Federal Funds Rate), respectively, also significantly impact the probability of an extreme event occurring. In line with theory, real output seems to significantly capture the negative feedback loop between increased (decreased) household wealth, consequent increased (decreased) consumption spending and the equivalent reflections in asset prices. Similarly, the Cox estimates feature the ripple effect of changes in the price of credit on earnings and stock prices, as reflected in the U.S. Federal Funds rate. Contrary, the signs of the coefficients of the price-to-book value, the dividend yield and inflation suggest the exact opposite;

the larger they are the higher the probability of a Black Swan. The dividend yield coefficient indicates that the return of a stock investment that may drive future extreme stock returns, might not be only dividend related. Also, contrary to real output estimation results, inflation does not seem to capture the feedback loop between household spending and stock returns under decreased purchasing power in the economy.

These first estimation results though, do not distinguish between positive and negative Black Swans. We do conduct similar Cox estimates with the same time-varying co-variates by adding the relevant dummy variable and the corresponding interaction terms:

$$
\begin{aligned}
h(t|Z) = h_0(t) \cdot exp(&b_1 \cdot \text{STOCK RETURNS}_{i,t} + b_2 \cdot \text{PRICE-TO-BOOK VALUE}_{i,t} + b_3 \cdot \text{DIV YIELD}_{i,t} \\
&+ b_4 \cdot \text{PRICE-TO-EARNINGS}_{i,t} + b_5 \cdot \text{IND PROD}_{i,t} + b_6 \cdot \text{FED FUNDS RATE}_{i,t} \\
&+ b_7 \cdot \text{INFLATION}_{i,t} + b_8 \cdot \text{POSITIVE BS}_{i,t} \\
&+ b_9 \cdot \text{POSITIVE BS}_{i,t} * \text{STOCK RETURNS}_{i,t} + b_{10} \cdot \text{POSITIVE BS}_{i,t} * \text{PRICE-TO-BOOK VALUE} \\
&+ b_{11} \cdot \text{POSITIVE BS}_{i,t} * \text{DIV YIELD}_{i,t} + b_{12} \cdot \text{PRICE-TO-EARNINGS}_{i,t} * \text{STOCK RETURNS}_{i,t} \\
&+ b_{13} \cdot \text{POSITIVE BS}_{i,t} * \text{INDUS PROD}_{i,t} + b_{14} \cdot \text{POSITIVE BS}_{i,t} * \text{FED FUNDS RATE}_{i,t} \\
&+ b_{15} \cdot \text{POSITIVE BS}_{i,t} * \text{INFLATION}_{i,t})
\end{aligned}
\tag{1.22}
$$

As it can be seen in Table 1.3, the distinction between positive and negative Black Swans is very important. Indeed the respective dummy variable (DummyPos Black Swan) is statistically significant and positive. The positive significant effect of the dummy on positive extreme events effectively captures our results of the Nelson-Allen non-parametric estimates, discussed in Section 1.3.1. The nature and significance of the dummy estimates confirms, thus, the fact that the number of months until a next positive Black Swan is estimated to be less than the number of months until a next negative Black Swan. This result supports that, not only are extremely high stock returns less frequent than extremely low stock returns, but also that, on average, the elapsed time (months) until extreme high prices is much more than time (months) until extreme returns' downfall.

The least significant coefficients in Table 1.2 do not have an impact on the average duration of a spell without a negative Black Swan, in the dummy Cox estimates. They are though statistically significant for the survival curves of the positive Black Swans. In particular, price-to-book value shortens the duration of a spell without a positive Black Swan. Also, a firm's share (relative) value, that is price-earnings ratio, shortens such a spell. Cox estimates suggest that, higher price-to-book value ratios, indicating that an investor might be paying too much relative to the remainder share value, seem to have a significant impact on stabilising prices. Also, relative to the benchmark model, the qualitative nature of investors' expectations on stock returns becomes apparent in the dummy Cox estimates. That is, the price-earnings ratio, initially shown to impact the imminence of extreme events, may be summarised into investors' expectations of high future growth rates. The latter expectations propagate in the stock prices and render highly extreme returns more frequent, that is, shorten the duration of a spell without a positive Black Swan.

Table 1.3: Cox coefficient estimates and test statistics of fitting the benchmark model with a dummy variable distinction, between positive and negative Black Swans

Based on 1137 events (63475 observations after removing missing observations) with Concordance 0.742 (Std.Error 0.009), Likelihood ratio test 858.4 (p-value ≤ 0.001), Wald test 875 (p-value ≤ 0.001), Score (logrank) test 943.7 (p-value ≤ 0.001). Standard errors are reported in parentheses and statistical significance is indicated as follows: *** $p < 0.01,^{**}$ $p < 0.05,^{*}$ $p < 0.10$.

Cox Estimation Results					
	Coeff.	Expected Coeff.	Std.Error(Coeff.)	z	$Pr(>\|z\|)$
(1) Stock Returns	-3.36^{***}	0.03	0.28	-12	< 0.0001
(2) Price-to-book value	0.002	1.002	0.001	1.20	0.23
(3) Dividend Yield	0.11	1.11	0.09	1.16	0.25
(4) Price-to-earnings	0.04	1.05	0.13	0.35	0.73
(5) Industrial Production	-81.84^{***}	0.00	7.33	-11.17	< 0.0001
(6) Federal Funds Rate	-0.19^{***}	0.83	0.01	-13.3	< 0.0001
(7) Inflation	1.05^{***}	2.85	0.19	5.5	< 0.0001
(8) DummyPos Black Swan	1.02^{***}	2.77	0.36	3	0.005
(9) Stock Returns*DummyPos Black Swan	0.910^{**}	2.483	0.372	2.44	0.01
(10) Price-to-book value*DummyPos Black Swan	0.01^{***}	1.01	0.00	4.00	< 0.0001
(11) Dividend Yield*DummyPos Black Swan	0.28	1.32	0.18	1.51	0.13
(12) Price-to-earnings*DummyPos Black Swan	-0.79^{***}	0.45	0.26	-3.02	0.003
(13) Industrial Production*DummyPos Black Swan	-0.43	0.65	13.91	0.0	0.98
(14) Federal Funds Rate*DummyPos Black Swan	0.07^{***}	1.07	0.02	2.9	0.003
(15) Inflation*DummyPos Black Swan	-0.64^{*}	0.53	0.35	-2	0.07

Similarly, higher real output and federal funds rate lengthen the duration of a spell without a negative Black Swan, rendering thus extreme stock price downfalls less frequent. An immediate reaction of the stock market to increased interest rates is, thus, suggested in the Cox model as a key aspect of the probability of extreme downfalls. As credit becomes more expensive and leads to cuts in consumption goods spending levels, the duration of a spell without a negative Black Swan lengthens significantly. The fact, though, that higher real output captures a negative feedback loop in stock returns in line with the theoretical prediction, may suggest that the rate by which output growth accumulates, and reflects on asset prices, is much higher.

1.3.3 Testing the Proportional Hazards (PH) assumption

As elaborated in Section 1.2, testing whether heterogeneity would affect the proportional hazards (PH) assumption, is commonly done graphically with the so-called Schoenfeld residuals. Schoenfeld (1982) proposed a definition of residuals for use with Cox proportional hazards regressions. These residuals are calculated for each co-variate, for completed spells only, and are based on contributions to the risk score of each observation. The latter risk score is nothing else than the hazard specification of equation (1.16). According to Therneau and Grambsch (2000), an indicator function $Y_j(t)$ is defined, according to which $Y_j(t) = 1$ if observation j is considered to be under risk, and 0 if not. Then at k_{t_h} event time the Schoenfeld residual is defined as

$$s(k) = Z_k - \frac{\sum_j^p Y_j(t_k) \cdot c_j(t_k) \cdot Z_j(t_k)}{\sum_j^p Y_j(t_k) \cdot c_i(t_k)} \tag{1.23}$$

$$s(k) = Z_k - \tilde{z}(\hat{b}, t_k) \tag{1.24}$$

Z_k is the co-variate vector of the observation experiencing an extreme event at time k, $\hat{b}$ is the estimate of b by maximising the partial likelihood function, and $\tilde{z}(\hat{b}, t_k)$ a weighted average of the estimated hazards of the co-variate values, for all units at risk at time k. he residual is then the co-variate value, minus the expected co-variate value at the time of the particular extreme event. Testing the time-varying regressors, corresponds to a similar test for a non-zero slope in a linear regression of the scaled Schoenfeld residuals. As non-proportionality may take forms that cannot be detected by non-zero slope tests alone, between the residuals and time, (e.g. quadratic relationships), we look at the residual graphs for evidence on a specific pattern that may indicate such a relationship. When plotted, these residuals should be straight horizontal lines.

This theoretical prediction translated into specific expected graphical evidence by the Schoenfeld (1982) method, consists of our *Hypothesis 3.* That is, the latter hypothesis is graphically tested in the Schoenfeld residuals graphs representations. We, thus, plot and infer on the Schoenfeld residuals and whether they exhibit a lack of a pattern. If indeed no pattern is apparent, i.e. a best-fit line is horizontal, then we have support to confirm our *Hypothesis 3* ; otherwise, we reject the Proportional Hazards assumption.

Figures 1.4 1.5 1.6 1.7 1.8 1.9 1.10 depict the Schoenfeld residuals for each co-variate we deploy in our model. Graphical representations show clearly that the theoretical prediction on the proportionality of the hazards cannot be rejected. More precisely, there is very little evidence to reject the proportional hazards (PH) assumption, and thus **Hypothesis 3**. Overall, we find that the ratio of the two differing hazards remains constant over time.

We robustify our analysis against the possibility of a dependency structure. A typical approach to robustify a survival analysis against the potentially correlated outcomes of a group of observations, is to include a random effects term in the model specification (Therneau, Grambsch, and Pankratz, 2003). The latter terms are known as *frailty* Gaussian terms. These terms are effectively treated in the same way as any other control variable, and the ensuing analysis (e.g. looking at the Schoenfeld residuals) is identical. We provide graphical representations for all the fifteen (15) benchmark model constituents when adding such a 'frailty' Gaussian term for each co-variate respectively, in the Appendix.

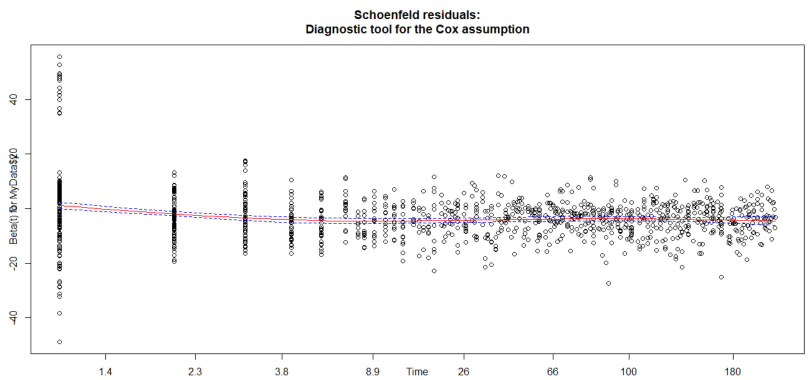


Figure 1.4: Schoenfeld residuals for Stock Returns

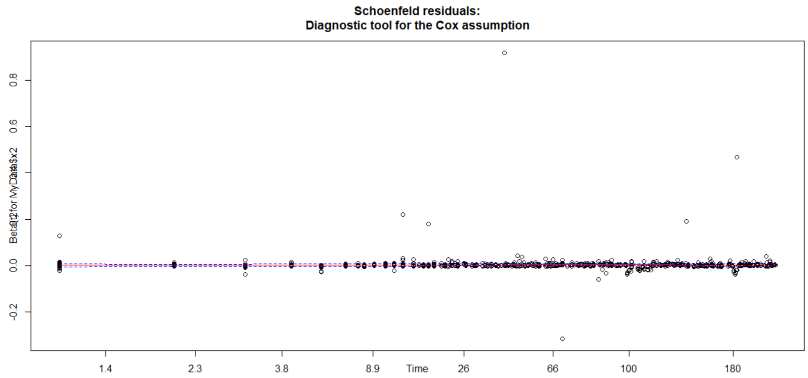


Figure 1.5: Schoenfeld residuals for Price-to-Book value co-variate

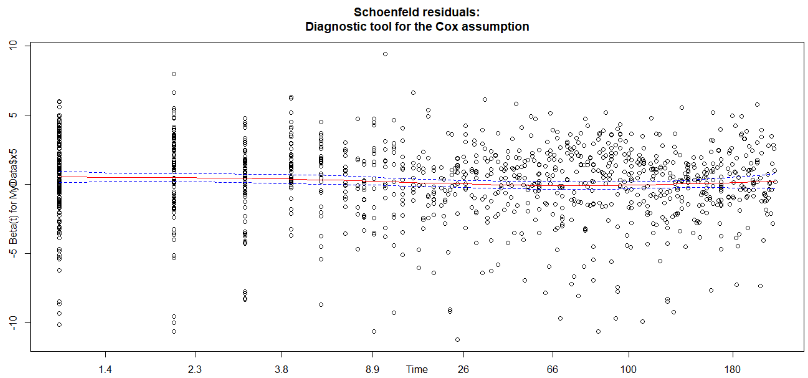


Figure 1.6: Schoenfeld residuals for Dividend Yield co-variate

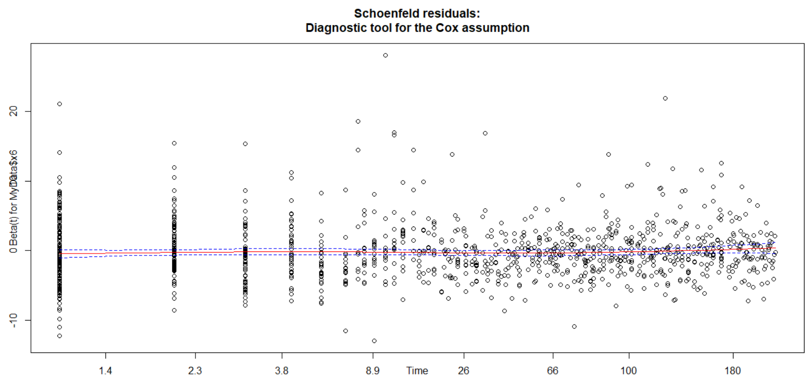


Figure 1.7: Schoenfeld residuals for Price-to-Earnings ratio co-variate

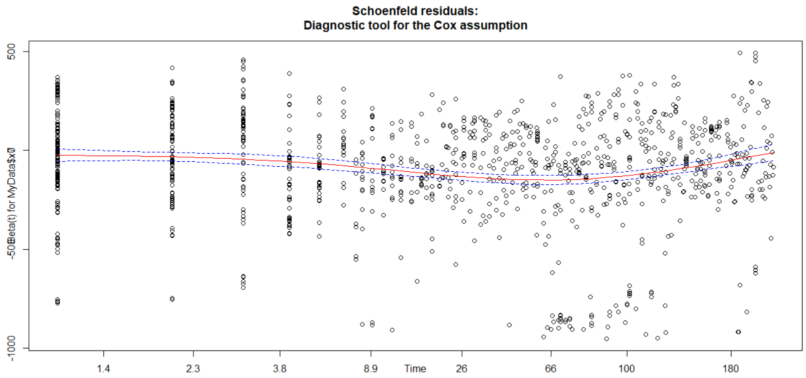


Figure 1.8: Schoenfeld residuals for U.S. Industrial Production co-variate

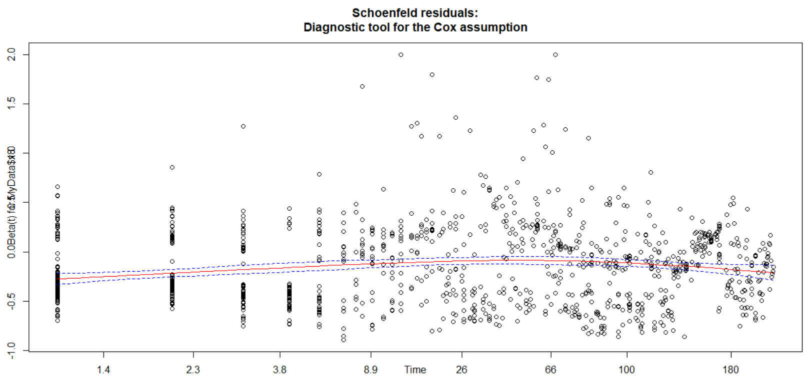


Figure 1.9: Schoenfeld residuals for U.S. Federal Funds Rate co-variate

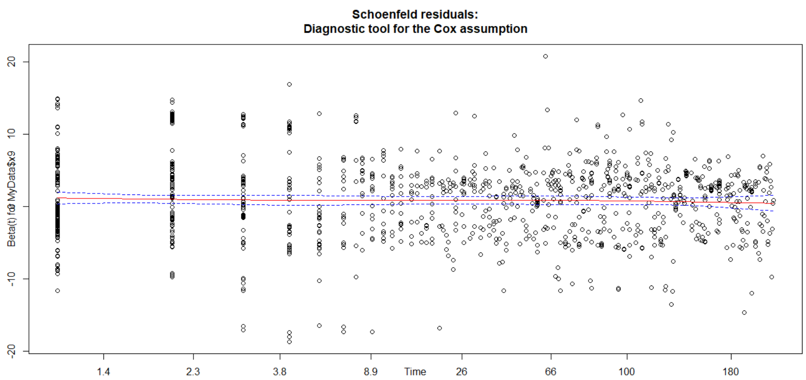


Figure 1.10: Schoenfeld residuals for U.S. PCE Inflation co-variate

1.4 Conclusion

In this study we have modelled extreme events' episodes, namely, Black Swans, using duration and survival analysis tools. We have deployed a time-varying set of data, that comprises of the largest historical time path of all stocks of the S&P500 stock market index. We chose and applied a set of key financial and macroeconomic variables based on existing literature on tail risk and early warning systems. We conducted the corresponding empirical exercise with a twofold objective: to test the predictability of existing literature prominent indicators relative to future extreme market events, and to infer on the qualitative nature of estimation results.

Among financial indicators, investors' expectations on future growth rates of stocks, as reflected in price-to-earnings ratios, seem to trigger a propagation mechanism with regards to the probability of extremely high stock returns. Also, at times where investors face higher costs of (stock) ownership relatively to the intrinsic value, stock prices seem to stabilise at rather moderate levels for longer time periods. In addition, an interestingly insignificant pattern is observed relative to the price-to-dividend ratio. In particular, the lack of impact of the dividend yield in the probability of future extreme stock prices realisation, when we distinguish between high increases and downfalls, suggests that the dividend-only return on investment may not be the main return on investment key driving force of future asset prices. Potentially, other types of return on investment such as shares of stocks and cash payments, more closely tied to financial liquidity levels, may have a stronger impact on extreme stock returns upturns and downturns.

Overall, the comprehensive framework that emerges from duration data analysis and from Cox time-varying co-variates' estimates, incorporates a mix of key financial performance and macroeconomic environment indicators. The fact that a qualitatively mix of factors exhibits high predictive power for future extreme events, implies that, understanding time-varying tail risk remains a constant feedback mechanism between main macroeconomic forces and investors' information, and evaluation of stock fundamentals.

We view our duration modelling approach, as one that may find implications in investment strategy formulation. In particular, by knowing which variable, and to what extent, helps us determine the time until the next Black Swan (extreme event), an investor is able to change accordingly their investment strategy. The investment strategy, depending on the market efficiency assumption adopted, can range from devising trading strategies to pursue abnormal profits, to hedging accordingly against the respective tail risk. We also see a potential for separately modelling time to extreme events, and the related hazards and Cox estimates, solely with regards to the 2008/2009 global financial crisis. We consider this particular crisis separately, as it would require segmenting the sample in the era before and after the 2008/2009 crisis, in order to infer on the differences. We view, thus, this particular time period as a special time frame for duration modelling, that certainly is worth exploring in future research.

Appendix

1.A Figures for Chapter 1

The graphs that follow, complement section 1.3.3 and robustify our survival analysis against potentially correlated outcomes of our specification. As we model and analyse panel data from all constituent shares in S&P500 across time, we wish to provide additional evidence for testing the Proportional Hazards (PH) assumption. We have already plotted and graphically tested the PH assumption for the benchmark model in the latter section. We recall at this point, that, in order to test whether the ratio of hazards between two observations with different co-variate values is constant, we plot and check the Schoenfeld residuals; that is we plot and check the differences between the co-variate value and the expected co-variate value, at the time of the extreme event [1] We take the analysis one step further: we control for potential correlations stemming from observations of the same groups (co-variates) across consecutive time points. We achieve control against the latter dependency structure, by estimating our model with interactions, and adding a random effect term for each co-variate. We then plot and check the corresponding Schoenfeld residuals for each co-variate, per dependency structure, and infer on the validity of the Proportional Hazards assumption. The random effect term is also known as "frailty" Gaussian term. The estimated "frailty" model is of the following form:

[1] We also mention again here that we identify extreme events (positive and negative) in stock returns data.

$$
\begin{aligned}
h(t|Z) = u_{i,t} \cdot h_0(t) \cdot exp(& b_1 \cdot \text{STOCK RETURNS}_{i,t} + b_2 \cdot \text{PRICE-TO-BOOK VALUE}_{i,t} + b_3 \cdot \text{DIV YIELD}_{i,t} \\
& + b_4 \cdot \text{PRICE-TO-EARNINGS}_{i,t} + b_5 \cdot \text{IND PROD}_{i,t} + b_6 \cdot \text{FED FUNDS RATE}_{i,t} \\
& + b_7 \cdot \text{INFLATION}_{i,t} + b_8 \cdot \text{POSITIVE BS}_{i,t} \\
& + b_9 \cdot \text{POSITIVE BS}_{i,t} * \text{STOCK RETURNS}_{i,t} + b_{10} \cdot \text{POSITIVE BS}_{i,t} * \text{PRICE-TO-BOOK VALUE} \\
& + b_{11} \cdot \text{POSITIVE BS}_{i,t} * \text{DIV YIELD}_{i,t} + b_{12} \cdot \text{PRICE-TO-EARNINGS}_{i,t} * \text{STOCK RETURNS}_{i,t} \\
& + b_{13} \cdot \text{POSITIVE BS}_{i,t} * \text{INDUS PROD}_{i,t} + b_{14} \cdot \text{POSITIVE BS}_{i,t} * \text{FED FUNDS RATE}_{i,t} \\
& + b_{15} \cdot \text{POSITIVE BS}_{i,t} * \text{INFLATION}_{i,t}) \\
& u_{i,t} \sim N(0, \sigma_u^2)
\end{aligned}
\tag{1.25}
$$

where u refers to the "frailty" (random effect) term derived from each co-variate, i to the various constituent shares of S&P500 and t to the consecutive time points of each co-variate series.

Figure 1.A.1 depicts the differences between the stock returns' values and expected stock returns' values at the particular time points of extreme events (extreme stock returns), when we control for potential correlation in stock returns time series' observations. The absence of a trend in the differences' graphical representation (that is, in the corresponding Schoenfeld residuals of stock returns) confirms the validity of *Hypothesis 3* (the Proportional Hazards (PH) assumption). We, thus, conjecture that the PH assumption holds and that the hazard rate (risk score) for stock returns' values (realisations) is constant. Figure 1.A.2 shows the differences between observed and expected price-to-book value realisations, at the time points when extreme stock returns occur, and when we control for correlation in stock returns' time series values. The trending line is horizontal, confirming that price-to-book value's differing hazards (risk score) remains invariant over time. Figure 1.A.3 presents Schoenfeld residuals for dividend yield values, at times of extreme stock returns and when we account for random effects of the latter. The graphical representation provides no evidence for violation of the PH assumption (*Hypothesis 3*). Hence, it allows us to conclude that, the risk score for the dividend yield also remains constant over timem when treating stock returns realisations as a potential source of heterogeneity. In Figure 1.A.4 we plot the differences accordingly, between the price-to-earnings values and expected price-to-earnings values, after controlling for potential correlated outcomes relative to stock returns. Again, we don't see graphical evidence claiming non-proportionality of the two hazard rates and we again

confirm *Hypothesis 3*. Figure 1.A.5 1.A.6 1.A.7 refer to the equivalent Schoenfeld residuals of the macroeconomic variables, when we include in the model a random effect term for potential stock returns' dependency structure. Neither of the three plotted residuals provide sufficient indication for questioning the PH assumption, and, consequently, we affirm that the risk score for the differences between the observed macroeconomic variables and their expected values, does not change over time (*Hypothesis 3* holds for the macroeconomic variables). In Figures 1.A.8 1.A.9 1.A.10 1.A.11 1.A.12 1.A.13 1.A.14 1.A.15, we show the corresponding Schoenfeld residuals for all the remaining terms of our estimated models. The latter terms, are terms that involve the interaction of each one of our co-variates with a dummy. The dummy indicates whether the extreme event used for identification is positive or negative. Similarly, to the preceding seven (7) figures, Figures 1.A.8 1.A.9 1.A.10 1.A.11 1.A.12 1.A.13 1.A.14 1.A.15 relate to random effects' estimation when controlling for potential correlation from the time series of stock returns in S&P500. The graphical depiction leads to the same conclusion: the risk score of an extreme even occurring is invariant over time and *Hypothesis 3* is confirmed for all remaining terms of our estimated models.

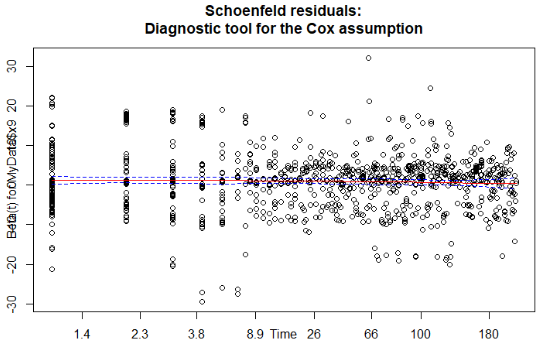


Figure 1.A.1: Gaussian frailty for Stock Returns- Schoenfeld Residuals for (1)

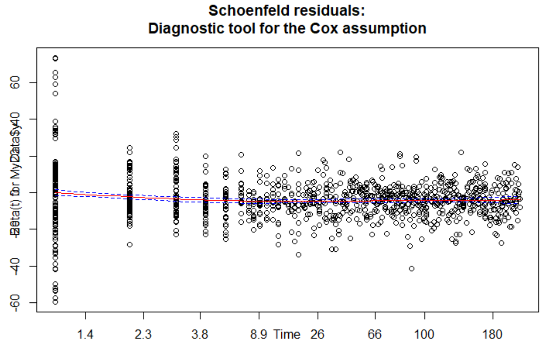


Figure 1.A.2: Gaussian frailty for Stock Returns- Schoenfeld Residuals for (2)

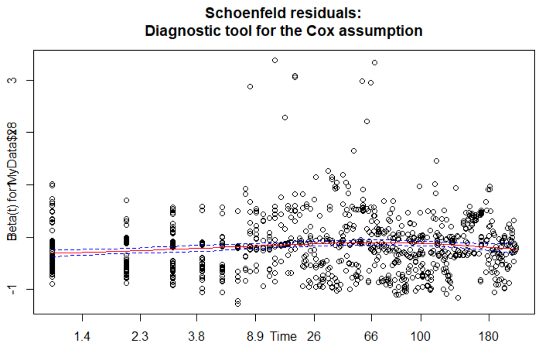


Figure 1.A.3: Gaussian frailty for Stock Returns- Schoenfeld Residuals for (3)

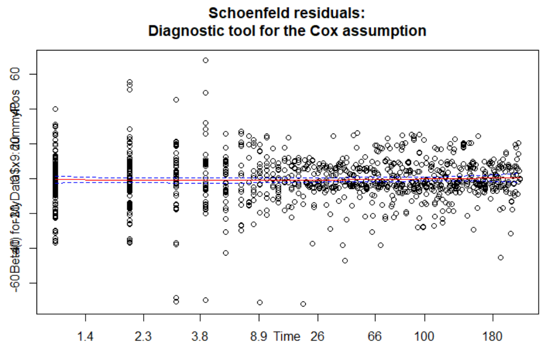


Figure 1.A.4: Gaussian frailty for Stock Returns- Schoenfeld Residuals for (4)

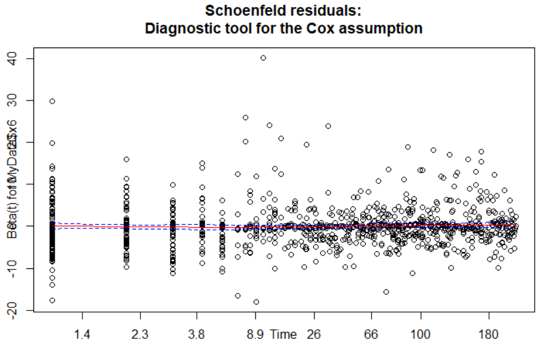


Figure 1.A.5: Gaussian frailty for Stock Returns- Schoenfeld Residuals for (5)

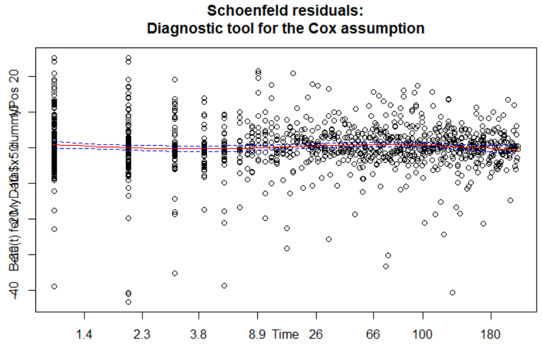


Figure 1.A.6: Gaussian frailty for Stock Returns- Schoenfeld Residuals for (6)

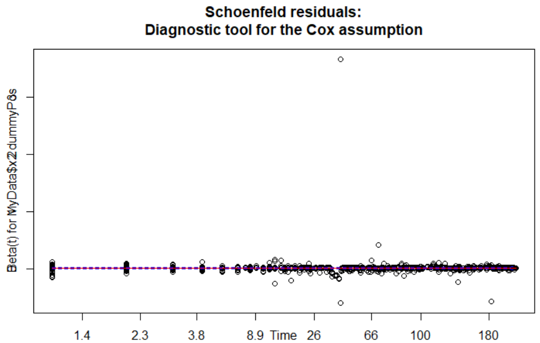


Figure 1.A.7: Gaussian frailty for Stock Returns- Schoenfeld Residuals for (7)

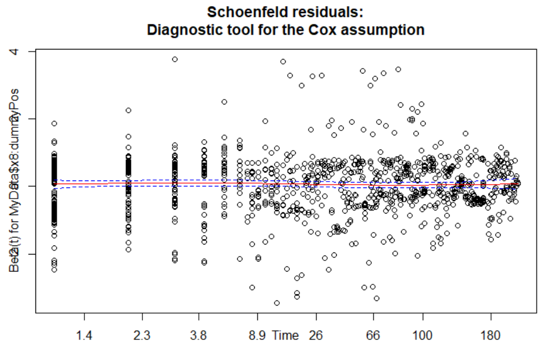


Figure 1.A.8: Gaussian frailty for Stock Returns- Schoenfeld Residuals for (8)

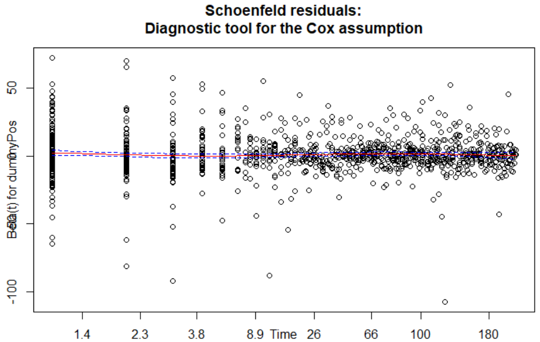


Figure 1.A.9: Gaussian frailty for Stock Returns- Schoenfeld Residuals for (9)

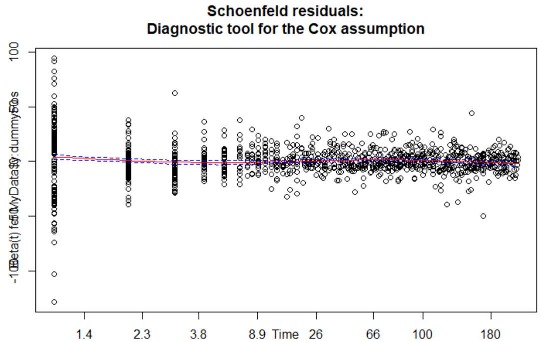


Figure 1.A.10: Gaussian frailty for Stock Returns- Schoenfeld Residuals for (10)

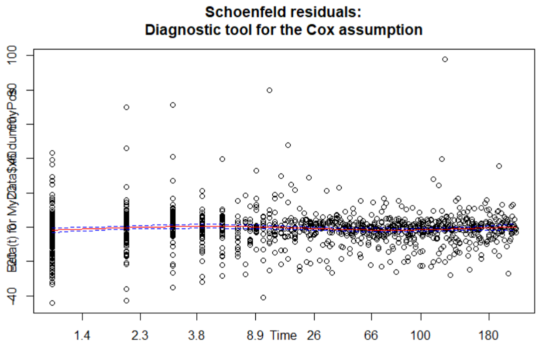


Figure 1.A.11: Gaussian frailty for Stock Returns- Schoenfeld Residuals for (11)

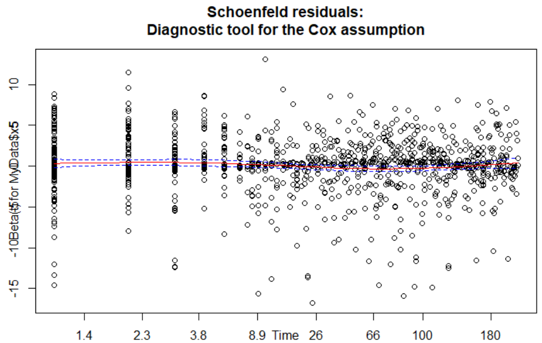


Figure 1.A.12: Gaussian frailty for Stock Returns- Schoenfeld Residuals for (12)

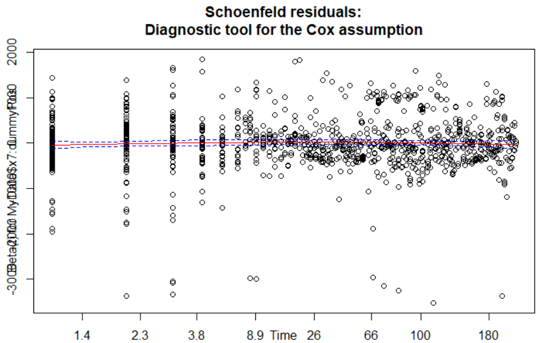


Figure 1.A.13: Gaussian frailty for Stock Returns- Schoenfeld Residuals for (13)

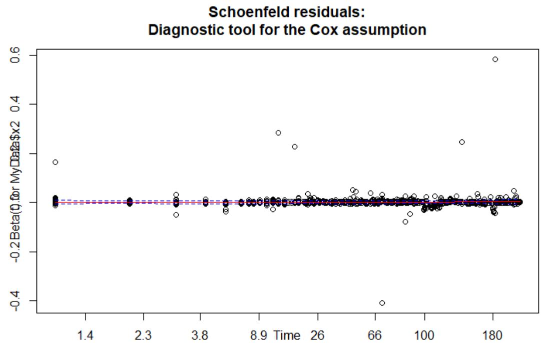


Figure 1.A.14: Gaussian frailty for Stock Returns- Schoenfeld Residuals for (14)

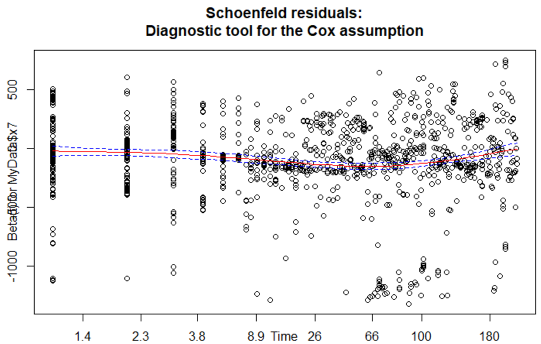


Figure 1.A.15: Gaussian frailty for Stock Returns- Schoenfeld Residuals for (15)

Chapter 2

Risk preferences in the laboratory: Isomorphic first-price auctions and the bomb risk elicitation task

2.1 Introduction

Economic and financial decision-making entails inherent levels of uncertainty about consumption, investment outcomes and, thus, optimal risky choice. In an attempt to unravel this uncertainty, economic agents are assumed to have stable risk preferences that, in theory, can be described by specific functional forms. However, uniform modelling of risk preferences, does not account for a critical, more realistic aspect, of risky behaviour: risky choice context dependence. It is mainly with recent experimental economics and finance research, that context dependence is brought into particular focus. A decision environment that satisfies properties of isomorphism is among the most reliable ones, for tracking such context dependence in risk behaviour. Isomorphism between two decision contexts, implies that the contexts' empirical values (choices) are simply the reverse mapping of one another. By consequence, isomorphic decision environments facilitate a theoretically valid, straightforward and concise comparison of risky choice.

This study, primarily attempts to investigate whether, identical risky choices and risk preferences, can be elicited across two risky choice problems, that exhibit isomorphism. It particularly focuses on whether the risky choice problem formulation impacts observed risk behaviour. It also examines whether willingness-to-pay is an aspect that distorts a prediction of stable preferences across two tasks. For this purpose, we apply two different isomorphic risky choice problems across the same pool of subjects. We apply the bomb risk elicitation method (Crosetto and Filippin, 2016), for it exhibits isomorphism with the standard private value sealed-bid FPA (Selten and Neugebauer, 2006), that we primarily apply. Risk preferences elicitation in the standard private value first-price auction (hereafter FPA) relates to eight market sizes $N = 2, 3, 4, 5, 6, 7, 8, 9$. We compare the bidding behaviour in these fist-price auction market sizes with the bomb risk elicitation task (hereafter BRET) behaviour. Both pure empirical choices (values) and risk preferences are elicited and compared across the two isomorphic tasks. Our motivation behind applying various market sizes, is that we also aim to explore how elicited risk behaviour changes when moving away from the theoretically most relevant market, with respect to isomorphism, market $N = 2$. Individual risk preferences are measured according to the constant relative risk aversion model of Cox, Smith and Walker [1]. We consider the experimental investigation and comparison of elicited risk choices and preferences across two isomorphic tasks, of incontestable importance for the context dependence discussion. We are mainly inspired by the work of Kahneman and Tversky (1981), Kahneman and Tversky (1986), Kahneman, Knetsch, and Thaler (1990), Kahneman and Tversky (1979), Lichtenstein and Slovic (1971), Lichtenstein and Slovic (1983), Isaac and James (2000) and Tversky (1969), for their research allow us to explore and attain our main research objectives. First, to infer on potential framing effects of isomorphic versions of an inseparable risky choice problem. Second, to infer on the stability of preferences, potential preference reversals and information processing considerations. And third, to investigate willingness-to-pay versus willingness-to-accept differences and relevance in our experimental context.

Kahneman and Tversky (1981) study choices among risky alternatives and show that bet (gamble) outcomes are typically coded as gains or losses, rather than final states of wealth. In their extended study on *"Rational choice and the framing of decisions"*, Kahneman and Tversky (1986) propose a value function of marginal changes of decreased impact, when deviating from a neutral reference outcome, with 0 expected value. The main property of the phenomenon of *loss aversion* they introduce, implies more sensitive responses to potential losses compared to potential gains. Similar findings relative to context dependence of risk behaviour are reported by Hershey and Schoemaker (1980) and Hershey, Kunreuther, and Schoemaker (1982), for the case of insurance formulated gambles. This study explores the potential for *loss* and *gain* framing effects, across two mathematically isomorphic problems of risky choice. The FPA and the BRET

[1] The constant relative risk aversion measure is presented in section 2.3

illustrate the differences in sensitivity, as they consist of two different frames of the same risky choice problem. Essentially, the problem formulation in the auction evokes a *gain* framing effect. In particular, the risky choice problem in the FPA is as follows: *"If your bid is the highest bid in the auction you win, and your gain will be the difference between your value and your bid. If the highest bid of the competitors exceeds your bid, you win nothing in that market."*. Subjects are basically induced to evaluate alternative sets of bets (gambles), initiating from a sure gain of 0. Thereafter, they are induced to mentally (roughly) evaluate the alternative gambles towards a potential gain, that departs from 0, rather than a sure loss. With regards to the potential gain, thus, there is a trade-off between the value and the bid. This trade-off, and the expectation about the highest competitive bid is mentally treated by subjects as the price proposal criterion. The FPA, thus, implicitly directs subjects to shape their strategy, and make a bidding choice, with regards to attaining a gain. In terms of discrete probabilities of eg. 1% increase per gamble, in the FPA, decision-making corresponds to a (more or less precise) mental accounting of the following set of gambles:

Choose between:

1. Bid the value (bid 2000): A sure gain of 0
2. 99% chance to gain $2000 - 1980 = 20$, and 1% chance to gain nothing...

1. Bid the value (bid 2000): A sure gain of 0
2. 98% chance to gain $2000 - 1960 = 40$, and 2% chance to gain nothing...

... The risk-neutral gamble:

1. Bid the value (bid 2000): A sure gain of 0
2. 50% chance to gain $2000 - 1000 = 1000$, and 50% chance to gain nothing...

and, accordingly, until the end of all gamble alternatives:

1. Bid the value (bid 2000): A sure gain of 0
2. 1% chance to gain $2000 - 20 = 1980$, and 99% chance to gain nothing...

Contrary, in the BRET the equivalent *loss* framing effect is evoked: *"Your task is to decide on the number of boxes you wish to collect, M. On the screen you see a square composed of* 100 *boxes,* *which are numbered from* 1 *to* 100*. One of these boxes contains a mine. The other boxes contain no mine. If this is the payment decisive task, your random draw will determine the number of the box that contains the mine. Click 'Start' and every two seconds a box is collected one by one. As soon as the number of boxes, you want to collect, M, is reached click 'Stop'.* ***If none of the collected boxes contains the mine, you earn* 0.60 *Euro for each box collected****. In other words, if your drawn number is larger than the number of boxes collected, M, you win* $(0.6 \cdot M)$ *Euro...****If one of the collected boxes contains the mine (the mine explodes), you win nothing****. In other words, if your drawn number is smaller or equal to M you win nothing...****Note if you choose*** $M = 100$***, the zero gain is a sure outcome.***. The above problem formulation in the BRET immediately translates to *"If you collect/choose a number of boxes M greater than the random draw (competitor) you lose"*. Contrary to the FPA, subjects are basically induced to evaluate alternative sets of bets (gambles), initiating from a sure loss of 60 (the entire maximum potential wealth). Thereafter, they are induced to evaluate the alternative gambles towards potential losses, rather than potential gains. Thus, this task potentially evokes the evaluation of the following type of sets of gambles:

Choose between:

1. Collect 100 out of 100 boxes: A sure loss of 60 Euros.
2. Collect 99 out of 100 boxes: A 1% chance to lose 0,60 Euros and 99% to lose 60 Euros.

1. Collect 100 out of 100 boxes: A sure loss of 60 Euros.
2. Collect 98 out of 100 boxes: A 2% chance to lose 1,2 Euros and 98% to lose 60 Euros.

... The risk-neutral gamble:

1. Collect 100 out of 100 boxes: A sure loss of 60 Euros.
2. Collect 50 out of 100 boxes: A 50% chance to lose 30 Euros and 50% to lose 60 Euros.

and, accordingly, until the end of all gamble alternatives:

1. Collect 100 out of 100 boxes: A sure loss of 60 Euros.
2. Collect 1 out of 100 boxes: A 99% chance to lose 59,4 Euros and 1% to lose 60 Euros.

We indeed find evidence of an evoked *loss* frame in the BRET responses, through the prism of CRRA elicited preferences. The latter results stem from the market with $N = 2$ competitors, that is the market that in a mathematical sense, is the most relevant to isomorphic properties.

Kahneman, Knetsch, and Thaler (1990) conducted an experiment that shows that median selling and buying prices for consumption goods differ significantly across subjects. More precisely, they show that willingness-to-accept a price greatly exceeds willingness-to-pay the same price, for the same good (endowment effect). This experiment also consists of a comparative study, where the BRET task, while isomorphic to the FPA, consists of a willingness-to-pay aspect of the same problem. In the BRET task, subjects face the implicit question of how much they are willing to pay, so as to accept an increase in the probability of losing, and a decrease in the potential payoff. We find that indeed, the willingness-to-pay question distorts risky choices in all markets. The magnitude of the latter distortion is significant in half of the markets, beyond the market of $N = 2$ competitors.

Isaac and James (2000) show that individual constant relative risk aversion preferences are not preserved across the FPA and the Becker-de-Groot Marschak (BGM) mechanism (Becker, DeGroot, and Marschak, 1964). This study investigates potential preference reversals in the psychological level, that confute the isomorphism between the two risky choice tasks. The latter preference reversals are studied also through the prism of a measure of constant relative risk aversion. Furthermore, Lichtenstein and Slovic (1971) study choice of preferred bets, the latter being clustered into those of higher probability of winning and those of higher payoffs. They detect inconsistency between prices and choices for risky prospects. Lindman (1971) applies similar experiments, and Grether and Plott (1979) replicate the Lichtenstein and Slovic (1971) experiments in choice of preferred bets. Both latter studies track similar inconsistencies. This study examines consistency of risk preferences also for and beyond the case, for which isomorphism holds (for market sizes $N = 2, 3, 4, 5, 6, 7, 8, 9$). In particular, we check whether information-processing considerations may account for inconsistency of choices (values) and risk preferences, across the tasks in those markets. As Lichtenstein and Slovic (1971) particularly observe, we check whether *"variations in response mode cause fundamental changes in the way people process information, and thus alter the resulting decisions"* (Lichtenstein and Slovic (1971), p.16). We study, thus, whether the potential that subjects' choices and preferences are contingent upon different anchors of decision-making, per context, exists. In the FPA, the anchor seems to be the value of the auction, and the amount to win. As, by definition, the auction rule requires comparison to the highest bid [1], that is, the chance event that may be closest to the value, the value itself becomes the anchor dimension of the context, in which the decision is being made. Also, in the FPA, the space of sets of bets that wins the auction, is specified as a continuous interval between the value and the conjectured highest competitive bid. In the BRET, the set of bets that wins the task is rather specified as a discrete (box-wise) space. The latter difference may, thus, induce different anchors of decision-making. In the BRET the decision rule contingent upon the sets of bets (gambles) is split into consecutive, equal probability, discrete decision problems with increasing probability of losing (risk), and higher outcomes (payoffs). As the latter decision problems in the BRET are defined and presented to be equiprobable, subjects are mostly induced to take a decision without a natural starting point Lichtenstein and Slovic (1971). It may also be the case, that i.e. agents' focus in this task is initially shifted to the segmentation of the probability space. In other words, they are induced i.e. to decide first upon the anchor of the probability of winning or losing, possibly, initiating from the probability of 50%. Any discrete bet choice higher or lower than the latter anchor, may consist of a secondary dimension, at which they declare how much they wish to deviate from this probability. We find and report preference reversals and information-processing considerations, that distort the assumption of isomorphic choices across the two tasks in all the markets, including the market with $N = 2$ competitors. The magnitude of these reversals is significant in half of the markets beyond the most theoretically relevant case, and in particular in markets with $N = 3, 4, 5$, and 7 competitors.

Another seminal study on inconsistency in risky behaviour, dates back to Hey and Orme (1991) pairwise choice question experiment. In this study, the authors estimate various preference functions, and observe inconsistent risk preferences across subjects within a group of cohorts. Also, in an experimental investigation for significant risk behaviour heterogeneity, Crosetto and Filippin (2016) derived varying constant relative risk aversion r_i coefficients across four different risk elicitation methods. [2]. They ascribe such inconsistency to the institutional format of the tasks and context dependence, complementing, thus, and enhancing Hey and Orme (1991) findings. Zhou and Hey (2018) also ascribe inconsistency of individual risky behaviour to context dependence. This study shows that the BRET is mathematically isomorphic to the FPA, and proceeds with a comparative study in risky choice, and risk preferences elicitation.

Turocy, Watson, and Battalio (2007) use market prices as a benchmark for risk-neutral bidding behaviour. They directly link and compare experimental price formation, to the risk

[1] The comparison to the highest bid in the auction is enforced irrespective of the market size.

[2] Their findings are also supported by systematic deviations of the task's estimates across the four risk elicitation methods, from simulation (expected) results.

neutral Nash equilibrium (RNNE) theory price (per market). They show that variant but strategically equivalent isomorphic implementations of the FPA (sealed versus Dutch), leads to higher (sealed) market prices in the laboratory and, by consequence, to differing risk preferences. This study does not proxy risk preferences by market price formation. However, it attempts to infer on whether variant but strategically equivalent isomorphic implementations of the same risky choice problem, elicit identical risk preferences. From another standpoint, Cox and James (2012) provide stark experimental evidence that non-traditional institutional formats of centipede games and isomorphic Dutch auctions, converge and fit to theoretical predictions, contrary to traditional formats. In particular and relative to isomorphism, they observe bids close to the risk neutral Nash equilibrium in *tree-format* Dutch auctions. The informational effects resulting from the *tree-format* Dutch auction render convergence to theory context specific, when experimentally compared to the isomorphic traditional *clock-format*. This study does not entirely incorporate the potential for informational effects in risk decision-making. The isomorphic implementation of the FPA, that is, the BRET, is a real-time risky choice problem. However it lacks the option of immediate task resolution and simultaneous decision-making (subjects) and chance event occurrence (the computerised bid in the case of the auction). However, it introduces an approach for future implementation of the two tasks, where decisions are simultaneous and, thus, the potential for informational effects may apply in context dependence.

Finally, isomorphism is deployed as a mathematical property of the choices, payoffs and strategies between the FPA and the BRET. It allows for the investigation of stability of choices and risk preferences across two isomorphic decision environments. Risky assets may occasionally exhibit properties of isomorphism, that is, properties of a correspondence of payoffs and strategies. However, the formulation of an asset's (investment's) discounted future cash flows, may be presented to potential investors in different frames. Ignorance of the equivalence of cash flows of two or more isomorphic portfolios may lead to suboptimal weights of the diversified basket of risky assets. Also, instability of preferences across portfolios with identical payoffs and different frames, may impact a portfolio position's marginal risk contribution. Thus, we think that the investigation of isomorphism in tasks that elicit risky choices and preferences, may contribute to optimise risky investment profiling, improve investment decisions, and hedge against unwanted excessive losses on one's portfolio.

This paper is organized as follows. In section and we present the FPA and BRET theoretical considerations. In section we elaborate on the definition and mathematical properties of isomorphism. In section we formulate a proof of isomorphism across the FPA and the BRET in the unit interval, for the theoretically most relevant market $N = 2$. We further formulate and present an extended proof in the unit interval, across the two tasks for the same market $N = 2$, based on the equivalence of strategies in the two tasks. In section 2.3 we present the CRRAM risk behaviour measures we deploy, and in section 2.4 we discuss the details of the experimental design of the two tasks. We formulate and present our testable hypotheses in section 2.5 and in section 2.6 we report our results. Section 2.7 summarises and concludes this study.

2.2 Theoretical considerations

2.2.1 Private value sealed-bid first-price auction

In the Selten and Neugebauer (2006) FPA, one bids against $N-1$ competitors. One's value is i.i.d. drawn from the unit interval $[0,1]$, with upper bound, thus, 1. Independent values v_i per bidder are private information. However, it is theoretically common knowledge that all competitors' values are i.i.d. variables from the same uniform interval $[0,1]$. If one's bid b_i exceeds all other $N-1$ competitors' bids, one wins the auction, and earns $v_i - b_i$, otherwise, earns 0. Vickrey (1961) shows that the risk-neutral bid in the FPA is derived as follows: all bidders' potential bids are maximally bounded by the uniformly distributed value v_i, and thus, all bid a fraction of their value $b_i^{\mathrm{N}} = a \cdot v_i^{\mathrm{N}}$. The winning condition of the auction relates directly to the probability that subject i bid is larger than the bid of all other competitors b_i^{N}. Since all bidders bid a fraction of their value v_i the latter probability is:

$$p\left(b_i^{\mathrm{N}} > a v_j^{\mathrm{N}}\right) = p\left(v_j^{\mathrm{N}} < \frac{b_i^{\mathrm{N}}}{a}\right) = \left(\frac{b_i^{\mathrm{N}}}{a}\right)^{N-1} \tag{2.1}$$

As winning the auction leads to a realised payoff equal to $v_i^{\mathrm{N}} - b_i^{\mathrm{N}}$, each bidder's utility is:

$$U(v_i, b_i) = (v_i - b_i) \cdot \left(\frac{b_i^{\mathrm{N}}}{a}\right)^{N-1} = b_i^{\mathrm{N\text{-}1}} \cdot v_i \cdot \left(\frac{1}{a}\right)^{N-1} - b_i^{\mathrm{N}} \cdot \left(\frac{1}{a}\right)^{N-1} \tag{2.2}$$

Vickrey (1961) hereafter also derives the risk neutral Nash equilibrium in the FPA:

$$b_i^* = \frac{N-1}{N} \cdot v_i \tag{2.3}$$

where $\frac{N-1}{N}$ is the equilibrium fraction of the value v_i, that each risk-neutral bidder i should bid. In other words, in the FPA, it is common knowledge that all competitors are, basically, risk neutral. This fact translates to the equivalent of bidding against a chance event, in the FPA.

2.2.2 The bomb risk elicitation task

The BRET consists of a decision-making task, that involves consecutive gamble outcomes related to 100 boxes, on a $10 \cdot 10$ onscreen square design. Each consecutive gamble (box) relates to an increasing payoff and risk. The latter risk involved in the task relates to the following decision setup: across the 100 boxes, one randomly selected box contains a mine. Subjects are asked to collect their preferred number of boxes out of 100. Should the mine, that is the chance event, be smaller or equal to the number of boxes collected, subjects earn 0. Should the opposite be true, they earn the payoff that corresponds to the number of the box they choose, in the task. Similarly to the FPA, all gambles values and the chance event (dice) are i.i.d. variables in the (normalised) uniform interval $[0, 1]$. In non-normalised terms, in BRET, subjects choose a number k in $[0, 100]$ and the chance event (dice) b is randomly determined in $[1, 100]$. Decision on the number of boxes k to collect is private, and the chance event is revealed only after the decision in the task has been made. Crosetto and Filippin (2016) define the decision rule as follows: if $b \leq k$, the mine is collected and subjects earn 0, otherwise ($b > k$) subjects earn $\gamma \cdot k$, where γ is an amount in Eurocents. As the payoff of each $n, (n + 1), (n + 2), ...$ gamble (box) increases, so does the cumulative probability of coinciding with the random number draw (mine), relative to the previous box and gamble. As the onscreen design reveals the gamble potential payoffs every 2 seconds, subjects choose between the two consecutive sets of lotteries, according to Crosetto and Filippin (2016):

$$L^k = \begin{cases} 0 & \frac{k}{100} \\ \gamma \cdot k & \frac{100-k}{100} \end{cases} \quad L^{k+1} = \begin{cases} 0 & \frac{k+1}{100} \\ \gamma \cdot (k+1) & \frac{100-k-1}{100} \end{cases}$$

The expected value of these sets of gambles is $\gamma \cdot (k - 0.01 \cdot k^2)$, with maximum at $k = 50$ (Crosetto and Filippin, 2016). We show and elaborate on the constant relative risk aversion risk neutral bidding choice in the BRET in section 2.3 on *Risk behaviour measures.*

2.2.3 Isomorphism: definition

The mathematical mapping that can be reversed by an inverse morphism, is known as isomorphism. (Mixed) strategy spaces inherit isomorphism, if the properties of the probability distributions involved with these strategy spaces, are not altered. Also, if the dimensionality of the probability spaces is identical, according to Gagen (2013). Gagen (2013) points out in particular, that, when the preservation structure is exact, then calculations within either space must give identical results. An isomorphism is a correspondence (relation) between objects, or systems of objects, expressing the equality of their structures in some sense. An isomorphism in an arbitrary category is an invertible morphism, that is, a morphism ϕ for which there exists a morphism ϕ^{-1}, such that $\phi^{-1} \cdot \phi$ and $\phi \cdot \phi^{-1}$ are both identity morphisms. The concept of an isomorphism arose in connection with concrete algebraic systems (initially, with groups), and was extended in a natural way to wider classes of mathematical structures (Mitchell (1965), Cohn (1981), Adámek (1983)).

Let A and A' be algebraic systems of the same type, written in the signature $F_i i \in I, P_j : j \in J$ with function symbols $F_i i \in I \cup P_j : j \in J$

$$A = [A; F_i i \in I, P_j : j \in J] \tag{2.4}$$

$$A' = [A'; F_i i \in I, P_j : j \in J] \tag{2.5}$$

An isomorphism, or isomorphic mapping, from A onto A is a one-to-one mapping ϕ from the set A onto the set A with the properties

$$\phi(F_i(a_1, ..., a_{n_i})) = F_i(\phi(a_1, ..., \phi(a_{n_i})) \tag{2.6}$$

$$P_j(a_1, ..., a_{m_j} \Leftrightarrow P_j(\phi(a_1, ..., \phi(a_{m_j})) \tag{2.7}$$

for all $a_1, a_2, ...$ in A and all $i \in I, j \in J$ (Mitchell (1965), Cohn (1981), Adámek (1983)).

2.2.4 Isomorphism for $N = 2$: proof in the unit interval $[0, 1]$

First of all, we need to demonstrate why the market of $N = 2$ competitors is theoretically the most relevant for isomorphism between the two tasks. We first show isomorphism in the unit interval $[0, 1]$. As discussed in the Selten and Neugebauer (2006) FPA section, the normalised value of subjects in the auction, is always equal to the upper bound of a uniform distribution of values in the interval $[0, 1]$, that is, 1. Subjects submit a bid against 1 competitor. Competitor's bids are randomly drawn from the same uniform interval $[0, 1]$. Subjects win the auction if their bid is higher than the bid of the competitor. The probability of winning p is, then, equal to the subjects' bid b_i. Accordingly, subjects lose the auction and make 0 gains if their bid is lower than the competitor's bid. Thus, the corresponding probability of losing the auction equals the counter probability of winning, that is $1 - p$, which in turn equals $1 - b_i$.

Similarly to the FPA, the normalised value of subjects in the BRET equals the upper bound of the same uniform distribution $[0, 1]$, that is 1. Subjects make a choice against the potential chance event in the calibrated strategy space of choices from $[0, 1]$. Instead of a continuous set of values in $[0, 1]$, a discrete set of values that correspond to the potential chance events, are formulated. The chance event (dice), is randomly drawn from the interval $[0, 1]$. Subjects win the task and realise a positive payoff conditional to the reverse rule that applies in the FPA: if their choice M_i is smaller than the chance event. The probability of winning p in the BRET is, then, equal to the choice M_i. Accordingly, subjects lose the task if their choice M_i is higher than the chance event. Thus, the corresponding probability of losing the task $1-p$ equals $1-M_i$. Since winning rules in the two risky choice problems are by definition converse, and values are in both cases are equal to 1, the choice M_i equals the counter of the bid b_i in the auction, that is $1-b_i$. By consequence, the bid b_i equals the counter choice in the bomb risk task, $1-M_i$ Thus, we conjecture that each and every choice b_i equals the counter choice $1-M_i$, for all potential bids b_i in the interval $[0,1]$, and the converse. The reverse mapping of choices in the two tasks can be easily shown to correspond to the respective space of payoffs in the unit interval $[0,1]$. Since every bid b_i and choice M_i correspond to the reverse mapping of one another in the unit interval $[0,1]$, each payoff $v_i - b_i = 1 - b_i$ corresponds to the reverse potential payoff M_i, and vice-versa. Thus, the two tasks consist of risky decision problems with a seemingly equality of structures (both in terms of choices and payoffs).

FPA

- Subject's value $v_i = 1$ and competitor's bid $b_i \sim [0,1]$

$$A = f_i(b_i) = \begin{cases} v_i - b_i, & b_i \geq b_j,\ p = b_i \\ 0 & b_i < b_j,\ 1-p = 1-b_i, \end{cases}$$

BRET:

- Only in one box a bomb $\mathbf{x}$ is randomly allocated: $x \sim [0,1]$

$$\acute{A} = f_i(M_i) = \begin{cases} M_i & M_i < x, \quad p = M_i \\ 0 & x \leq M_i, \quad 1-p = 1-M_i \end{cases}$$

- $\mathbf{1 - b_i = M_i \Leftrightarrow b_i = 1 - M_i}$
- $\mathbf{v_i - b_i = 1 - b_i = M_i \Leftrightarrow b_i = 1 - M_i}$

2.2.5 Isomorphism for $N = 2$: extended proof in the unit interval $[0, 1]$ Equality of structures and equivalence of strategies

For isomorphism to hold between the two tasks it suffices to show that the equality of structures is translated into equivalence of strategies. It suffices to show that for a choice ϕ in the strategy space of the FPA (morphism ϕ), there exists a choice ϕ^{-1} in the strategy space of the BRET (morphism ϕ^{-1}), such that $\phi^{-1} \cdot \phi$ and $\phi \cdot \phi^{-1}$ are both identity morphisms. Formally defined, the normalised strategy space whereby subjects make risky choices and the value of the chance event (dice) is drawn, is $[0, 1]$ (0 to 100 boxes) in the BRET. The normalised strategy space whereby subjects submit (choose) their bids in the FPA and competitors' bids are drawn is $[0, 1]$, as well. Vickrey (1961) shows that the risk-neutral bid is

$$b_i^* = \frac{N-1}{N} \cdot v_i \tag{2.8}$$

where

$$\frac{N-1}{N} \tag{2.9}$$

is the equilibrium fraction of the value v_i that each risk-neutral bidder i should bid. The equilibrium fraction of the value v_i that each risk-neutral bidder i should bid is, thus, defined as the upper bound of the risk neutral Nash equilibrium strategy in the FPA. This upper bound in the market with $N = 2$ competitors is equal to $\frac{1}{2}$,:

$$b_i^* = \frac{N-1}{N} \cdot v_i = \frac{2-1}{2} \cdot 1 = \frac{1}{2} \tag{2.10}$$

(Crosetto and Filippin, 2016) show that the risk-neutral choice in the BRET is $M = 50$. Since the winning condition is the converse in the BRET, the normalised upper bound of the risk neutral strategy in the BRET should be $1 - \frac{50}{100}$. In other words, an identity morphism exists: the upper bound of the risk-neutral strategy in the FPA equals the upper bound of the risk-neutral strategy in the BRET. In the following, we use the notation b_i^{FPA} and b_i^{BRET} to refer to the choices (bids and box choices) in each task. The $*$ always refers to the equilibrium.

$$\begin{cases} \bar{b}_i^{*,FPA} = \frac{N-1}{N} \cdot v_i = \frac{2-1}{2} \cdot 1 = \frac{1}{2} \\ \bar{b}_i^{BRET} = 1 - \frac{50}{100} = \frac{1}{2} \end{cases} \tag{2.11}$$

$$\bar{b}_i^{*,FPA} = \bar{b}_i^{BRET} \Leftrightarrow \bar{b}_i^{*,FPA} = 1 - \bar{b}_i^{BRET} \tag{2.12}$$

In order to show isomorphism, it suffices to identify similar identity morphisms $\phi^{-1} \cdot \phi$ and $\phi \cdot \phi^{-1}$ (identity bid and box choices in the two tasks) evaluated also in the lower bounds of the risk neutral strategies. Smith (1991) defines the generalised equilibrium bid function of the FPA, where values are allowed to be drawn from a uniform distribution with upper and lower bound $\bar{v}$ and $\underline{v}$ as follows:

$$b_i^{*,FPA} = \underline{v} + \frac{N-1}{N} \cdot (v_i - \underline{v}) \tag{2.13}$$

The risk-neutral Nash equilibrium bid in the FPA (Vickrey, 1961) has an important implication. The common knowledge that competitors' bids in the FPA are randomly drawn from the interval $[0, 1]$, corresponds to drawing values from the interval $[0, \frac{N}{N-1}]$, that is, $[0, 2]$, and bidding the risk-neutral strategy (Selten and Neugebauer, 2006).

$$b_i^* = \frac{N-1}{N} \cdot v_i \Leftrightarrow v_i = \frac{N}{N-1} \cdot b_i^* \tag{2.14}$$

The lower and upper bound of the value of the set of consecutive gambles (bets) in the bomb-risk elicitation task is 0 and 1, respectively. For the theoretically most relevant case of the market with $N = 2$ competitors, the choices evaluated at the lower bounds of the values 0 and 0, respectively, in the two tasks are:

$$\begin{cases} \underline{v}_i^{FPA} = 0 \Leftrightarrow \underline{b}_i^{*,FPA} = \underline{v} + \frac{N-1}{N} \cdot (v_i - \underline{v}) = 0 + \frac{2-1}{2} \cdot (0-0) = 0 \\ \underline{v}_i^{BRET} = 0 \Leftrightarrow \underline{b}_i^{BRET} = 1 - \frac{M}{100} = 1 - \frac{0}{100} = 1 \end{cases} \tag{2.15}$$

Thus, identity morphisms of the choices between the two tasks exist, also, at the lower bounds of the risk neutral strategies.

$$\underline{b_i}^{*,FPA} = \underline{b_i}^{BRET} \Leftrightarrow \underline{b_i}^{*,FPA} = 1 - \underline{b_i}^{BRET} \tag{2.16}$$

Similarly, identity morphisms can also be evaluated at the upper bounds of the risk-neutral strategies, once more, via the Smith, 1991 generalised equilibrium bid function:

$$\begin{cases} \bar{v}_i^{FPA} = 2 \Leftrightarrow \bar{b}_i^{*,FPA} = \underline{v} + \frac{N-1}{N} \cdot (v_i - \underline{v}) = 0 + \frac{2-1}{2} \cdot (2-0) = 1 \\ \bar{v}_i^{BRET} = 1 \Leftrightarrow \bar{b}_i^{BRET} = 1 - \frac{M}{100} = 1 - \frac{1}{100} = 0 \end{cases} \tag{2.17}$$

Thus, assuming strict monotonicity, we have proved that strategies (choices, morphisms) in the FPA correspond to the inverse strategies (choices, morphisms) in the full range of the $[0, 1]$ interval of values. The last condition for isomorphism to hold, as defined in 2.3 and 2.4, is that the one-to-one mapping between the tasks holds also for the corresponding probabilities of strategies (choices). The equilibrium probability of winning the auction (Vickrey, 1961) is

$$p_i^* = \left(\frac{b_i^*}{a^*}\right)^{N-1} = v_i^{(N-1)} \tag{2.18}$$

Furthermore, the probability of winning in the BRET is derived from the winning condition: one wins if their box choice is lower than the chance event. Thus, the latter probability equals $\frac{100-M}{100}$. The probabilities in the two tasks, evaluated at the lower and upper bound 0 and 1 of the interval $[0, 1]$, from which chance events (competitor's bids and dice) are drawn, are, thus:

$$\begin{cases} \underline{v}_i^{FPA} = 0 \Leftrightarrow \underline{p}_i^{*,FPA} = \left(\frac{b_i^*}{a^*}\right)^{N-1} = v_i^{(N-1)} = 0^{(2-1)} = 0 \\ \underline{v}_i^{BRET} = 0 \Leftrightarrow \underline{p}_i^{*,BRET} = \frac{100-M}{100} = \frac{100-0}{100} = 1 \end{cases} \tag{2.19}$$

$$\begin{cases} \bar{v}_i^{FPA} = 1 \Leftrightarrow \bar{p}_i^{*} FPA = \left(\frac{b_i^*}{a^*}\right)^{N-1} = v_i^{(N-1)} = 1^{(2-1)} = 1 \\ \bar{v}_i^{BRET} = 1 \Leftrightarrow \bar{p}_i^{*} BRET = \frac{100-M}{100} = \frac{100-100}{100} = 0 \end{cases} \tag{2.20}$$

which results to:

$$\begin{cases} p_i^{BRET} = 1 - p_i^{FPA} \end{cases} \tag{2.21}$$

We can thus infer that the theoretical requirements for isomorphism to hold between the FPA and the BRET (choices-strategy spaces) are fulfilled. Conditional to strict monotonicity, the two tasks can be assumed to exhibit isomorphism in the experimental implementation of risky choice.

2.3 Risk behaviour measures

Isomorphism across the FPA and the BRET overall implies that, individual risk choices and, constant relative risk aversion preferences should be consistent across tasks. Our proof and proposed isomorphic properties between the two tasks in sections 2.2.4 and 2.2.5, provide a sound theoretical ground for a straight-forward risk behaviour comparison. The latter comparison is conducted through choices and elicited constant relative risk aversion in the two tasks. We, thus, derive the implied constant relative risk aversion measure per subject and task, and infer on the observed risk behaviour, relative to our hypotheses.

The measure we use to elicit risk preferences within cohorts is the risk aversion measure derived from the constant relative risk aversion model (hereafter CRRAM) of Cox, Smith, and Walker (1982). The latter is defined as the inverse function of the equilibrium bid. That is, given i.i.d. uniformly distributed values v_i over the interval $[0, 1]$, and assuming that the maximum potential bid b_i in the auction is the risk neutral bid ($b_i^* \leq \frac{N-1}{N} \cdot v_i$), the Nash equilibrium bid in the CRRAM is:

$$b_i^{\mathrm{N}}(v_i, r_i) = \left(\frac{N-1}{N-1+r_i}\right) \cdot v_i \tag{2.22}$$

Similarly to the risk neutral Nash equilibrium, that assumes identical subjective probabilities and strategies among bidders, the CRRAM equilibrium strategy crucially depends on an identical common belief: that all competitors bid constant fractions of their value (Selten and Neugebauer, 2006). Reformulating the CRRAM, one derives the implied CRRAM risk measure for the FPA as follows:

$$r_i^{\mathrm{N}}(b_i) = \frac{(N-1)\cdot(1-b_{i,N})}{b_{i,N}} \tag{2.23}$$

Equation 2.23 is applied for each market size $N = 2, 3, 4, 5, 6, 7, 8, 9$ per subject and task. For the purpose of comparability, the CRRAM risk measure needs to adjust accordingly. That is, to properly reflect the risk aversion parameter in the isomorphic space of choices in the BRET. Since the BRET $b_{i,N}$ corresponds to the inverse choice (inverse box) $(100 - M_i)$, the CRRAM risk measure formulation for the BRET is, thus:

$$r_i^{\mathrm{BRET}} = \frac{(2-1)\cdot[1-(100-M_i)]}{100-M_i} \tag{2.24}$$

2.4 Experimental Design

The experimental sessions were conducted at Luxembourg Institute of Socio-Economic Research (LISER), and Radboud University Experimental Economics laboratories. The 144 subjects that participated in the experiment were recruited with ORSEE ((Greiner, 2015)). The average earnings per subject was 30 Euro and the experiment was programmed with the z-Tree software ((Fischbacher, 2007)).

First-price auction: The type of auction we apply in our risk elicitation study is the Selten and Neugebauer (2006) first-price sealed-bid auction presented in section 2.2.1, for eight market sizes $N = 2, 3, 4, 5, 6, 7, 8, 9$. All bidders, subjects and computerised competitors, are assigned a standard value $v_i = 1000 * N$ ECU. The computerised competitors' bids are independently and uniformly distributed in the interval $[0, 1000 * N]$, that is the interval bounded by the standard value v_i of the auction. The highest bidder wins the auction, pays her bidding price and, by consequence, realises a payoff equal to $v_i - b_i$. Each bidder is, thus, allowed to submit a bid up to their value v_i.

$$f_i(b_i^N) = \begin{cases} (1000 \cdot N) - b_i^N & b_i^N \geq b_j^N \\ 0 & \text{otherwise} \end{cases}$$

Bomb risk elicitation task: The BRET mainly differs from the FPA. Instead of an onscreen numerical bid input, a real-time 10*10 square box visually transforms every two seconds upon the subject clicking on a *START* button. The square box area changes by unravelling each of the 100 virtual boxes' content to the subject, as time elapses. The latter content is the visual depiction of equiprobable gambles-outcomes, each corresponding to one box. Subjects are asked to choose how many boxes they wish to collect by clicking on a *STOP* button. The chance outcome and the subject's payoff relate to the random draw of a number from 1 to 100 from an urn, in the following way: if the M_i number of boxes collected by the subject was larger than the random number (*dice*), subjects lost all accumulated earnings up to M_i. Otherwise, subjects earned the payoff that corresponded to box M_i (their choice). Each box collected had a value of 0.60 Eurocents, and in case of a payoff larger than 0, subjects earned 0.60*M_i. The visual transformation of the task occurred every two seconds (each box unravelled every two seconds). The random number draw occurred only after subjects determined their choice M of how many boxes they wish to collect. Subjects were informed that collecting 100 boxes leads to a sure loss. The BRET implies that the more risk-averse the subject, the smaller the number M_i of boxes collected should be. Risk-neutrality corresponds to $M_i = 50$. The BRET payoff function has the following form

$$f_i(M_i) = \begin{cases} 0 & \frac{M_i}{100} \\ 0.60 \cdot M_i & \frac{100-M_i}{100} \end{cases}$$

2.5 Testable hypotheses

Based on the theoretical analysis and predictions, we formulate our testable hypotheses as follows:

Hypothesis 1: Bidding versus bet selection attributes of the FPA and the BRET, respectively, could lead to preference reversals in the psychological level. The latter preference reversals coincide with divergence from the prediction of isomorphic choices across the two tasks.

Hypothesis 2: The loss framing of risky choice (BRET), could elicit lower constant relative risk aversion (CRRA) preferences, relatively to the gain framing (FPA).

Hypothesis 3A: Elicited CRRA preferences in the auction of $N = 2$ competitors should correspond to identical elicited CRRA preferences in the BRET. As the two decision setups are isomorphic, individual CRRA $r_{i,N}$ parameters in the auction should exhibit a one-to-one relationship to individual CRRA $r_{i,N}$ parameters in the BRET.

Hypothesis 3B: For auctions markets with more than $N = 2$ competitors, CRRA preferences should be consistent across the FPA and the BRET. Isomorphism beyond the market $N = 2$ implies CRRA preferences of the same qualitative nature.

Since one-to-one mapping between the two tasks results from the same type of preferences, theory suggests that isomorphism should be detected in the constant relative risk aversion $r_{i,N}$ measures, within subjects. In an ordinary least squares regression context, isomorphism should also be reflected in terms of the beta coefficients. A unit-increase in risk aversion levels in the BRET should, thus, increase risk aversion levels in the auction by exactly one-unit (slope equal to 1). At the same time the corresponding intercept should equal 0.

2.6 Results

We hereby report our parametric analysis results, preceded by summary statistics, and the risk measures' $r_i^{\text{FPA-N}}(b_i)$ and $r_i^{\text{BRET}}(b_i)$ scatter plots and Pearson correlations: (Figures 2.6.3 to 2.6.10). Scatter plots 2.6.1 shows how choices for the FPA, relate to choices for the BRET.

Table 2.6.1: Summary Statistics

This table reports summary statistics of all elicited CRRA risk measures per task and market size. Numerical indices N refer to the market size of the FPA. The coefficient acronyms *FPA* and *BRET* refer to the first-price auction and the bomb risk elicitation task, respectively. Standard errors are reported first in parentheses, t-statistics second, and statistical significance is indicated as follows: *** $p < 0.01,^{**}$ $p < 0.05,^{*}$ $p < 0.10$.

	Mean	Median	Std.Dev.	Min.	1st Qu.	3rd Qu.	Max.
r_i^{BRET}	0.89	0.72	0.65	0	0.53	1.08	5.14
$r_{i,2}^{\text{FPA}}$	1.33	0.92	2.42	0	0.54	1.22	15.95
$r_{i,3}^{\text{FPA}}$	3.17	1	23.45	0	0.40	1.33	258.87
$r_{i,4}^{\text{FPA}}$	6.27	1	28.35	0	0.43	1.64	184.5
$r_{i,5}^{\text{FPA}}$	1.71	1	2.88	0	0.76	1.71	25.85
$r_{i,6}^{\text{FPA}}$	5.33	1.43	19.97	0	0.99	2.50	130.14
$r_{i,7}^{\text{FPA}}$	1.81	1	2.07	0	0.67	2.39	15
$r_{i,8}^{\text{FPA}}$	0.12	1.49	34.78	0	0.78	2.18	204.32
$r_{i,9}^{\text{FPA}}$	2.64	1	4.93	0	0.67	2.29	40

Scatter plot 2.6.2 shows the equivalent relationship between the CRRAM risk measures $r_i^{\text{N}}(b_i)$ and $r_i^{\text{BRET}}(b_i)$, of the FPA and the BRET, respectively. The scatter plots provide initial evidence on the trends and nature of these relationships, in the most theoretically relevant market, that is market $N = 2$. The OLS fitted values line gives a first indication whether choices and risk preferences deviate or approach isomorphism. The latter is represented by the dashed green line. Scatter plots of market size $N = 2$ tract a rather controversial risk behaviour within cohorts, between the two tasks. Similarly to the Figures 2.6.1 2.6.2, we cite the scatter plots of CRRA risk preferences in the FPA and the BRET, in Figures 2.6.3 2.6.4 2.6.5 2.6.6 2.6.7 2.6.8 2.6.9 2.6.10. Each of the latter figures corresponds to a market size in increasing order. Similarly, to the market with 2 competitors, in markets with $3, 5$ and 9 competitors, we graphically observe inconsistent risk preferences across the two tasks. What is, though, necessary in order to infer on our hypotheses, is whether the fitted values graphical evidence reflects significant deviations from isomorphism. [1].

[1]Please note that the green diagonal in the scatter plots of the CRRAM risk preferences, is not a 45 degrees line in the (X, Y) coordinates. For these markets, we fit each graph's dimensions to optimally depict the data per market size

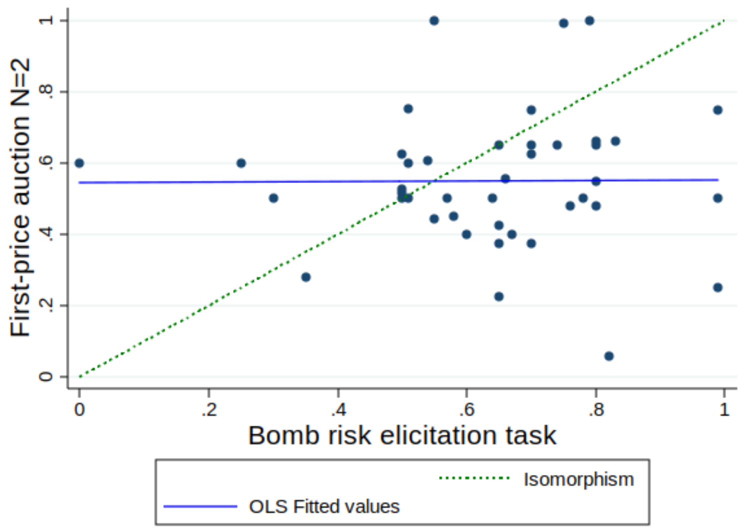


Figure 2.6.1: FPA bids vs BRET choice $N = 2$

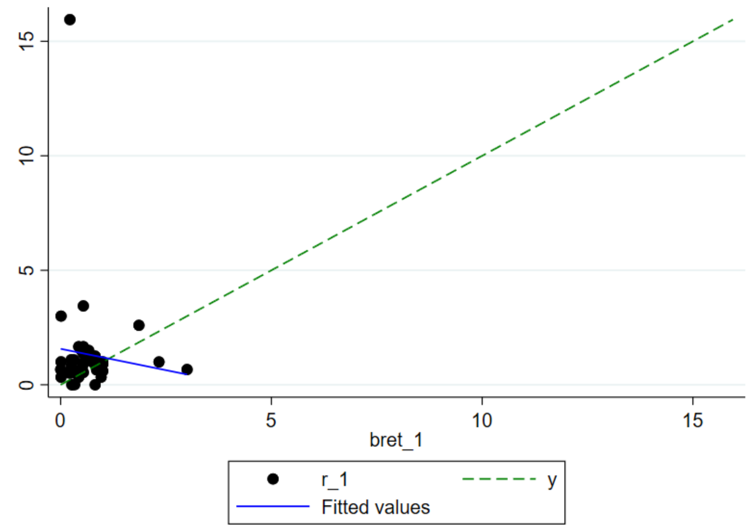


Figure 2.6.2: CRRAM r_i FPA vs BRET $N = 2$

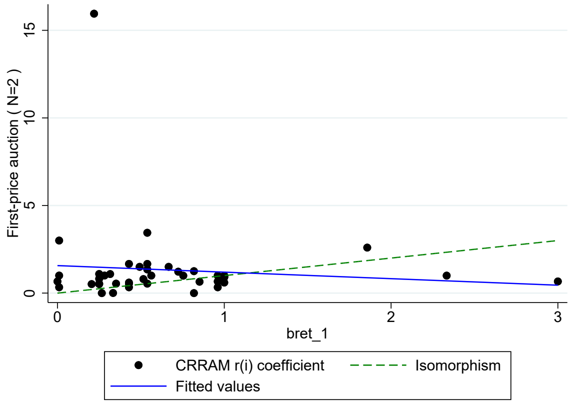


Figure 2.6.3: CRRA FPA vs BRET $r_i^{(b_i)}$ $N = 2$

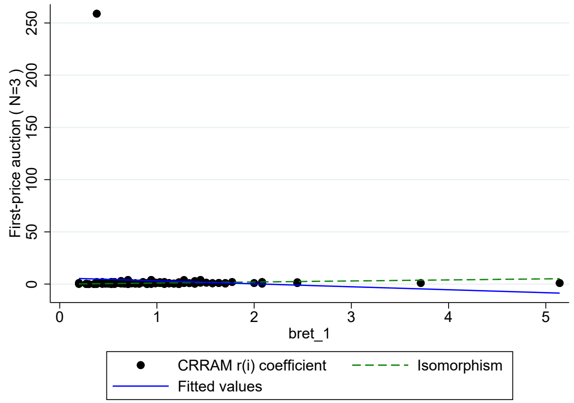


Figure 2.6.4: CRRA FPA vs BRET $r_i^{(b_i)}$ $N = 3$

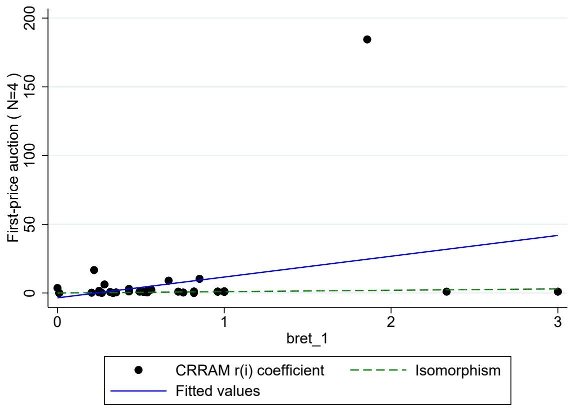


Figure 2.6.5: CRRA FPA vs BRET $r_i^{(b_i)}$ $N = 4$

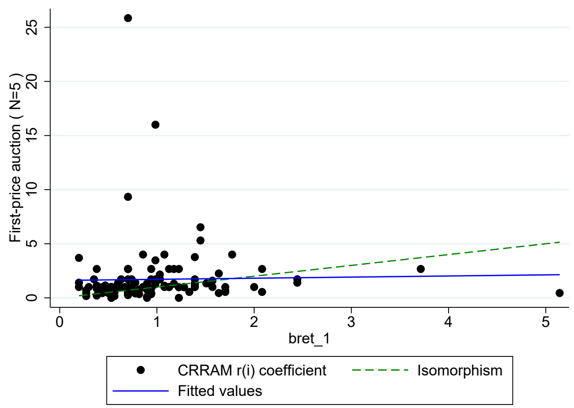


Figure 2.6.6: CRRA FPA vs BRET $r_i^{(b_i)}$ $N = 5$

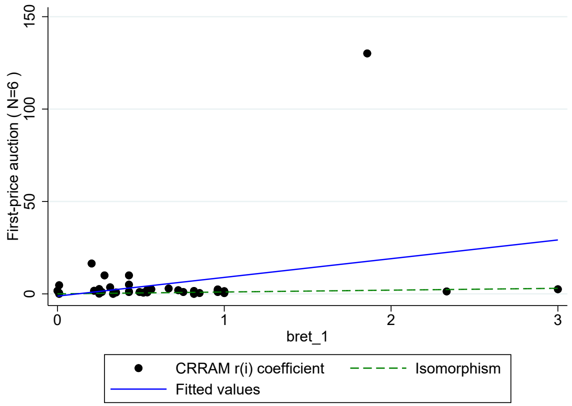


Figure 2.6.7: CRRA FPA vs BRET $r_i^{(b_i)}$ $N = 6$

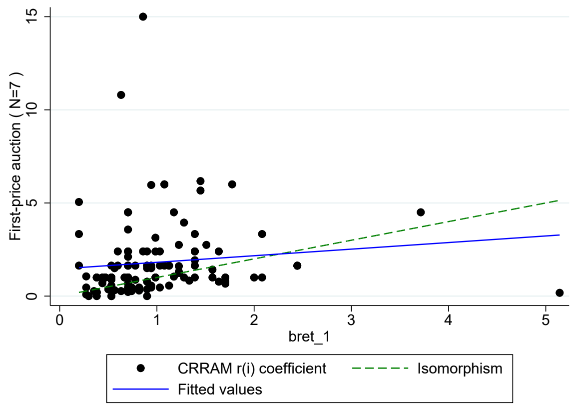


Figure 2.6.8: CRRA FPA vs BRET $r_i^{(b_i)}$ $N = 7$

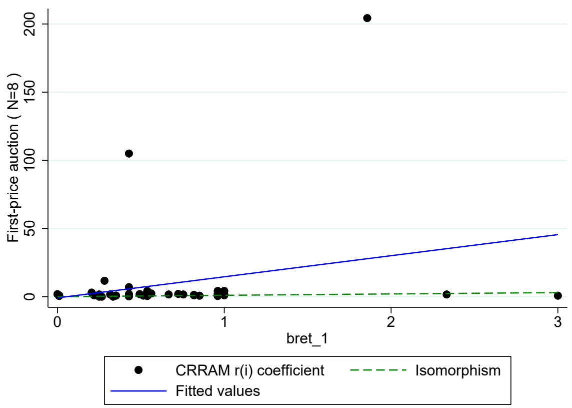


Figure 2.6.9: CRRA FPA vs BRET $r_i^{(b_i)}$ $N = 8$

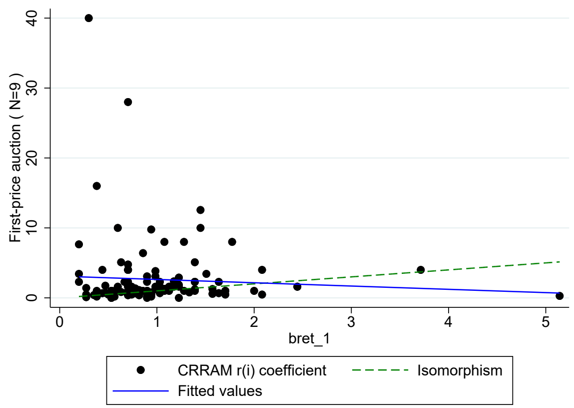


Figure 2.6.10: CRRA FPA vs BRET $r_i^{(b_i)}$ $N = 9$

Table 2.6.2 reports Pearson correlations of the elicited CRRA coefficients $r_{i,N}$ and r_i^{BRET}, among the FPA and the BRET. The elicited individual CRRA preferences of cohorts are positively and moderately correlated in 30% of the markets, namely sizes 4, 6 and 8 competitors. The correlation, of CRRA preferences in the most theoretically relevant market, though, indicates a rather inverse relationship in elicited risk preferences between the tasks. The BRET seems to elicit lower levels of risk aversion relative to the FPA in the latter market. Similarly, correlations between the CRRA measures of the two tasks in the markets with 3 and 9 competitors also track lower risk aversion levels in the BRET. Thus, preliminary evidence supports the potential for a *loss* frame in the BRET, as well as preference reversals and inconsistencies ,that we hereafter para metrically explore.

Table 2.6.2: CRRA preferences correlations

This table reports the Pearson correlations of elicited CRRA measures $r_{i,N}$ (FPA) and r_i^{BRET} (BRET). Numerical index N refer to the market size of the FPA. Statistical significance is indicated as follows: $^{***}\ p < 0.01, ^{**}\ p < 0.05, ^{*}\ p < 0.10$.

	r_i^{BRET}	$r_{i,2}^{\text{FPA}}$	$r_{i,3}^{\text{FPA}}$	$r_{i,4}^{\text{FPA}}$	$r_{i,5}^{\text{FPA}}$	$r_{i,6}^{\text{FPA}}$	$r_{i,7}^{\text{FPA}}$	$r_{i,8}^{\text{FPA}}$	$r_{i,9}^{\text{FPA}}$
r_i^{BRET}	1	-0.091	-0.078	0.314**	0.023	0.299*	0.111	0.262*	-0.062

Observation 1: Risky choice differs significantly across the FPA and the BRET. Isomorphism is not detected across the tasks' observed choices in the market with $N = 2$ competitors. Significant preference reversals are observed in half of the markets, namely of $N = 3, 4, 5$ and 7 competitors.

Support: Let us briefly recall that isomorphism between two contexts is valid when two conditions hold simultaneously. Those correspond to estimation intercepts equal to 0 and BRET risk aversion coefficients equal to 1. For this purpose, the Wald test-statistic tests the hypothesis that the second criterion of isomorphism is satisfied, that is that $M_i = 1$. The null hypothesis of isomorphism is rejected at the 5% level if the Wald test p-value is lower than 0.05. Results regarding risky choices between the FPA and the BRET indicate preference reversals, that confute the isomorphism between the two tasks. Similarly to Lichtenstein and Slovic (1971), Lichtenstein and Slovic (1983), Lindman (1971) and Grether and Plott (1979), we find that the choices across the two risky prospects of the FPA and the BRET differ significantly, in the market with $N = 2$ competitors. That is, we find that a preference reversal occurs in the theoretically most relevant market, that disproves isomorphic risky decision-making across the two tasks. As shown in

Table 2.6.3, isomorphism in the latter market is not preserved, as the Wald test statistic p-value of 0.000 rejects the hypothesis of a one-to-one reverse mapping of choices between the FPA and the BRET (a slope equal to 1). The same holds for all other markets beyond the market $N = 2$. In particular, in half of the markets, namely of $N = 3, 4, 5$ and 7 competitors, isomorphism is rejected, and the corresponding magnitude of the risky choices' observed distortion is statistically significant. The latter magnitude is reflected in the significant BRET choice coefficients for markets of $N = 3, 4, 5$ and 7 competitors. We track, thus, similarly to the aforementioned studies, significant inconsistencies between risky choices, in decision-making contexts that are deemed to be isomorphic. The parametric results provide evidence that supports our *Hypothesis 1*, that bidding versus bet selection could lead to preference reversals in the psychological level, and, thus, divergence from the prediction of isomorphic choices, across the two tasks. It seems, thus, plausible, as Lichtenstein and Slovic (1971), and Lichtenstein and Slovic (1983) find and report, that some information-processing considerations account for the significant divergence of choices, across the two tasks, in the aforementioned markets. The coefficients support that, one unit of increase in the bidding choice in the FPA decreases the observed gamble (box) choice in the BRET, by a rather smaller amount. The significant divergence and preference reversal indicates that, indeed, different anchors of decision-making may apply in the two tasks, with the discrete equiprobable gambles (choices) in the BRET inducing risky decision-making without a natural starting point. Bidding choices closer to the value in the FPA rather point to an anchor of decision-making, indeed contingent upon the value of the FPA. *Hypothesis 2* and the findings that follow (*Observation 2*), projects and extends this potential of different anchoring dimensions of decision-making in the psychological level. In particular it projects the comparison to the CRRAM risk measures of the two tasks, and extends to the potential *loss* and *gain* framing effects, induced by the problem formulation (Kahneman and Tversky, 1981). It is of interest to also report that our findings also partly complement Kahneman, Knetsch, and Thaler (1990). As we state in our introductory discussion, we consider the potential for the BRET to reflect the willingness-to-pay question, relative to the isomorphic willingness-to-ask question, in the FPA. We think that rejection of isomorphism in the market with $N = 2$ competitors, and higher bidding choices (prices) in the FPA relative to the gamble choices in the BRET, partly reflect the decoupling between the willingness-to-accept and the willingness-to-pay the same price, for the same expected value (outcome).

Table 2.6.3: Univariate regression results: FPA b_i vs. BRET M_i

This table reports the BRET choices coefficient M_i regressed on the FPA choices $b_{i,N}$, per market. Numerical indices N refer to the market size of the FPA. The 'Wald p' line contains the p-values of the Wald test of H_0: the beta coefficient of the BRET M_i choice equals 1. Standard errors are reported in parentheses.Statistical significance is indicated as follows: *** $p < 0.01,^{**}$ $p < 0.05,^{*}$ $p < 0.10$.

$b_{i,N}$	$N = 2$	$N = 3$	$N = 4$	$N = 5$	$N = 6$	$N = 7$	$N = 8$	$N = 9$
Intercept	0.543***	0.503***	0.455***	0.612***	0.706***	0.595***	0.667***	0.787***
	(0.080)	(0.086)	(0.118)	(0.081)	(0.121)	(0.090)	(0.120)	(0.099)
M_i	-0.010	−0.275**	−0.395**	−0.215*	-0.046	−0.298**	-0.180	-0.041
	(0.137)	(0.130)	(0.173)	(0.113)	(0.183)	(0.127)	(0.168)	(0.146)
Wald p	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000
Observations	42	121	42	121	42	121	42	121
R^2	0.000	0.032	0.109	0.026	0.002	0.057	0.028	0.000

Observation 2: Isomorphism is rejected in the most theoretically relevant case of $N = 2$ competitors. Loss framing effects relevant to the BRET formulation elicit indeed smaller levels of risk aversion in the latter task, relative to the FPA.

Support: Table 2.6.4 reports OLS regressions assessing the relationship between the CRRA coefficients of the FPA ($r_{i,N}$) and the BRET (r_i^{BRET}). The CRRA risk measure elicits inconsistent preferences in the two tasks for the theoretically most relevant market, that is $N = 2$. In particular, the Wald test p-value of 0.007 rejects isomorphism and *Hypothesis 3A*, where individual CRRA parameters in the FPA and the BRET are assumed to be identical. CRRA preferences are not preserved across the two tasks for the market with $N = 2$ competitors. We rather observe smaller elicited levels of risk aversion in the BRET relative to the FPA in the latter market ($r_i^{\text{BRET}} = -0.373$). CRRA preferences comparison, seems to, indeed, capture the differences in the sensitivity of responses to potential losses (BRET), compared to potential gains (FPA). Our results are in line with the context dependent *loss* and *gain* frames introduced and reported by Kahneman and Tversky (1981), and Kahneman and Tversky (1986), and further supported by Hershey and Schoemaker (1980), and Hershey, Kunreuther, and Schoemaker (1982). We find, thus, that the problem formulation indeed impacts observed risk behaviour of agents, and we have evidence to confirm *Hypothesis 2*. What is rather revealing, is that we track inconsistent CRRA elicited preferences and framing effects, not only across two different risk elicitation institutions, but between two institutions that exhibit isomorphic properties in a mathematical sense. Also, similarly to the reported divergent CRRA elicited preferences between the first-price auction and the Becker-de-Groot Marschak mechanism, our results complement Isaac and James (2000) findings.

Table 2.6.4: Univar. regression results: CRRAM r_i risk preferences

This table reports the BRET CRRA risk preferences r_i^{BRET} regressed on the FPA CRRA risk preferences $r_{i,N}^{\text{FPA}}$, per market. Numerical indices N refer to the market size of the FPA. The 'Wald p' line contains the p-values of the Wald test of H_0: the beta coefficient of the BRET r_i^{BRET} choice equals 1. Standard errors are reported in parentheses.Statistical significance is indicated as follows: $^{***}\ p < 0.01, ^{**}\ p < 0.05, ^{*}\ p < 0.10$.

$r_{i,N}^{\text{FPA}}$	$N = 2$	$N = 3$	$N = 4$	$N = 5$	$N = 6$	$N = 7$	$N = 8$	$N = 9$
Intercept	1.570**	5.930	−3.514	1.608***	−1.218	1.460***	−0.872	3.102***
	(0.670)	(5.094)	(6.467)	(0.407)	(4.497)	(0.356)	(7.863)	(0.959)
r_i^{BRET}	−0.373	−2.830	15.138	0.103	10.129	0.353	15.460	−0.470
	(0.489)	(3.107)	(16.007)	(0.227)	(11.109)	(0.314)	(17.688)	(0.602)
Wald p	0.007	0.220	0.382	0.000	0.416	0.042	0.418	0.016
Observ.	42	121	42	121	42	121	42	121
R^2	0.008	0.006	0.099	0.000	0.089	0.012	0.068	0.003

Observation 3: Subjects exhibit consistent risk behaviour in almost 60% of the markets beyond the market with $N = 2$ competitors, where CRRA preferences are elicited. The latter markets are those with $N = 3, 4, 6$ and 8 competitors.

Support: In half of the market sizes, that is markets of $N = 3, 4, 6$ and 8 competitors, isomorphism between the two tasks holds. Overall, the null hypothesis that risk behaviour is isomorphic in the two tasks cannot be rejected at the 5% significance level for the latter markets. The corresponding Wald test p-values suggest that risk behaviour is rather consistent in these markets, through the prism of CRRA preferences: $0.312, 0.220, 0.415$ and 0.418, respectively (Table 2.6.5). When, thus, moving away from the market with $N = 2$ competitors, we indeed find evidence that CRRA preferences are of the same qualitative nature across the tasks in 50% of the markets. We, thus, have support to partly confirm *Hypothesis 3B*.

Table 2.6.5: Univar. regression results: CRRAM r_i risk preferences

This table reports the BRET CRRA risk preferences r_i^{BRET} regressed on the FPA CRRA risk preferences $r_{i,N}^{\text{FPA}}$, per market. Numerical indices N refer to the market size of the FPA. The 'Wald p' line contains the p-values of the Wald test of H_0: the beta coefficient of the BRET r_i^{BRET} choice equals 1. Standard errors are reported in parentheses.Statistical significance is indicated as follows: $^{***}\ p < 0.01, ^{**}\ p < 0.05, ^{*}\ p < 0.10$.

$r_{i,N}^{\text{FPA}}$	$N = 2$	$N = 3$	$N = 4$	$N = 5$	$N = 6$	$N = 7$	$N = 8$	$N = 9$
Intercept	1.570^{**}	5.930	-3.514	1.608^{***}	-1.218	1.460^{***}	-0.872	3.102^{***}
	(0.670)	(5.094)	(6.467)	(0.407)	(4.497)	(0.356)	(7.863)	(0.959)
r_i^{BRET}	-0.373	-2.830	15.138	0.103	10.129	0.353	15.460	-0.470
	(0.489)	(3.107)	(16.007)	(0.227)	(11.109)	(0.314)	(17.688)	(0.602)
Wald p	0.007	0.220	0.382	0.000	0.416	0.042	0.418	0.016
Observ.	42	121	42	121	42	121	42	121
R^2	0.008	0.006	0.099	0.000	0.089	0.012	0.068	0.003

2.7 Conclusion

This study explores elicited risk choices and preferences across two isomorphic tasks, namely, the FPA and the BRET. Motivated by the context dependence discussion in existing literature, we study an interesting case of risk behaviour elicitation, that implies isomorphic responses across two decision environments. We show the isomorphism in the payoff and strategy space of the two tasks in a mathematical sense, and we infer on the potential for framing effects (Kahneman and Tversky (1981),Kahneman and Tversky (1986), Hershey and Schoemaker (1980), Hershey, Kunreuther, and Schoemaker (1982),Tversky (1969)), preference reversals, and consistency of risk preferences beyond the theoretically valid case for isomorphism, in individual risk behaviour (Isaac and James (2000), Lichtenstein and Slovic (1971), Lichtenstein and Slovic (1983), Lindman (1971), Grether and Plott (1979)). We also address the question whether distortions of the nature of a willingness-to-pay and willingness-to-accept question, may disrupt the stability of preferences assumed by isomorphism (Kahneman, Knetsch, and Thaler (1990)).

We detect a violation of the theoretical assumption of isomorphic risk choices and CRRA preferences, between the FPA and the BRET. We particularly find that this violation can be explained by *loss* and *gain* framing effects, evoked by each task, respectively. We also detect preference reversals and information-processing considerations, that distort the assumption of isomorphism across the two tasks. The latter preference reversals, apply both to the most theoretically relevant case of isomorphism ($N = 2$ competitors), as well as to 50% of the market sizes beyond $N = 2$. The magnitude of these reversals is significant in half of the markets beyond the most theoretically relevant case, and in particular in markets with $N = 3, 4, 5$, and 7 competitors. With regards to the willingness-to-pay question, we confirm that it may consist of an aspect that distorts risky choices in all markets. The latter question is relevant for the BRET, and the magnitude of the latter distortion is significant in half of the markets, beyond the market of $N = 2$ competitors.

We overall contribute to the literature on risk preferences elicitation and context-dependence, to the literature on preference reversals, as well as to that of further distortions that may affect choices, preferences and strategy formulation between different decision environments. Through the lens of a straightforward theoretical assumption, we have, thus, provided evidence on context dependence of risk preferences, stability of preferences in the psychological level, and, framing effects.

Finally, we see a potential for extending the genuine comparison between the two institutional formats, beyond the scope of our study. The BRET exhibits very particular informational characteristics. More precisely, its structure and design is similar to a *tree-format* first-price auction version (Cox and James, 2012). The potential for the investigation of isomorphic tasks with institutional formats that do and do not feature informational effects, can be easily established. The FPA comes in an institutional format without any particular visual or conceptual representation of the strategy space (clock-format). Contrary, the BRET represents the gradual isomorphic visual and conceptual representation of the entire strategy space of the first-price auction (tree-format). Given that one experimentally imposes the same time limit for both the FPA and the BRET [1], the two tasks allow subjects for the same portion of time for decision-making. The latter features may help to further explore what are the roots of the observed risk behaviour. By examining whether the induced conceptualisation and visibility of the strategy space explains experimental evidence, one may take one step further into understanding whether informational effects also impact risk behaviour. The informational effects resulting from the *tree-format* Dutch auction render convergence to theory context specific, when experimentally compared to the isomorphic traditional *clock-format* (Cox and James, 2012). That is, while and due to the BRET being isomorphic to the FPA, a straightforward analogy of this context-dependence study, offers fertile ground for future research, in the spirit of Cox and James (2012). Thus, we consider designing and experimentally applying the same tasks, in a dynamic version of the experiment. Simultaneous decision-making between subjects and the computerised bid (FPA), and the chance event occurrence (bomb exploding, BRET), along with repeated rounds of both tasks with feedback, [2] may allow for investigating the presence or absence of informational effects, relative to risk-neutral bidding. Such an extension may enrich the study of risk behaviour across isomorphic tasks. It may also extend inference on the theoretical prediction of isomorphic risk behaviour against the potential for framing effects, preference reversals, and other distortions implied by the context, nature and formulation of the risky choice problem.

[1] We have also experimentally imposed the same time limit for the FPA and the BRET in our one-shot experimental implementation.

[2] Feedback may be provided similarly to Selten and Neugebauer (2006).

Appendix

2.A Instructions

First-price auction

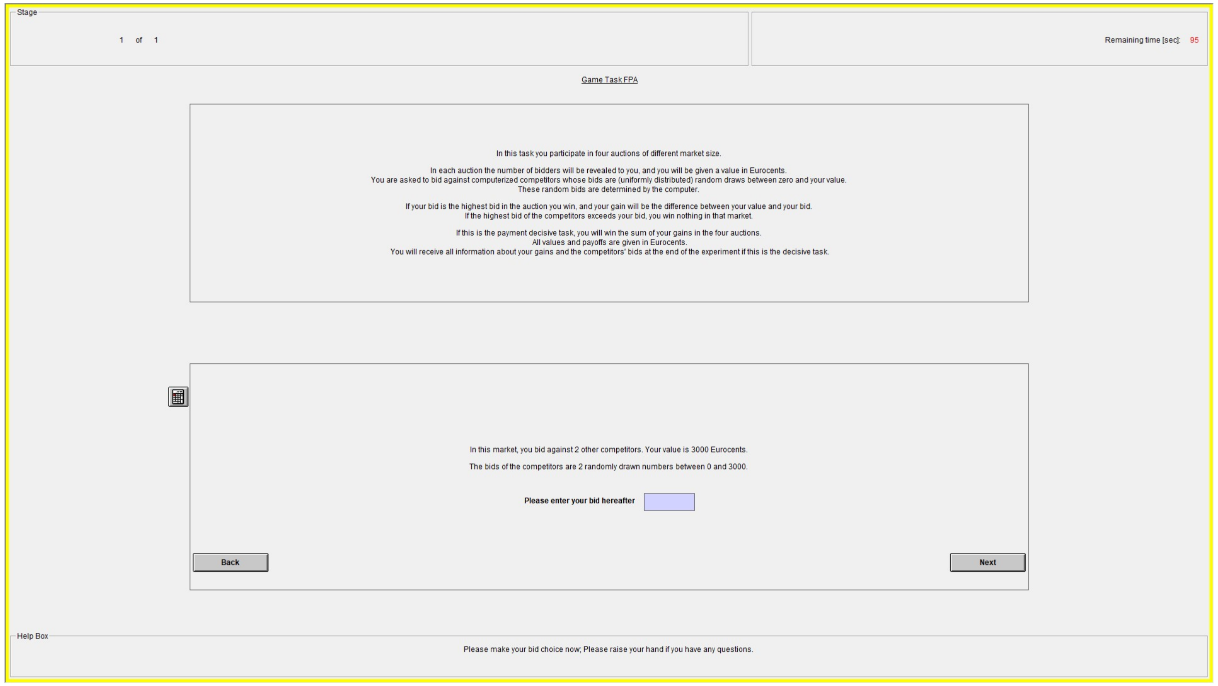
Game Task FPA: In this task you participate in four auctions of different market size. In each auction the number of bidders will be revealed to you, and you will be given a value in Eurocents. You are asked to bid against computerized competitors whose bids are (uniformly distributed) random draws between zero and your value. These random bids are determined by the computer. If your bid is the highest bid in the auction you win, and your gain will be the difference between your value and your bid. If the highest bid of the competitors exceeds your bid, you win nothing in that market. If this is the payment decisive task, you will win the sum of your gains in the four auctions. All values and payoffs are given in Eurocents. You will receive all information about your gains and the competitors' bids at the end of the experiment if this is the decisive task. help box Please raise your hand if you have any questions.

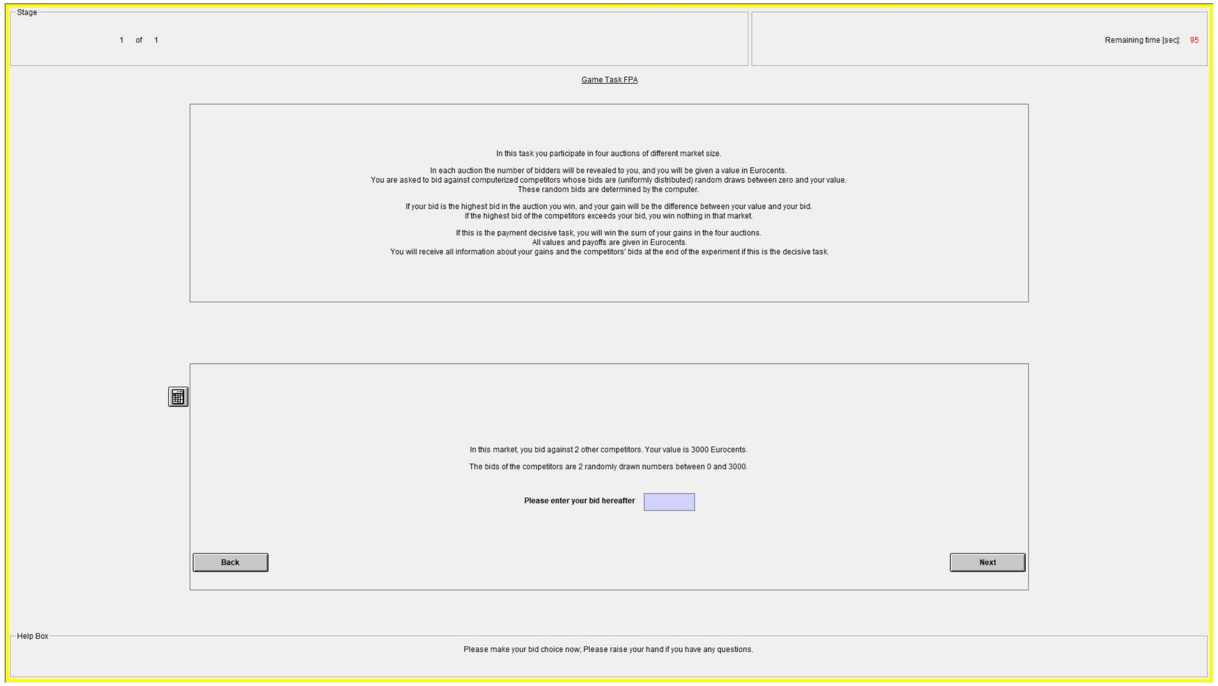
In this market, you bid against 2 other competitors. Your value is 3,000 Eurocents. The bids of the competitors are two randomly drawn numbers between 0 and 3,000. Please enter your bid hereafter:

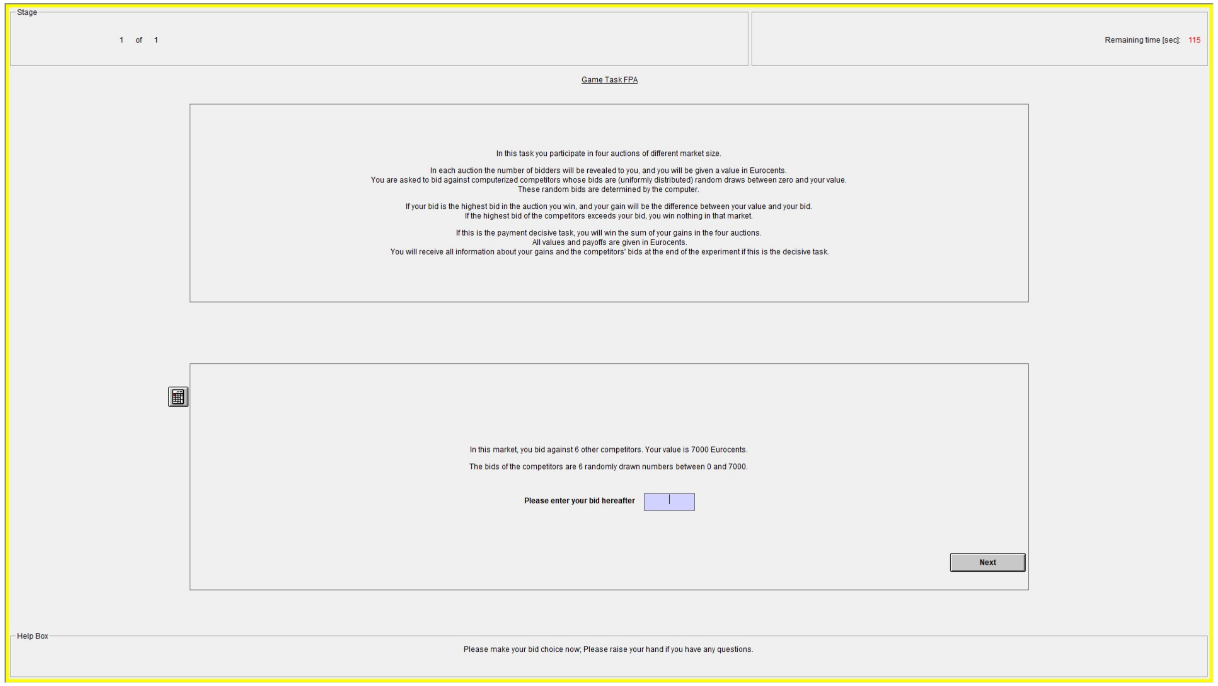
In this market, you bid against 4 other competitors. Your value is 5,000 Eurocents. The bids of the competitors are two randomly drawn numbers between 0 and 5,000. Please enter your bid hereafter:

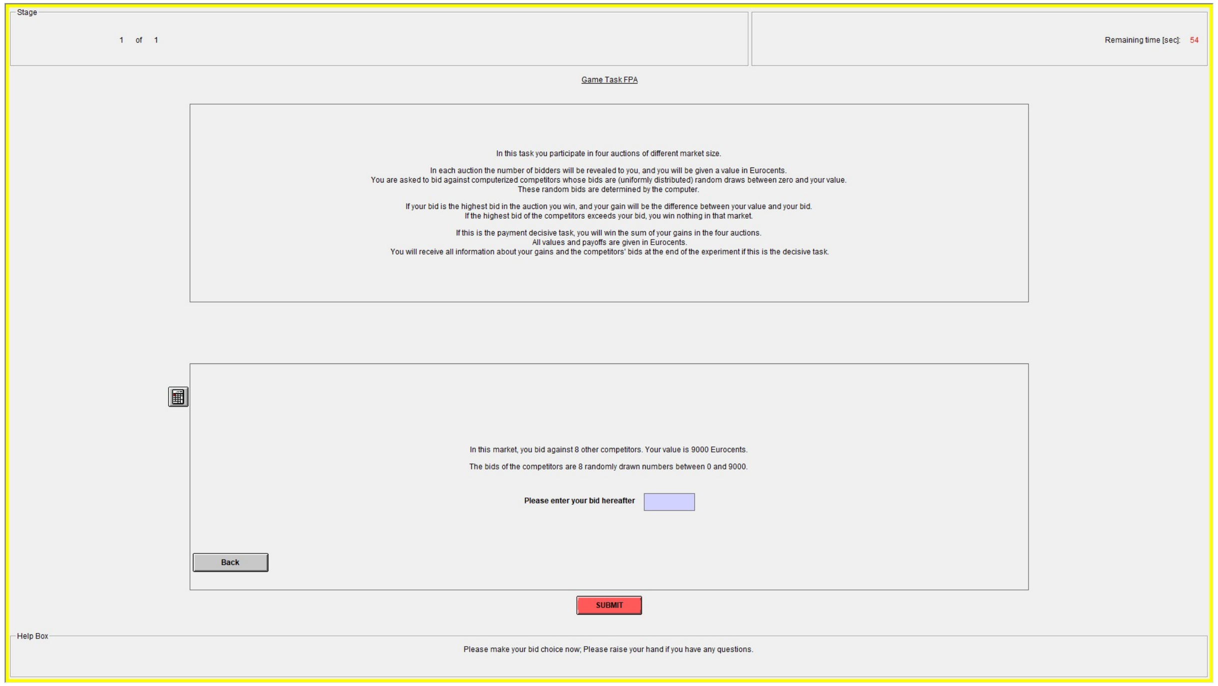
In this market, you bid against 6 other competitors. Your value is 7,000 Eurocents. The bids of the competitors are two randomly drawn numbers between 0 and 7,000. Please enter your bid hereafter:

In this market, you bid against 8 other competitors. Your value is 9,000 Eurocents. The bids of the competitors are two randomly drawn numbers between 0 and 9,000. Please enter your bid hereafter:


Stage
1 of 1
Remaining time [sec]: 95
Game Task FPA
In this task you participate in four auctions of different market size.
In each auction the number of bidders will be revealed to you, and you will be given a value in Eurocents.
You are asked to bid against computerized competitors whose bids are (uniformly distributed) random draws between zero and your value.
These random bids are determined by the computer.
If your bid is the highest bid in the auction you win, and your gain will be the difference between your value and your bid.
If the highest bid of the competitors exceeds your bid, you win nothing in that market.
If this is the payment decisive task, you will win the sum of your gains in the four auctions.
All values and payoffs are given in Eurocents.
You will receive all information about your gains and the competitors' bids at the end of the experiment if this is the decisive task.
In this market, you bid against 2 other competitors. Your value is 3000 Eurocents.
The bids of the competitors are 2 randomly drawn numbers between 0 and 3000.
Please enter your bid hereafter
Back
Next
Help Box
Please make your bid choice now; Please raise your hand if you have any questions.

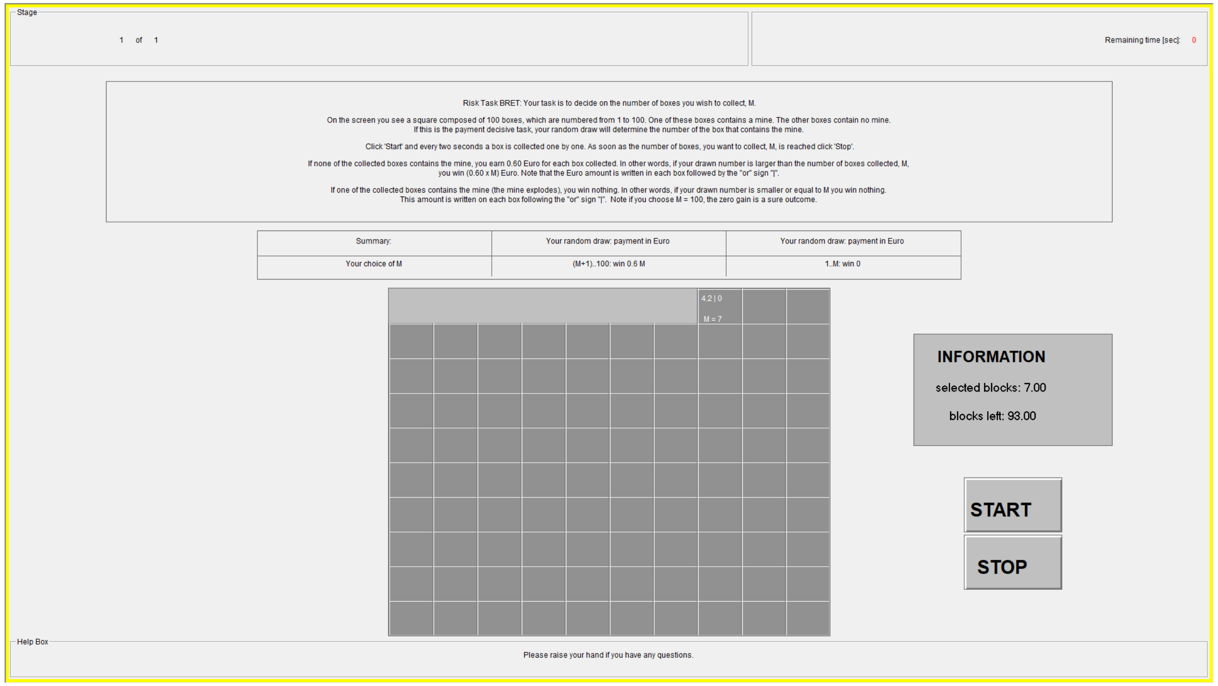

Stage
1 of 1
Remaining time [sec]: 95
Game Task FPA
In this task you participate in four auctions of different market size.
In each auction the number of bidders will be revealed to you, and you will be given a value in Eurocents.
You are asked to bid against computerized competitors whose bids are (uniformly distributed) random draws between zero and your value.
These random bids are determined by the computer.
If your bid is the highest bid in the auction you win, and your gain will be the difference between your value and your bid.
If the highest bid of the competitors exceeds your bid, you win nothing in that market.
If this is the payment decisive task, you will win the sum of your gains in the four auctions.
All values and payoffs are given in Eurocents.
You will receive all information about your gains and the competitors' bids at the end of the experiment if this is the decisive task.
In this market, you bid against 2 other competitors. Your value is 3000 Eurocents.
The bids of the competitors are 2 randomly drawn numbers between 0 and 3000.
Please enter your bid hereafter
Back
Next
Help Box
Please make your bid choice now; Please raise your hand if you have any questions.


Stage
1 of 1
Remaining time [sec]: 115
Game Task FPA
In this task you participate in four auctions of different market size.
In each auction the number of bidders will be revealed to you, and you will be given a value in Eurocents.
You are asked to bid against computerized competitors whose bids are (uniformly distributed) random draws between zero and your value.
These random bids are determined by the computer.
If your bid is the highest bid in the auction you win, and your gain will be the difference between your value and your bid.
If the highest bid of the competitors exceeds your bid, you win nothing in that market.
If this is the payment decisive task, you will win the sum of your gains in the four auctions.
All values and payoffs are given in Eurocents.
You will receive all information about your gains and the competitors' bids at the end of the experiment if this is the decisive task.
In this market, you bid against 6 other competitors. Your value is 7000 Eurocents.
The bids of the competitors are 6 randomly drawn numbers between 0 and 7000.
Please enter your bid hereafter
Next
Help Box
Please make your bid choice now; Please raise your hand if you have any questions.


Stage
1 of 1
Remaining time [sec]: 54
Game Task FPA
In this task you participate in four auctions of different market size.
In each auction the number of bidders will be revealed to you, and you will be given a value in Eurocents.
You are asked to bid against computerized competitors whose bids are (uniformly distributed) random draws between zero and your value.
These random bids are determined by the computer.
If your bid is the highest bid in the auction you win, and your gain will be the difference between your value and your bid.
If the highest bid of the competitors exceeds your bid, you win nothing in that market.
If this is the payment decisive task, you will win the sum of your gains in the four auctions.
All values and payoffs are given in Eurocents.
You will receive all information about your gains and the competitors' bids at the end of the experiment if this is the decisive task.
In this market, you bid against 8 other competitors. Your value is 9000 Eurocents.
The bids of the competitors are 8 randomly drawn numbers between 0 and 9000.
Please enter your bid hereafter
Back
SUBMIT
Help Box
Please make your bid choice now; Please raise your hand if you have any questions.

Bomb Risk Elicitation task

Risk Task BRET: Your task is to decide on the number of boxes you wish to collect, M. On the screen you see a square composed of 100 boxes, which are numbered from 1 to 100. One of these boxes contains a mine. The other boxes contain no mine. If this is the payment decisive task, your random draw will determine the number of the box that contains the mine. Click 'Start' and every two seconds a box is collected one by one. As soon as the number of boxes, you want to collect, M, is reached click 'Stop'. If none of the collected boxes contains the mine, you earn 0.60 Euro for each box collected. In other words, if your drawn number is larger than the number of boxes collected, M, you win (0.6 M) Euro. Note that that Euro amount is written in each box followed by the "or" sign "|". If one of the collected boxes contains the mine (the mine explodes), you win nothing. In other words, if your drawn number is smaller or equal to M you win nothing. This amount is written on each box following the "or" sign "|". Note if you choose M = 100, the zero gain is a sure outcome.


Stage
1 of 1
Remaining time [sec]: 0
Risk Task BRET: Your task is to decide on the number of boxes you wish to collect, M.
On the screen you see a square composed of 100 boxes, which are numbered from 1 to 100. One of these boxes contains a mine. The other boxes contain no mine.
If this is the payment decisive task, your random draw will determine the number of the box that contains the mine.
Click 'Start' and every two seconds a box is collected one by one. As soon as the number of boxes, you want to collect, M, is reached click 'Stop'.
If none of the collected boxes contains the mine, you earn 0.60 Euro for each box collected. In other words, if your drawn number is larger than the number of boxes collected, M,
you win (0.60 x M) Euro. Note that the Euro amount is written in each box followed by the "or" sign "|".
If one of the collected boxes contains the mine (the mine explodes), you win nothing. In other words, if your drawn number is smaller or equal to M you win nothing.
This amount is written on each box following the "or" sign "|". Note if you choose M = 100, the zero gain is a sure outcome.
Summary:
Your random draw: payment in Euro
Your random draw: payment in Euro
Your choice of M
(M+1)..100: win 0.6 M
1..M: win 0
4.2 | 0
M = 7
INFORMATION
selected blocks: 7.00
blocks left: 93.00
START
STOP
Help Box
Please raise your hand if you have any questions.

Chapter 3

Information Effects and Aggregation via Procedurally Fair Co-determination in Corporate Governance

3.1 Introduction

Imagine a joint venture firm with several partners who jointly have to decide on a major investment. Even when the investment itself is clearly defined, its future consequences for the partners, and altogether for the firm, may be difficult to predict. However, ignorance of the future impact can be reduced by investing more effort in collecting and analysing all available information. Investing in information search can, thus, help to predict the future more reliably. Only when all partners maximally invest in area-specific information search, ambiguity of the result is attenuated. We develop and apply a fair decision-making mechanism, that allows for private investment in costly information search. One could assume that information search reduces the length of one's ambiguity interval relative to the project's value. Reporting intervals in order to decide on an investment, however, would be problematic, since effort in information search is hidden. Partners could report more narrow intervals in order to hide shirking. Therefore, our fair mechanism restricts partners to state just one value, in the following, a bid.

With fair group decision-making in corporate governance, one obviously hopes to gather the widespread information in the firm. Only by information aggregation, and in conditions under which, potential failure to implement an overall beneficial project limits underbidding, an investment can be deemed recommendable. Group decision-making mainly considers partnerships where, all essential stakeholders collectively take investment decisions. For this reason, the fair mechanism seems suitable for small joint venture start-up firms. In that sense, even a field application of the mechanism seems possible. One could argue against this, that corporate governance involves lots of minor managerial decisions. In our view, these are often handled by making individual partners solely responsible in decision-making, conditional on their special competences. Thus, we focus at major investment decisions (policy changes), that crucially affect all partners, and which should not be implemented against the explicit wish of one of them.

A prominent part of corporate governance existing literature, primarily focuses on potential opportunism on behalf of firm managers at the cost of shareholders' interests (Jensen and Meckling (1976), Fama and Jensen (1983)). Fama and Jensen (1983) stress the relevance of managers' competences and knowledge to efficient decision-making, in non-complex firms. They acknowledge that the agency problem that arises from the overlap of decision management over decision control, though, may harm residual claimants. Fama and Jensen (1983) suggest to *"restrict residual claims to the most important decision agents"*. We design, apply and suggest a fair mechanism, that allocates decision management and control only to area-specific competent partners. The mechanism accounts for accruing payoffs only for those area-specific agents [1]. These payoffs operate as the residual claims assigned only to the firm decision makers. We also introduce ambiguity relative to investments' values, that controls for the nature and degree of information and knowledge that is crucial for decision-making. The residual claims depend on the decision-making behaviour of partners in the form of bids, as well as to their level of investment in information search. In particular, partners are restricted into one group decision on every investment, after privately and individually investing in information search, about the true project value. Each of the managers has a benefit or cost from the implementation of the potential project. If the sum of benefits exceeds the sum of costs the project should be implemented. The mechanism suggests that each party shall state their benefits or costs. The theoretical solution is not clear, though, as every party has an incentive to inflate their cost, shade the benefit, accordingly. Therefore, this setup allows us to track partners' bidding behaviour, as a function of the knowledge that is required for efficient decision-making, and according to commonly accepted bidding rules. We find that the mechanism encourages truth-telling in bidding with increased information search. Efficiency in terms of truthful bidding is bounded, by those partners that do not want to stand in the way of an overall beneficial project. We define the bidding behaviour

[1] We describe extensively the fair mechanism and the resulting payoff function in the next section.

that deflates one's cost as *limited opportunism*. Coming, thus, to desirable decision outcomes is achieved by the mechanism, for most of the information search spectrum, while opportunism is limited.

Recently, behavioural approaches towards corporate governance have also expanded (Ees, Gabrielson, and Huse, 2009). Venture capital relationships and relevant types of covenants are particularly studied and investigated (Cumming and Johan, 2006). This investigation distinguishes between contracts that regulate the terms of limited partnerships in venture capital, and contracts that identify veto and control rights in the latter partnerships. As veto and control rights are legally relevant to joint ventures, we introduce these properties in group decision-making. In particular, the fair mechanism primarily satisfies similar requirements as FPAs (Guth (2011)), (Kagel, 1995): guarantees equal treatment when individual values are substituted by individual bids, grants individual veto power by bidding low enough, and remains overbidding proof while providing underbidding incentives. The mechanism checks whether the sum of individual bids by all partners suffices to cover the costs of the investment, possibly including a surplus demand for such a measure. If this is true, the investment is implemented. Project values are arbitrarily drawn from a uniform distribution. What a partner earns is his individual value, minus the bid, plus an equal share of the non-negative (bid) surplus, minus the costs. We view a fair mechanism in group decision-making with the aforementioned properties, as a proposal to potentially substitute complex legal covenants, that mainly target towards tackling agency problems. We think that the latter can be proxied by such a fair group decision-making design, that shares essential common market rules.

Landier et al. (2013) explore the impact of managers' independence in decision-making quality. They provide evidence that a high fraction of independent executives (high internal governance), predicts high future performance (returns). We consider veto power, private costly search and private bidding, as properties that proxy to a large extent managers' (partners') independence. Landier, Sraer, and Thesmar (2009) develop an organisational decision-making setup with two agents, a decision maker and an implementer. The agents are assigned different roles relative to the decision process, obtain different levels of information relative to projects values and have intrinsic preferences. The decision maker decides the project to invest to and the implementer privately chooses between two effort levels to exert on project implementation (costly high effort and low effort). Projects can fail or deliver a profit to the firm owner. Information relative to project profitability is modelled by a commonly observed signal or, alternatively, consists of private information to the decision maker. Both agents obtain private benefits when their preferred project materialises. In the decision-making process, the owner chooses between either homogeneous or heterogeneous organisational design (convergent versus divergent intrinsic preferences on projects). Landier, Sraer, and Thesmar (2009) explore the impact of convergence and divergence in preferences. They also introduce a moral hazard in decision-making by allowing for investment in effort in project implementation. The authors assume that successful project implementation requires costly unobserved effort on behalf of the implementer. Their study shows that there is an overall benefit stemming from divergence (dissent) that improves corporate decisions (efficiency), and that relates to the external signal or private information on project profitability (project value). More precisely, they show that such dissent is optimal and imposes efficient implementation constraints that discipline decision-making, when information is useful and uncertainty is high. The decision-maker is led to use more objective information in their decision process by anticipating the effort, which the implementer is willing to provide to the project to increase profitability. Our fair mechanism, with the form, bidding rules and properties already described, renders managers (partners) individually competent for decision-making. Also, through value ambiguity and information search, the mechanism partly allows biases relative to the project value to cancel out in the decision making process. Our mechanism consists, thus of an experimental analogue to the model of Landier, Sraer, and Thesmar (2009). Similar to the latter, it allows for a minimum payoff per manager given project implementation, as well as the option for investment in value information search. We ensure the potential for lack of congruence and divergent preferences introduced in Landier, Sraer, and Thesmar (2009), by allowing for a separate value-bid per manager, that declares the latter's preference towards project implementation. The project implementation decision rule is contingent upon costly private investment in information search, while the latter works similarly to the private signal agents receive in Landier, Sraer, and Thesmar (2009). The mechanism ensures private benefits incentives expressed in the monetised payoff function. It also internalises the motivation of positive value bidders, by introducing a negative value bidder per group and experimental round. Overall, we are actually introducing the option for a potential lack of congruence, by allowing for ambiguous valuations and individual veto power. With our mechanism design, thus, we introduce veto power as a form of theoretical dissent, which can similarly foster the use of objective information relative to the project value and thus, enhance corporate performance efficiency. As already stated, we do find that the fair mechanism enhances efficiency, by leading to increased truth-telling, and limiting opportunism significantly. We do also provide preliminary evidence that the majority of profitable projects are funded, and that, thus, some indication for value-based efficiency also exists. We do observe that profitable funding overall prevails even when partners underbid, and thus behave in a rather opportunistic way. Overall, our results show that private information search, veto power, and equal treatment, as basic properties of group decision-making, improve the performance and limit partners' opportunistic incentives. However, as expected, there is still a degree of opportunism (underbidding), not entirely vanishing with veto power and equal treatment.

We also concentrate on extending and testing a fair mechanism, as relative (payoff) standing and inequity aversion are proved to account for a key aspect of strategic human behaviour (Bolton and Ockenfels (2000)). Various fair mechanisms have been examined and applied to other collective action tasks. Güth, V.M.Levati, and Montinari (2014) examine collective public ranking of alternatives via bidding. Cicognani et al. (2015) and Güth et al. (2014) investigate public project provision via bidding, respectively. Cicognani et al. (2015) implement a fair public provision mechanism. They show that outcome based social preferences (Fehr and Schmidt, 1999) are replaced by the mechanism's procedural fairness and that, often, the socially best project gets implemented. Güth et al. (2014) observe, though, significant deviations from efficient project implementation, when two (rather than one) types of projects are experimentally involved.

Alberti, Güth, Kliemt and TsuTsui (2016), consider a setup with a manager representing the shareholders, that states their surplus claim and maintains the final decision right on investment. Instead, we focus on a joint venture, where partners are privately informed about different aspects that determine the profitability of the investment. In that context, our proposed bidding mechanism is not an imposed instrument, that the stakeholder representative uses to elicit available information at lower hierarchy levels. It is rather a group decision-making mechanism among equals. Another essential property of the mechanism that is introduced for the first time in corporate governance decision-making, is the option for partners to choose how precise information they obtain relative to the project value. To our knowledge, no corporate governance decision making model so far has allowed for ambiguous investment values, which, in our view are pervasive in the field. Ambiguous project values, not only let the effort exerted in information search vary, but also question what underbidding means. Would one bid the lowest possible value realisation or select only a bid in the lower half of one's ambiguity interval ? Behaviourally, having to invest in costly effort to obtain more precise value information, and to bid, furthermore, allows for opportunism in a double sense: both by avoiding private search cost and by underbidding, e.g. one's lowest possible value realisation. We examine, thus, for the first time how freely determined value information impacts decisions, truth-telling and efficiency, in a theoretically and behaviourally well-established decision environment. Our primary focus is on the extent and the origins of truth-telling and, efficiency and the potential for limited opportunism under the proposed mechanism.

The rest of the paper is structured in the following way: in Section 3.2 we describe the mechanism theoretically, along with the introduced payoff function. In Sections 3.3 and 3.4 we present the experimental design of the mechanism, and our testable hypotheses. In Section 3.5 we present and elaborate on our non-parametric (Section 3.5.1) and parametric results (Section 3.5.2). Section 6 summarises and concludes the paper.

3.2 The mechanism

The three partners $i = 1, 2, 3$, to whom we refer as bidders $i = 1, 2, 3$, individually state a monetary bid $b_i in \in \mathbb{R}$. Individual bids can be positive, as well as negative. Decisions can be understood as a fundamental deviation from the status quo, whose estimated cost of change equals $C \in \mathbb{R}$. In a purely financial organisational setup, decisions refer to investment decisions on particular projects. Ambiguous valuations can be, thus, understood as the discounted future expected cash flows on investment (the projects net present value).

A positive C translates to costly investing; a is negative C could refer to the cost of an investment, to outsourcing some costly tasks, or to selling some part of the previous activities [1]. Although we have normalised C to 0 in the experiment for the sake of simplicity, we maintain it when presenting the institutional framework more generally. Also, we assume that C is common knowledge, since we want to focus mainly on ambiguity of private information. The fair mechanism can be described as follows:

Bidders $i = 1, 2, 3$ state their bids b_1, b_2, b_3 in order to decide on an investment. If

$$\frac{b_1 + b_2 + b_3}{3} \geq C \tag{3.1}$$

the investment (project) is realised, otherwise the status quo is maintained. For $i = 1, 2, 3$, we denote the more or less precisely known value $v_i \in \mathbb{R}$ of bidder i, in case of validity of equation (3.1). The status quo is normalised to $v_i = 0$ for $i = 1, 2, 3$. The resulting payoffs when (3.1) holds are:

$$E + v_i - b_i + \frac{b_1 + b_2 + b_3 - C}{3} - C(e_{i,t}) \tag{3.2}$$

[1]The latter especially when referring to a structural policy change

for $i = 1, 2, 3$, where E corresponds to the subjects' initial endowment. In case of maintained status quo, they equal 0.

In this decision-making setup, the basic properties can be easily identified. If one substitutes v_i by b_i for $i = 1, 2, 3$ and neglects private information costs, all three bidders i earn the same, i.e. the mechanism guarantees equal treatment. By bidding low enough, each individual bidder $i = 1, 2, 3$ can question (3.1) and, thus, make sure that the status quo prevails. Finally, every $b_i \geq v_i$ is weakly dominated by $b_i = v_i$, whereas underbidding $b_i \leq v_i$, may pay. Altogether, the mechanism relies to the same basic properties as the frequently employed FPA.

The way information search $e_i \in$0,1,2,3,4,5,6, $withcosts$c$_i(e_i)$ attenuates ambiguity about the project value v_i is shown in Table 3.2.1 below:

Table 3.2.1: Information search levels, ambiguity intervals and corresponding costs

$e_{i,t}$	0	1	2	3	4	5	6
$C(e_{i,t})$	0	0.5	1	1.5	2	2.5	3
$l(e_{i,t})$	64	32	16	8	4	2	1

The lowest row specifies the length $l(e_{i,t})$ of bidder $i's$ ambiguity interval, when bidder i invests in information search level $e_{i,t}$ and pays the corresponding cost $c(e_i)$. Without investment in information search ($e_{i,t} = 0$), the interval precision is 64 (digits-integers). With maximum investment in information search $e_{i,t} = 6$, one acquires full value knowledge, at the cost of 3 ECU (Experimental Currency Units=Francs).

3.3 Experimental designs

Participants were recruited by LISER-LAB [1] with the use of recruitment software ORSEE (Greiner, 2015). The experiment was programmed and computerised in the experimental software zTree (Fischbacher, 2007). The experiment in total comprised of six experimental sessions of 1.5 hours each. In order to better evaluate our hypotheses relative to a fair mechanism in corporate governance, we designed and implemented two treatments. In the first treatment partners freely choose their information search level, and in the second, the latter is randomly assigned per period and subject (partner). Experimental sessions and, thus, data on the two treatments are equal.

Participants first received written instructions that they were asked to carefully read. The

[1] Luxembourg Institute for Socio-Economic Research

instructions were read aloud by the experimenter. Questions were privately answered by reference to the related points in the instructions. The experiment was programmed to allow for a within-subjects variation, within each treatment (free choice and randomly assigned information search). All participants faced two conditions; once they repeatedly interacted with the same cohorts (within a constant group of partners) for 20 periods, and once they interacted in randomly formed groups every subsequent period, for another 20 periods (Table 3.3.1). In both conditions, participants received feedback on their bid $b_{i,t}$, their value $v_{i,t}$, the average bid of their group, and their period payoff in the current, and all previous periods. No information was provided on the value, bid or period payoffs of the other two group members, at any period. We also applied a cross-over design within sessions in order to test for a potential order effect. In particular, two out of the three sessions per treatment initiated by random cohorts interaction (*Strangers*), and one by constant (*Partners*), respectively.

Table 3.3.1: Treatment design

Re-matching order		Treatment	
		Choose	Assigned
P: Partners	P_{1-20}, S_{21-40}	40 Periods	40 Periods
S: Strangers	S_{1-20}, P_{21-40}	40 Periods	40 Periods

We designed and applied a comprehension test of the fair mechanism (payoff) function before every experimental session. The comprehension test ensured that, all participants, have comprehended negative value bidding implications in the mechanism payoff function. In particular, each participant was asked to submit three bids, one negative and two positive, to calculate the average bid of the group, as well as the payoff of each partner (group member). In cases of false answers or queries, the experimenter privately guided participants until every participant successfully completed the test. That is, only after successful completion of the comprehension test the experiment was launched. At the end of each part of the experiment, the experimenter asked for a randomly selected participant to draw a number from 1 to 20 from an opaque urn of 20 numbers, in order to define the payoff period of all participants. At the end of the first part, a second set of instructions was provided to the participants. The second set of instructions elaborated on the procedures of the second 20 periods. Similarly to the first part of the experiment, the instructions for the second 20 periods were read aloud by the experimenter, and any questions were answered privately.

Information search: free-choice: What is experimentally applied is to let partners $i = 1, 2, 3$ choose their investment in information search, as presented in Table 3.2.1. At each and every successive period, a random integer $v_{i,t}$ is drawn for each $i = 1, 2, 3$ from a uniform distribution. Partners receive information on whether their private value is positive or negative, before submitting their bid in all periods. They privately choose their information search level $e_{i,t}$. Each partner is then informed that their value $v_{i,t}$ is some integer between $\underline{V_{i,t}}$ and $\overline{V_{i,t}}$. The latter information is always relative to their level $e_{i,t}$ with corresponding length $l(e_{i,t})$. Of course, each partner $i = 1, 2, 3$ only learns about the lower $\underline{V_{i,t}}$ and upper bound $\overline{V_{i,t}}$ of their own ambiguity interval, and of the length $l(e_{i,t})$. Then, each partner states the bid.

Information Search: random assignment: In this treatment, partners are randomly assigned their information search level $e_{i,t}$, each period. A random integer value $v_{i,t}$ is again drawn for each $i = 1, 2, 3$ from a uniform distribution. Similarly to the first treatment, partners first receive information on whether their private value is positive or negative. According to the randomly assigned information search level $e_{i,t}$, each partner is again informed that their value $v_{i,t}$ is some integer between $\underline{V_{i,t}}$ and $\overline{V_{i,t}}$ with corresponding length $l(e_{i,t})$. Each partner $i = 1, 2, 3$ still only learns about the lower $\underline{V_{i,t}}$ and upper end $\overline{V_{i,t}}$ of their own ambiguity interval and length $l(e_{i,t})$. Thereafter, each $i = 1, 2, 3$ similarly states the bid.

To capture the richness of possible cases in the limited framework of only three interacting stakeholders, we experimentally apply a condition relative to the project value $v_{i,t}$: always one out of three partners faces an ambiguity interval with $\overline{V_{i,t}} < 0$, each successive period. That is, in each round, one of the three interacting partners is assigned a negative value. The selection of the partner is random at each round, and does not at all relate to investment in information search. The other two partners, respectively, always face a randomly drawn positive value $v_{i,t}$, from the equivalent positive domain of the uniform distribution. In all cases, the sum of the lower bounds $\underline{V_{i,t}}$ with all three partners investing 0 in information search is positive, i.e. by implementing the investment, the firm is definitely better off. The three bids determine, as already defined, whether 3.1 is valid. If so, payoffs accrue according to 3.2, minus the corresponding search costs $c(e_{i,t})$. If not, the status quo prevails with 0-payoffs for all bidders who, however, still have to pay their search costs $c(e_{i,t})$. After each round, another round begins, with new investment in information search and bids, except for the last round. Each round is based on newly generated, more or less narrow, value intervals, for each $i = 1, 2, 3$. Bidders are endowed in each round with 3 $Francs$, so as to avoid an additional risk of losses due to costly information search. However, in case of overbidding $b_{i,t} > v_{i,t}$, they anyhow face that risk. The latter risk can only be mitigated by not overbidding the higher bound of one's ambiguity interval $\overline{V_{i,t}}$.

It is essential to highlight again that, although partners interact repeatedly, they never receive feedback information about others' information search nor others' ambiguity intervals. They actually learn only about the average bid of their group, and about their period payoff. Feedback referring to all past periods accrues and is provided to each partner after the first round, and until the last one. Bidders' period payoff is, thus:

$$v_{i,t} - b_{i,t} + \frac{b_1 + b_2 + b_3 - C}{3} + E - c(e_{i,t}) \tag{3.3}$$

if

$$\frac{b_1 + b_2 + b_3 - C}{3} \geq C \tag{3.4}$$

while, equal to

$$E - c(e_{i,t}) \tag{3.5}$$

if

$$\frac{b_1 + b_2 + b_3 - C}{3} < C \tag{3.6}$$

E stands for the endowment of 3 ECU (Francs) provided to subjects, and C, as already mentioned, is normalised to 0. Payoffs are calculated in *ECU* (Experimental Currency Unit), whose conversion rate is 0.33, thus 1 Franc=0.33 Euro. At the end of the second 20 rounds, all participants replied to a computerised questionnaire. The questionnaire included questions relative to personal characteristics of participants (i.e. age, gender), standard overconfidence and cognitive reflection tasks' (CRT), as well as some more general questions (i.e. conformity questions on honesty, leadership, trust). Finally, participants were privately paid their randomly selected period payoff, plus a show up fee of 10 ECU (Francs).

3.4 Hypotheses

Ambiguity confounds the analysis whether participants are underbidding (due to underbidding incentives) or overbidding (possibly triggered by corporate identity concerns). Actually it renders also truthful bidding ambiguous. What can be said clearly is that bids $b_i<\underline{V_i}$ are underbidding and that bids $b_i>\overline{V_i}$ are overbidding. The latter would indicate that i does not want to block a project which $i's$ partners might consider profitable. We expect:

Hypothesis 1: Fairness in group decision-making (bidding) in corporate governance leads, overall, to profitable investments. In other words, a fair bidding mechanism with ambiguous valuations and private investment in costly information search, leads mostly to profitable funding decisions.

Hypothesis 2: Fairness in group decision-making (bidding) in corporate governance limits opportunism at the expense of other stakeholders.

Hypothesis 3: Overbidding in the form of $b_i > \overline{V_i}$ is rare and mainly due to bidders with $\overline{V_i}<0$, who may not want to block an overall profitable investment. Bids b_i are mainly concentrated in the lower half of one's ambiguity interval.

3.5 Experimental Results

3.5.1 Non-parametric statistical analysis

Observation 1: The vast majority of profitable projects are funded. Indication for value-based $v_1 + v_2 + v_3 \geq 0$ efficiency exists, both with endogenously chosen and exogenously assigned information search.

Figure 3.5.1 illustrates the distribution of relative frequencies of project implementation conditional on project profitability. Some indication for value-based efficient outcomes is suggested by experimental data. We test, at this stage, whether funded and non-funded profitable projects are equiprobable. In Table 3.5.1, the binomial test p-values 0.000 (endogenous information precision) and 0.020 (exogenous information precision) imply that the latter are not equiprobable. The null hypothesis that the proportion of funded profitable projects equals that of not funded profitable ones, is rejected at the 5% level in favour of funded profitable projects. Thus, we have some evidence to partly support Hypothesis 1. In Section 3.5.5 we complement our inference on whether the mechanism leads to efficient (desirable) outcomes from the perspective of truth-telling.

Figure 3.5.1: Relative frequencies of project implementation conditional on project profitability

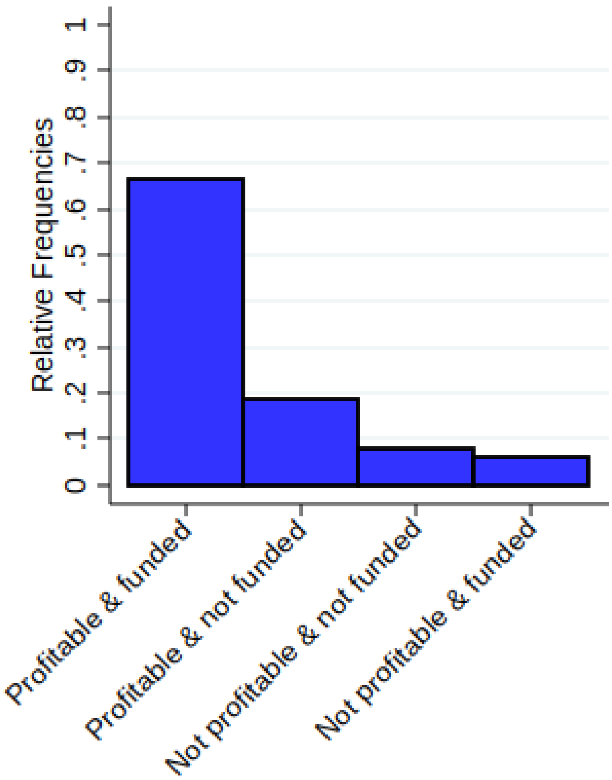
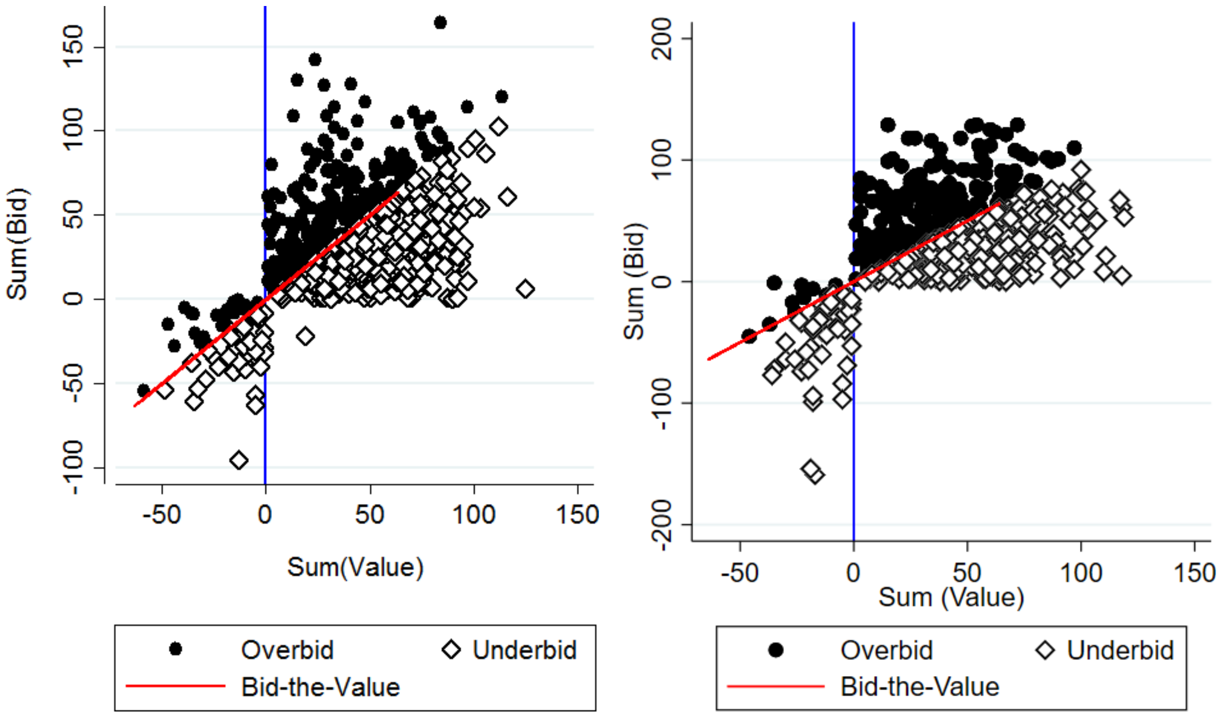


Table 3.5.1: Binomial test results

This table reports Binomial test statistical results relative to our prior that funded profitable projects outweigh not funded profitable projects. N_1 and N_2 refer to the number of the test observations in treatments with free choice and random assignment of information search, respectively. Significant differences relative to outcomes probabilities are indicated as follows: *** $p < 0.01,^{**}$ $p < 0.05,^{*}$ $p < 0.10$.

	Endog. Information Binomial test p-value		*Exog. Information Binomial test p-value*		*Observations*
	[Observed k]	*[Expected k]*	*[Observed k]*	*[Expected k]*	N_1,N_2
Pr($k \geq$ obs. K)	0.000***		0.020**		(18,2), (15,5)
	[18]	[10]	[15]	[10]	

Observation 2: Without considering different value precision levels, profitable funding in a procedurally fair corporate governance mechanism, overall prevails even when partners underbid their project values.



Endogenous Exogenous

Figure 3.5.2: Funded profitable and non-funded non-profitable projects

Support: Funded profitable outcomes are statistically shown to outweigh the proportion of not funded profitable outcomes in the mechanism. We are thus, particularly interested in testing whether the type of bidding behaviour impacts this preliminary evidence of value-based efficiency, without conditioning into information search. Figure 3.5.2 segregates group observations according to overbidding and underbidding (red diagonal), and project profitability $(v_1 + v_2 + v_3)$ and implementation $(b_1 + b_2 + b_3)$, respectively. We focus on funded (implemented) and not funded (not implemented) profitable projects. Graphical evidence shows that, those outcomes' distribution is equally dispersed across the two types of bidding behaviour.The pattern does not seem to change when partners are randomly assigned or choose their information search level. We statistically infer on whether the strategically dominant behaviour (underbidding) prevents profitable outcomes from realising: we test our data on the aggregate level (on the overall mean bidding behaviour across all periods) per group of partners. Binomial test statistics, without any distinction across the various information search levels, are reported in Table 3.5.2. Both when partners choose and are randomly assigned their investment in information search, funding profitable projects prevails also in the presence of underbidding. Qualitatively, this result allows us to conjecture that missing out on profitable funding is prevented by a procedurally fair mechanism, even in the presence of opportunism on behalf of the partners. Thus, we have some additional evidence to support Hypothesis 1.

Table 3.5.2: Binomial test results

This table reports Binomial test statistical results on whether overbidding and underbidding are equiprobable among funded profitable projects. The test is conducted across the two alternative conditions of investing in information search (free choice versus random assignment). N_1 and N_2 refer to the number of the test observations in the first and second condition of investing information search, respectively. Significant differences relative to outcomes probabilities are indicated as follows: *** $p < 0.01,^{**}$ $p < 0.05,^{*}$ $p < 0.10$.

	Endog. Info Binomial test p-value [Observed k]	*[Expected k]*	*Exog. Info Binomial test p-value [Observed k]*	*[Expected k]*	Observations
					N_1,N_2
$\Pr(k \geq \text{obs. } K)$	0.001***		0.007***		(2,16), (2,13)
	[2]	[9]	[2]	[7.5]	

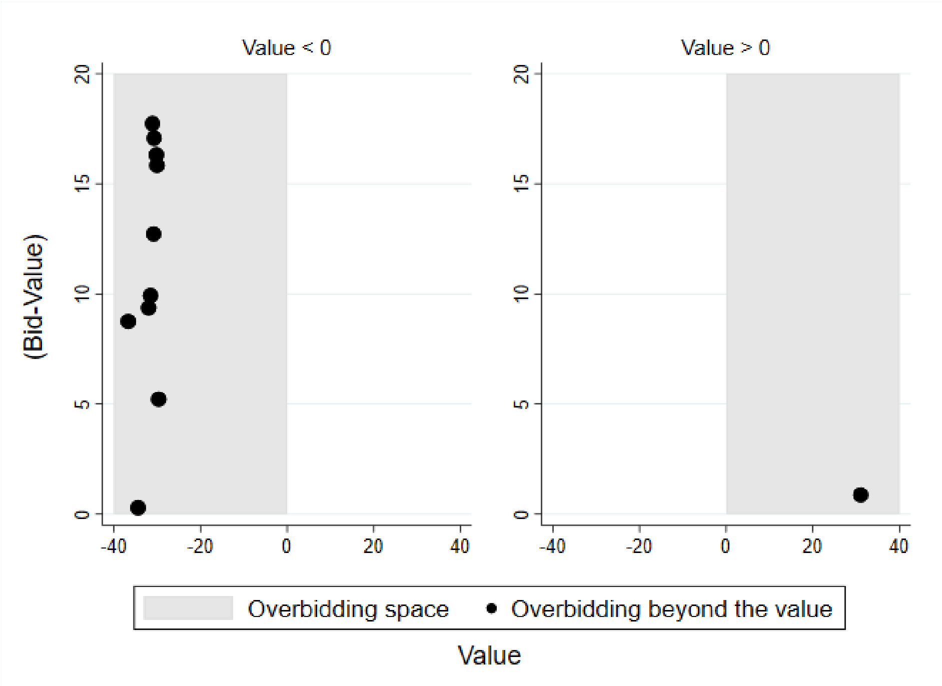
Observation 3: Overstating one's benefit, whilst limited, is significant and more pronounced with negative values.

We theoretically predict that group overbidding is mainly due to partners with negative projected future project cash flows (values) when veto power, equal treatment and private costly effort are ensured. Our relevant hypothesis (*Hypothesis* 3) is confirmed at the 1% significance level. The Wilcoxon signed-rank test in Table 3.5.3 refers to the H_0 hypothesis whether overbidding (average bidding behaviour) differs between certain and ambiguous value knowledge (all other information search levels). The test affirms that overbidding is significantly extended from those shareholders that do not wish to stand in the way of a profitable investment Z-statistic$=-2.803$, p-value$=0.005$. Indeed, crowding in corporate identity seems to occur mainly when partners confront negative project values. Overbidding observations distribution in the negative valuation panels of Figures 3.5.3 strongly confirms the significance of our prediction and hypothesis. It is noteworthy that the result holds irrespective of whether one chooses or not to invest in costly effort. Imposed costly precision may be seen as an information asymmetry that cannot be always be circumvented by a shareholder willing to search for more value precision. This finding proposes, thus, that private bidding limits opportunism, especially when seemingly viewing oneself as the only one blocking a profitable investment (Hypothesis 2 and 3).

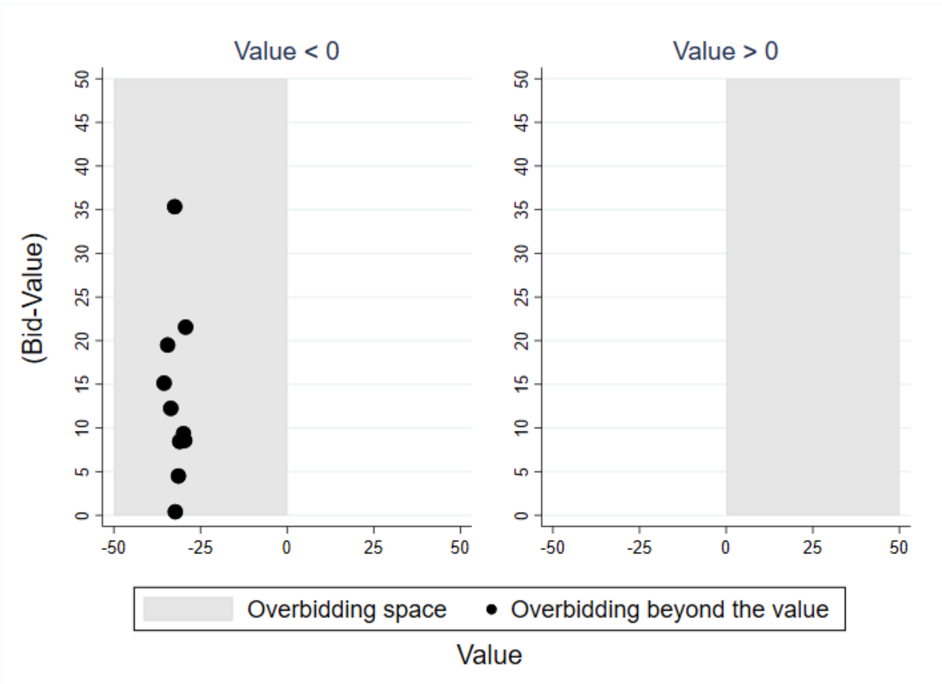
Table 3.5.3: Wilcoxon signed-rank test results

This table reports Wilcoxon signed-rank test statistical results relative to our prior that the average bidding behaviour of shareholders changes with certain knowledge of the value, relative to ambiguity. N_1 and N_2 refer to the number of the test observations in treatments with endogenous and exogenous information search, respectively. Significant differences relative to outcomes probabilities are indicated as follows: *** $p < 0.01,^{**}$ $p < 0.05,^{*}$ $p < 0.10$.

	Endog. Information Wilcoxon signed-rank p-value	*Exog. Information Wilcoxon signed-rank p-value*	*Observations*
	[Z-statistic]	*[Z-statistic]*	N_1,N_2
P-value	0.005***	0.000***	(10,1),(10,0)
Z-statistic	[-2.803]	[-]	



Endogenous



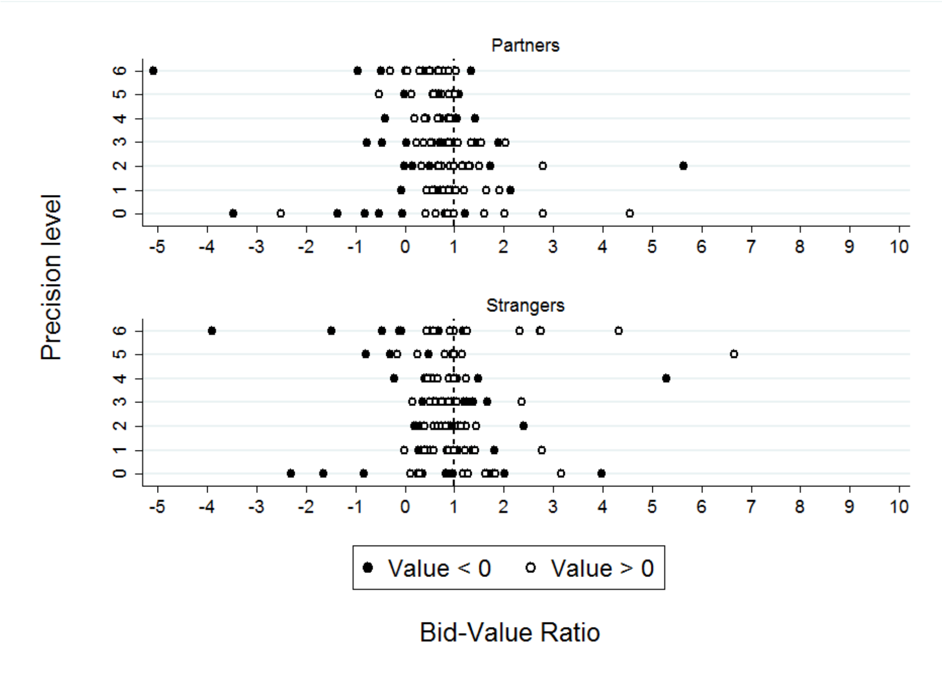
Exogenous

Figure 3.5.3: This graph provides experimental evidence that, opportunism in group decision-making is limited by the mechanism, irrespective of the condition under which partners invest in information search (free choice or random assignment). Limited opportunism mainly stems from negative value bidders that do not wish to prevent an overall beneficial investment (policy change). Limited opportunism is reflected in bids above the value and opposes to underbidding, that pays off a private benefit conditional on project implementation. Observations correspond to average overbidding values across periods, distributed conditional to project profitability (project value).

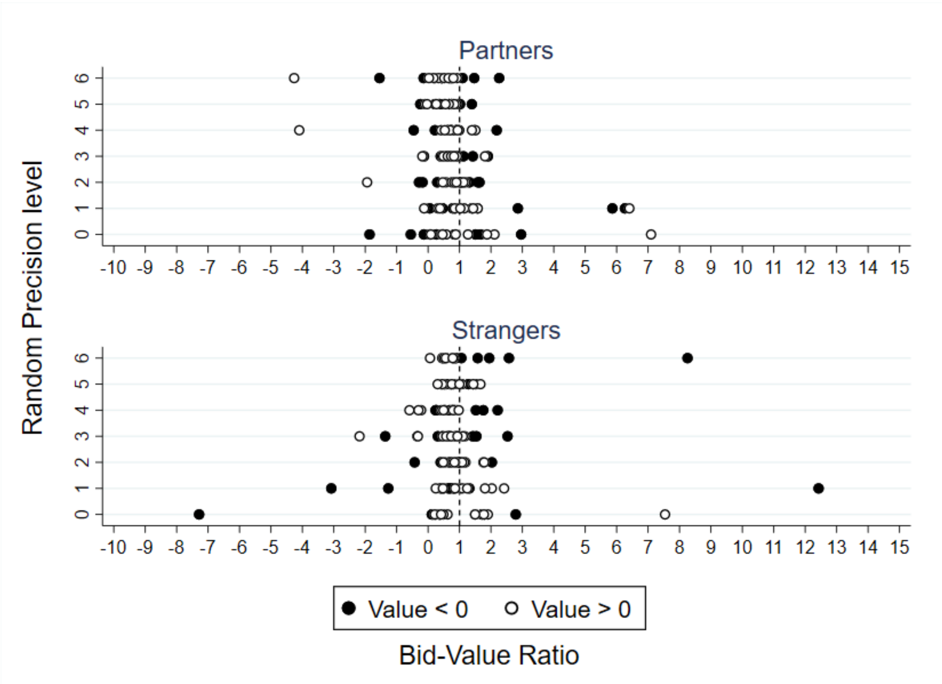
Observation 4: There is preliminary evidence that, with free choice of information search and non-stable partnerships, the mechanism limits opportunism beyond the negative value domain.

Support: Figure 3.5.4 (higher panel) depicts the distributional mean bid-to-value ratios per group across all experimental periods. Observations in white markers correspond to bidding behaviour with positive values while those in black markers to bidding with negative values, respectively. The overall prevailing pattern that arises in the data relates to mostly underbidding with positive values in most precision levels, and overbidding with negative values [1]. In a first-level analysis, we focus and examine separately free choice and random assignment in information search, and stable and non-stable partnerships. With such a partitioning of experimental data, opportunism seems to be limited also by positive value bidders. Understating one's benefits is rather limited with positive values, non-stable partnerships and free investment in value precision. This observation is significant when one compares average bidding in full value knowledge to bidding in ambiguity (including all other search levels). That is, in non-stable partnerships opportunism is limited by the bidding mechanism not only by those who do not want to stand in the way of an overall profitable investment, but also from corporate partners that discount positive future cash flows, with certainty. This trend and shift in bidding behaviour appears in the lower panel of Figure 3.5.4. In Table 3.5.4, it is confirmed by the Wilcoxon signed-rank test p-value of 0.0367, in favour of a significantly higher mean bid-value ratio with full value knowledge (Z-statistic=2.090). This result reinforces at a first level our Hypothesis 2 and indicates stronger crowding in corporate identity in non-stable partnerships. In addition, in non-stable partnerships, we detect a tendency for extended overbidding in the negative value domain (Z-statistic=-2.191, p-value=0.084). However, in order to ultimately infer on whether non-stable partnerships trigger bidding behaviour that limits opportunism beyond stable partnerships, we rely on a parametric analysis of the data (Section 3.5.2 and beyond). Overall, we find particularly interesting the fact that, limited opportunism is detected also in the case of non-stable partnerships, in general. Evidence of limited opportunism also in the absence of feedback on the other partners' bidding behaviour, renders the mechanism a candidate for joint ventures of single, and short term project collaborations (start-ups).

[1] Table 3.5.6 and Table 3.5.7 in the parametric analysis section (Section 3.5.2)



Endogenous



Exogenous

Figure 3.5.4: This graph depicts the distribution of group bids across all levels of information search, across negative and positive value bidders and conditional to the type of partnership (stable versus non-stable). Statistical tests on partitioned experimental data provide evidence that, in non-stable partnerships, opportunism is limited both by negative and positive value bidders. The latter is valid when partners freely choose their information search level. Contrary, when partners are imposed randomly how much effort to exert in value information search, opportunism is limited only in stable partnerships, and only by negative value bidders. The charts vertical axes correspond to information search and the horizontal axis to bidding behaviour (expressed by the bid-value ratio)

Table 3.5.4: Wilcoxon signed-rank test results

This table reports Wilcoxon signed-rank test statistical results relative to our theoretical prediction that procedurally fair private bidding limits free riding in the shoulders of the rest of the shareholders. N_1 and N_2 refer to the number of the test observations in treatments with endogenous and exogenous information search, respectively. Significant differences relative to outcomes probabilities are indicated as follows: *** $p < 0.01,^{**}$ $p < 0.05,^{*}$ $p < 0.10$.

	Endogenous Information Wilcoxon signed-rank				*Observations*
	Strangers p-value		*Partners p-value*		
	[Z-statistic]		*[Z-statistic]*		*N*
	$V_i < 0$	$V_i > 0$	$V_i < 0$	$V_i > 0$	
P-value	0.084*	0.0367**	0.138	0.0367**	10,10
Z-statistic	[-2.191]	[2.090]	[-1.481]	[-2.090]	

Observation 5: There is preliminary evidence that with random assignment of information search, non-stable partnerships and full value knowledge, opportunism is not limited by negative value bidders.

Compared to free choice of the information search level, with random assignment, opportunism is not as limited in non-stable partnerships. Non-stable partners underbid their values when they know the latter with certainty and when they are positive, as shown in the lower panel of Figure 3.5.4. Subjects in this case seem to behave in a consistently opportunistic way, irrespective of the accuracy by which they know their value. The corresponding Wilcoxon signed-rank z-statistic$=-1.886$ and p-value$=0.059$ in Table 3.5.5 reflect a tendency for more extended underbidding with certain value knowledge. Also, overbidding does not prevail either with negative future cash flows, compared to the case where partners freely choose how much they wish to invest in costly effort. The prevailing bidding behaviour in non-stable partnerhips with full value knowledge is rather opportunistic. In particular, more opportunistic than in ambiguity (Z-statistic=2.090 and p-value=0.0367 in favor of more extended underbidding). In stable partnerships, though, the patterns of bidding behaviour are similar to those with free choice in information search. In all cases, we ultimately rely on a parametric analysis of the data (Section 3.5.2 and beyond), in order to infer on the overall significant factors of limited opportunism induced by the mechanism.

Table 3.5.5: Wilcoxon signed-rank test results

This table reports Wilcoxon signed-rank test statistical results relative to our theoretical prediction that procedurally fair private bidding limits free riding in the shoulders of the rest of the shareholders. N_1 and N_2 refer to the number of the test observations in treatments with endogenous and exogenous information search, respectively. Significant differences relative to outcomes probabilities are indicated as follows: $^{***}\ p < 0.01, ^{**}\ p < 0.05, ^{*}\ p < 0.10$.

	Exogenous Information Wilcoxon signed-rank				*Observations*
	Strangers p-value		*Partners p-value*		
	[Z-statistic]		*[Z-statistic]*		*N*
	$V_i < 0$	$V_i > 0$	$V_i < 0$	$V_i > 0$	
P-value	0.036**	0.059*	0.284	0.092**	10,10
Z-statistic	[2.090]	[-1.886]	[-1.070]	[-1.682]	

3.5.2 Parametric analysis

In order to further investigate our non-parametric results, we conduct a parametric analysis over our set of experimental data. Summary statistics of bids and values are already suggestive of our non-parametric results. As shown in Table 3.5.6 and Table 3.5.7, overbidding is the average bidding behaviour when the project is deemed unprofitable with low, medium, high, full and extinct knowledge of the project value. The latter holds both in the case where partners choose and are randomly assigned their level of information search.

Table 3.5.6: Summary statistics

This table reports summary statistics of projects' values and bids across precision levels, for $V_{i,t} > 0$ and $V_{i,t} < 0$ values with ***endogenous*** information search.

Endogenous Information Search	Mean Std.Dev Freq.	0	1	2	3	4	5	6
$V_i < 0$	Value	-28.402	-32.368	-30.861	-35.046	-32.588	-30.847	-30.4
		18.199	19.13	18.060	18.551	18.653	18.930	18.204
		134	114	144	151	141	46	70
	Bid	-5.082	-20.894	-21.802	-29.258	-27.805	-22.771	-10.157
		28.377	19.662	24.402	24.137	23.989	22.858	31.012
		134	114	144	151	141	46	70
$V_i > 0$	Value	30.254	32.968	33.975	31.170	33.520	32.743	30.147
		17.849	18.185	18.713	18.190	18.586	19.305	17.927
		232	251	282	294	296	82	163
	Bid	18.047	21.351	27.843	19.189	22.757	19.560	18.159
		22.776	18.462	20.206	17.650	18.927	27.303	20.327
		232	251	282	294	296	82	163
Observations = 2400								

We estimate probit regressions with random effects. We are basically interested to compute the probability that a randomly chosen subject overbids their project value, when considering the population of the observations' distribution. We regress the probability of overbidding one's value on dummy variables that reflect : the project's profitability ($V_{i,t} < 0$ or $V_{i,t} > 0$), the imposed or assigned level of information search $e_{i,t}$, the repetitive type of partners matching (random partners versus constant partners matching), the order of the latter matching in experimental sessions (Period $1 - 20$ constant partners, Period $21 - 40$ random partners and vice-versa), a dummy on whether partners are randomly assigned or choose their level of information search and

Table 3.5.7: Summary statistics

This table reports summary statistics of projects' values and bids across precision levels, for $V_i > 0$ and $V_i < 0$ values with ***exogenous*** information search.

Endogenous Information Search	Mean Std.Dev Freq.	0	1	2	3	4	5	6
$V_i < 0$	Value	-29.125	-30.534	-33.958	-32.008	-34.675	-31.755	-31.168
		17.201	18.237	18.144	18.099	16.938	18.112	19.431
		96	101	97	123	117	143	113
	Bid	-11.979	-17.514	-23.010	-19.024	-21.192	-20.079	-14.575
		30.741	28.841	30.041	30.193	29.782	31.111	34.064
		96	101	97	123	117	143	113
$V_i > 0$	Value	34.762	33.186	31.645	32.341	32.439	32.439	34.425
		19.170	19.690	17.993	18.710	18.952	19.199	19.199
		232	215	231	214	223	251	214
	Bid	18.997	18.997	18.997	18.240	20.489	21.837	17.5329
		20.242	19.498	19.703	22.374	21.787	20.494	23.892
		232	215	231	214	223	251	214
Observations = 2370								

the experimental round t. We use the probit specification with random effects that is evaluated at the mean, conditional on the observations of our independent variables' sample realisation, across time and subjects. Random effects control for this precise repetitive nature of our experimental study, that produces panel data (40 periods, 120 subjects). In particular,

$$\begin{aligned} Pr(b_{i,t} > median(\underline{V_{i,t}}, \overline{V_{i,t}})) = Pr(&\alpha_0 + \beta_1 \cdot \text{NEG VALUE}_{i,t} + \beta_2 \cdot \text{INFO SEARCH}_{i,t} \\ &+ \beta_3 \cdot \text{ENDOGENOUS INFO}_{i,t} + \beta_4 \cdot \text{PARTNERS}_{i,t} \\ &+ \beta_5 \cdot \text{ORDER PARTNERS}_{i,t} + \beta_6 \cdot \text{t}_{i,t+\epsilon_{i,t}+u_i)} \\ &\epsilon_{i,t} \sim N(0,1), u_i \sim N(0, \sigma_u^2) \end{aligned} \tag{3.7}$$

where, $NEGVALUE_{i,t} = 1$ when $V_{i,t} < 0$, $ENDOGENOUSINFO_{i,t} = 1$ when partners choose their investment in information search, and, $PARTNERS_{i,t} = 1$ when partners are matched repetitively in constant groups, and 0 otherwise.

3.5.3 Robustness check

We rely in a probit specification to test and further explore our hypotheses 2 and 3, after fitting linear probability specifications with our main variables of interest. In particular, we estimate the linear probability model with random and fixed effects respectively, as below. $Overbid_{i,t}$ corresponds to a dummy variable conditional on the bid $b_{i,t}$ exceeding or not the one's value.

Random effects specification

$$\begin{aligned} Overbid_{i,t} = \alpha_0 + \beta_1 \cdot \text{NEG VALUE}_{i,t} + \beta_2 \cdot \text{INFO SEARCH}_{i,t} + \beta_3 \cdot \text{ENDOGENOUS INFO}_{i,t} \\ + \beta_4 \cdot \text{PARTNERS}_{i,t} + \beta_5 \cdot \text{ORDER PARTNERS}_{i,t} + \beta_6 \cdot \text{t}_{i,t} + \epsilon_{i,t} + u_i \\ + \beta_7 \cdot \text{NEG VALUE}_{i,t} \cdot e_{i,t} \end{aligned} \tag{3.8}$$

Fixed effects specification

$$\begin{aligned} Overbid_{i,t} = \beta_1 \cdot \text{NEG VALUE}_{i,t} + \beta_2 \cdot \text{INFO SEARCH}_{i,t} + \beta_3 \cdot \text{ENDOGENOUS INFO}_{i,t} \\ + \beta_4 \cdot \text{PARTNERS}_{i,t} + \beta_5 \cdot \text{ORDER PARTNERS}_{i,t} + \beta_6 \cdot \text{t}_{i,t} + \alpha_i + \epsilon_{i,t} \\ + \beta_7 \cdot \text{NEG VALUE}_{i,t} \cdot e_{i,t} \end{aligned} \tag{3.9}$$

We compare and choose between random and fixed effects specification based on the Hausman test on the linear probability models. Table 3.5.8 shows the estimated coefficients across the two parameter estimators along with their differences in levels and standard errors. The p-value of the χ^2-stat of the Hausman test is insignificant in the 5% and only significant in the 10% level. The H_0 hypothesis is, thus, not rejected, and the suggested model is indeed the one that incorporates random effects. Also, we focus our choice criteria in the interaction term between the information search level and positive and negative value projects, accordingly. The relative differences of the two models estimated coefficients in the latter differ to a substantially low degree and, in particular, range from $0.13\% - 7.65\%$. The Hausman test result and the relative differences, thus, confirms the robustness of our model selection criterion. However, as a linear probability model is misspecified when the probability is the object of the parametric investigation [1] we estimate the probit model specification with random effects.

[1]The linear probability model renders by default possible to get a $\hat{y} < 0$ or $\hat{y} > 1$

Table 3.5.8: Hausman test results

This table reports the Hausman test results for linear probability models of specifications (3.9) and (3.10). The Hausman test mainly tests whether significant correlation between the individual i specific component and the regressors is detected. The H_0 hypothesis of the test assumes both consistency and efficiency for the random effects estimator : Cov($a_i, x_{i,t} = 0$). Contrary, H_1 assumes Cov($a_i, x_{i,t} \neq 0$), and, if accepted, points the choice criterion to the fixed effects specification.

	Fixed eff. (b)	Random eff. (B)	(b-B)	$\sqrt{diag(V_b - V_B)}$ S.E	Rel. diff. $\frac{(b-B)}{(b)}\%$
PARTNERS$_i$	0.0255358	0.0245361	0.0009997	0.0002649	
ORDER PARTNERS$_i$	0.135175	0.0000127	0.1351623	0.0682614	
ROUND$_t$	-0.0007173	-0.000731	0.0000137	.	
NEG VALUE$_{i,t} \cdot e_{i,t}$					
0 1	-0.5422152	-0.5371888	-0.0050264	0.0047689	0.93%
0 2	-0.4881308	-0.4799333	-0.0081974	0.0051319	1.68%
0 3	-0.525727	-0.5250657	-0.0006614	0.0055694	0.13%
0 4	-0.5380977	-0.537343	-0.0007547	0.0060337	0.14%
0 5	-0.6116407	-0.6068136	-0.0048271	0.0040962	0.79%
0 6	-.0622562	0.067016	-0.0047599	0.004772	7.65%
1 0	0.0911328	0.0904717	0.0006611	0.001377	0.73%
1 1	-0.1134667	-0.1072891	-0.0061776	0.0047788	5.44%
1 2	-0.17297	-0.1666813	-0.0062887	0.0055207	3.64%
1 3	-0.187811	-0.1846351	-0.003176	0.0053929	1.69%
1 4	-0.2217861	-0.2163227	-0.0054633	0.0058952	2.46%
1 5	-0.2322248	-0.2280399	-0.004185	0.0041894	1.80%
1 6	-0.5259041	-0.520315	-0.0055891	0.004458	1.06%
Hausman χ^2-stat=23.62 p-value=0.0982					

3.5.4 Limiting opportunism: probit regression results

In Table 3.5.9, we can distinguish the highly significant positive marginal effect of negative project values in the probability of overbidding. We should recall here the fact that the frequency of unprofitable projects in the data sample is 0.33%, that is half the frequency of profitable projects. This result complements and supports our non-parametric test result that, on average, overbidding occurs to a significantly larger extent due to negative value bidders (Wilcoxon signed-rank test Z-statistic $= -2.803$, p-value=0.005). Contrary, increased precision relative to the project value decreases the probability of overbidding one's value by a lower, whilst, highly significant level. Experimental repetition, and in that sense, learning, increases the probability of overbidding. This result may be naturally interpreted as some degree of adjustment in undertaking the risk of not recovering from potential losses, after interacting for multiple periods. These results persist irrespective of whether one chooses or is randomly assigned their investment in information search.

Table 3.5.9: Probit marginal effects-Overbid one's value

This table reports the probit regression results with random effects for specification (3.7). The probability of overbidding one's value is regressed against six regressors. Statistical significance is indicated as follows: $^{***}\ p < 0.01, ^{**}\ p < 0.05, ^{*}\ p < 0.10$.

Overbid$_{i,t}$	dy/dx	δ method Std.Error	Z-stat	P-value
NEGVALUE$_{i,t}$	0.311***	0.025	12.35	0.000
INFO SEARCH$e_{i,t}$	-0.037***	0.004	-8.43	0.000
ENDOGENOUS INFO$_{i,t}$	0.009	0.029	0.33	0.745
PARTNERS$_{i,t}$	0.002	0.015	0.14	0.890
ORDER PARTNERS$_{i,t}$	-0.016	0.031	-0.53	0.593
ROUND$_{i,t}$	-0.001***	0.000	-2.63	0.009
Log-like=-2586.32	Obs.=4770	Subjects=120	Wald-stat.=208.12	p-value=0.000

Since we are interested into further investigating the nature and size of the detected negative effect per information search level, we estimate our probit model marginal effects by treating $e_{i,t}$ as an indicator variable. In Table 3.5.10 we get a coefficient per level of investment in information search. Without any distinction between positive and negative value bidders, higher levels of information search significantly decrease the probability of overbidding one's value, relative to

Table 3.5.10: Probit marginal effects-Overbid one's value

This table reports the probit regression results with random effects for specification (3.8). The probability of overbidding one's value is regressed against five regressors, with $e_{i,t}$ treated as an indicator variable. Statistical significance is indicated as follows: $^{***}\ p < 0.01, ^{**}\ p < 0.05, ^{*}\ p < 0.10$.

$\text{Overbid}_{i,t}$	dy/dx	δ method Std.Error	Z-stat	P-value
NEG $\text{VALUE}_{i,t}$	0.312***	0.025	12.39	0.000
INFO $\text{SEARCH}e_{i,t}$				
1	0.003	0.027	0.12	0.902
2	-0.015	0.027	-0.56	0.575
3	−0.070**	0.029	-2.42	0.016
4	−0.114***	0.032	-3.56	0.000
5	−0.162***	0.029	-5.45	0.000
6	−0.208***	0.031	-6.69	0.000
ENDOGENOUS $\text{INFO}_{i,t}$	0.006	0.029	0.23	0.817
$\text{PARTNERS}_{i,t}$	0.002	0.015	0.14	0.887
ORDER $\text{PARTNERS}_{i,t}$	-0.018	0.031	-0.59	0.557
$\text{ROUND}_{i,t}$	−0.001***	0.000	-2.67	0.008
Log-like=-2581.94	Obs.=4770	Subjects=120	Wald-stat.= 246.42	p-value=0.000

null information about the value (0 level). Beyond level 2, the negative impact in the probability of overbidding becomes significant and gradually increases. The significantly limited opportunism induced by negative value bidders [1], reflected in the marginal effect of size 0.312 can, thus, be reversed-counterbalanced by investment in information search. We further test whether the relative differences of these marginal effects are significant. In other words, we further test whether higher information search levels decrease the probability of overbidding even further, relative to any lower level. Indeed, the relative differences of the marginal effects are significant, as shown in Table 3.5.11. Investing in very high precision about the value (eg. level 5 and 6), significantly decreases the probability of overbidding even further, relatively to any lower level. Gradual (one unit) increased knowledge about the value extends the negative impact in the probability of overbidding, thus, substantially. Overall, the detected limited opportunism with negative values, and the latter results, support a rationale of higher potential for the mechanism to limit opportunism with accurate information about the value.

Table 3.5.11: This table reports the relative differences of the estimated marginal effects, among the various information search levels. The estimated marginal effects refer to the probability of overbidding one's value, thus, to limiting opportunism. Values in parentheses correspond to the Wald test χ^2-stat p-values. The $H0$ of the Wald test assumes that the relative difference of the estimated marginal effects of two information search levels is 0. $H1$ assumes that the latter significantly differs from 0.

INFO SEARCH$e_{i,t}$	1	2	3	4	5	6
0	0.003	-0.015	-0.071^{**}	-0.115^{***}	-0.162^{***}	-0.208^{***}
	(0.902)	(0.575)	(0.016)	(0.000)	(0.000)	(0.000)
1		-0.019	-0.074^{***}	-0.118^{***}	-0.166^{***}	-0.212^{***}
		(0.448)	(0.001)	(0.000)	(0.000)	(0.000)
2			-0.056^{***}	-0.099^{***}	-0.147^{***}	-0.193^{***}
			(0.009)	(0.000)	(0.000)	(0.000)
3				-0.044	-0.091^{***}	-0.138^{***}
				(0.110)	(0.000)	(0.000)
					(0.070)	(0.000)
4					-0.048^{*}	-0.094^{***}
5						-0.046^{*}
						(0.057)

In order to explore this rationale and to test also para-metrically *Hypotheses* 2 and 3, we must first differentiate between the marginal effects of negative and positive value bidders. We must ensure that the negative marginal impact of information search does not dominate the limited opportunism stemming from negative value bidders. For this purpose, we estimate (3.7)

[1] The highly significant positive effect of negative project values to the probability of overbidding.

with the corresponding interaction term:

$$
\begin{aligned}
Pr(b_{i,t} > median(\underline{V_{i,t}}, \overline{V_{i,t}})) = Pr(&\alpha_0 + \beta_1 \cdot \text{NEG VALUE}_{i,t} + \beta_2 \cdot \text{INFO SEARCH}_{i,t} \\
&+ \beta_3 \cdot \text{ENDOGENOUS INFO}_{i,t} + \beta_4 \cdot \text{PARTNERS}_{i,t} \\
&+ \beta_5 \cdot \text{ORDER PARTNERS}_{i,t} + \beta_6 \cdot \text{t}_{i,t} + \epsilon_{i,t} + u_i \\
&+ \beta_7 \cdot \text{NEG VALUE}_{i,t} \cdot e_{i,t})
\end{aligned}
\tag{3.10}
$$

In Table 3.5.12 we show that, the negative effect in the probability of overbidding per precision level does not outweigh the fact that negative value bidders mitigate opportunism. We actually find that, the probability of overbidding with negative value bidders differs and raises significantly for all levels of information search, relative to positive value bidders. The main pattern of overbidding that we trace relates to extinct and full value knowledge. Partners seem to overbid to the largest extent when they know their value with certainty and when they are entirely unaware about it (positive marginal effects of 0.451 and 0.445, respectively). We show the relative differences of the marginal effects between negative and positive value bidders, also, for the intermediate levels of information search in Table 3.5.14. The latter are rather insignificant, whereas overbidding with full value knowledge differs significantly from all lower levels beyond level 1. These findings, and especially the evidence of substantially limited opportunism with full value precision, strongly confirm our *Hypotheses* 2 and 3. They show that the mechanism induces decisions that limit opportunism. The latter decisions mainly stem from those partners that do not want to stand in the way of an overall profitable investment. With respect to positive value bidders, contrary, we find that underbidding one's value significantly extends with higher investment in information about the value. Table 3.5.13 shows that the relative differences in underbidding, among the three highest levels of information search, are significant.

Table 3.5.12: Probit marginal effects-Overbid one's value

This table reports the probit marginal effects with random effects for specification (3.10). The probability of overbidding one's value is regressed against six regressors with $e_{i,t}$ treated as an indicator variable and an interaction term between negative project values and information search. Statistical significance is indicated as follows: $^{***}\ p < 0.01, ^{**}\ p < 0.05, ^{*}\ p < 0.10$.

Overbidi,t	dy/dx	δ method Std.Error	Z-stat	P-value
ENDOGENOUS INFO$_{i,t}$	0.007	0.029	0.27	0.791
PARTNERS$_{i,t}$	0.002	0.015	0.19	0.849
ORDER PARTNERS$_{i,t}$	-0.018	0.032	-0.59	0.557
ROUND$_{i,t}$	-0.001^{***}	0.000	-2.67	0.008
NEG VALUE$_{i,t} \cdot e_{i,t}$			χ^2-stat	
0 1	0.025^{***}	0.035	0.72	0.469
0 2	0.046^{***}	0.037	-1.22	0.221
0 3	-0.023^{***}	0.037	-0.64	0.520
0 4	-0.077^{**}	0.037	-2.05	0.041
0 5	-0.121^{***}	0.033	-3.59	0.000
0 6	-0.207^{***}	0.31	-6.50	0.000
			χ^2-stat	
1 0	0.445^{***}	0.057	55.82	0.000
1 1	0.373^{***}	0.054	54.98	0.000
1 2	0.246^{***}	0.059	12.49	0.000
1 3	0.299^{***}	0.056	27.23	0.000
1 4	0.326^{***}	0.057	38.91	0.000
1 5	0.317^{***}	0.056	33.59	0.000
1 6	0.451^{***}	0.061	71.21	0.000
Log-like=-2561.74	Obs.=4770	Subjects=120	Wald-stat.= 297.24	p-value=0.000

Table 3.5.13: This table reports the relative differences of the estimated marginal effects for positive value bidders, among the various levels of investment in information search. The estimated marginal effects refer to the probability of overbidding one's value, thus, to limiting opportunism. Values in parentheses correspond to the Wald test χ^2-stat p-values. The $H0$ of the Wald test assumes that the relative difference of the estimated marginal effects of two information search levels is 0. $H1$ assumes that the latter significantly differs from 0.

NEG VALUE$_{i,t} \cdot e_{i,t}$	$0 \cdot 1$	$0 \cdot 2$	$0 \cdot 3$	$0 \cdot 4$	$0 \cdot 5$	$0 \cdot 6$
$0 \cdot 0$	0.026	0.046	−0.024	−0.078**	−0.122***	−0.208***
	(0.469)	(0.221)	(0.519)	(0.040)	(0.000)	(0.000)
$0 \cdot 1$		0.020	−0.050	−0.104***	−0.148***	−0.233***
		(0.552)	(0.129)	(0.001)	(0.000)	(0.000)
$0 \cdot 2$			−0.070**	−0.124***	−0.168***	−0.254***
			(0.024)	(0.000)	(0.000)	(0.000)
$0 \cdot 3$				−0.054*	−0.098***	−0.184***
				(0.087)	(0.002)	(0.000)
$0 \cdot 4$					−0.044	−0.130***
					(0.166)	(0.000)
$0 \cdot 5$						−0.086***
						(0.001)

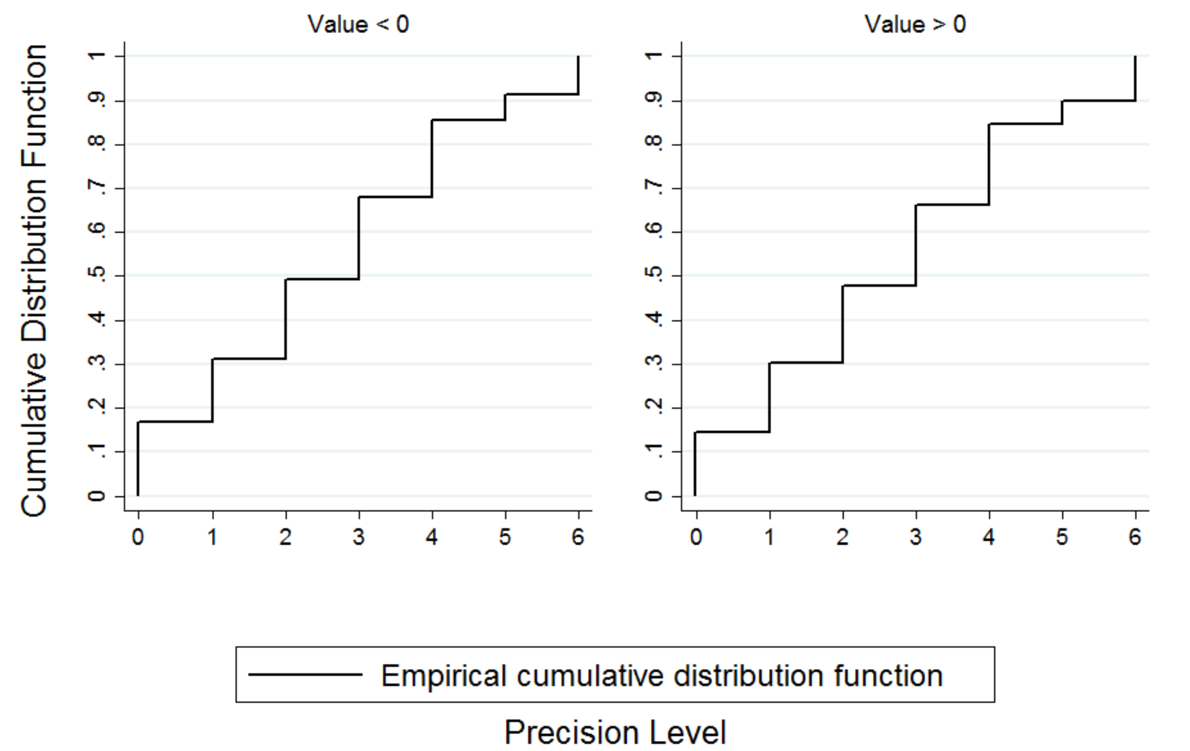
Table 3.5.14: This table reports the relative differences of the estimated marginal effects between negative and positive value bidders, among the various levels of investment in information search. The estimated marginal effects refer to the probability of overbidding one's value, thus, to limiting opportunism. Values in parentheses correspond to the Wald test χ^2-stat p-values. The $H0$ of the Wald test assumes that the relative difference of the estimated marginal effects of two information search levels is 0. $H1$ assumes that the latter significantly differs from 0.

NEG VALUE$_{i,t} \cdot e_{i,t}$	$1 \cdot 1$	$1 \cdot 2$	$1 \cdot 3$	$1 \cdot 4$	$1 \cdot 5$	$1 \cdot 6$
$1 \cdot 0$	−0.072	−0.199**	−0.146**	−0.119	−0.128*	0.006
	(0.285)	(0.020)	(0.050)	(0.102)	(0.083)	(0.933)
$1 \cdot 1$		−0.127	−0.074	−0.047	−0.056	0.078
		(0.100)	(0.288)	(0.465)	(0.399)	(0.2534)
$1 \cdot 2$			0.053	0.080	0.071	0.205**
			(0.490)	(0.320)	(0.369)	(0.010)
$1 \cdot 3$				0.027	0.018	0.152**
				(0.655)	(0.788)	(0.026)
$1 \cdot 4$					−0.009	0.125*
					(0.889)	(0.051)
$1 \cdot 5$						0.134**
						(0.029)

3.5.5 Truth-telling

Group decision-making in view of a fair mechanism requires the analysis of experimental data, also, through the prism of truth-telling. The mechanism is deemed successful by also investigating whether truthful bidding is reinforced with higher levels of information search. Higher information search should induce decisions closer to the true value. Figure 3.5.5 presents the cumulative distribution of information search levels with negative, and positive values respectively. Information search levels distribution does not seem to vary across the two types of valuation for most levels of investment in information search. There is a tendency for cohorts to compensate a very small portion of investment in full knowledge about the value, from the negative, to the positive project value domain. That is, partners tend to choose a bit more frequently to invest in certainty about the value, when their private value is positive. The difference, though, seems to be rather insignificant.

Figure 3.5.5: Cumulative distribution of information search



We investigate truth-telling by regressing the absolute deviation of subjects' bids from the corresponding true values, $\mathrm{TRUTH}_{i,t}$, on the following variables: a dummy on whether a project is profitable ($V_{i,t} > 0$) or non-profitable ($V_{i,t} < 0$), the level of investment in information search $e_{i,t}$, the repetitive type of partners' matching (random versus constant), the order of the latter matching in experimental sessions (Period $1-20$ constant, Period $21-40$ random and vice-versa), a dummy disentangling choice from random assignment of the information search level, and the experimental round t.

A measure that does not strictly show how close one's decision is to the true value may simply indicate a different type of behaviour relative to the true value, and not necessarily truth-telling. A positive deviation signals underbidding in the negative value domain, and overbidding, in the positive value domain, and vice-versa. We restrict, thus, the measure of truth-telling to the absolute deviation of bids from the true values $\text{TRUTH}_{i,t}$, as we are interested into a uniform measure of truthful bidding, irrespective of the type of bidding behaviour.

We estimate the following OLS specification with random effects [1]:

$$\begin{aligned}\text{TRUTH}_{i,t} = \alpha_0 &+ \beta_1 \cdot \text{NEG VALUE}_{i,t} + \beta_2 \cdot \text{INFO SEARCH}_{i,t} + \beta_3 \cdot \text{ENDOGENOUS INFO}_{i,t} \\ &+ \beta_4 \cdot \text{PARTNERS}_{i,t} + \beta_5 \cdot \text{ORDER PARTNERS}_{i,t} + \beta_6 \cdot \text{t}_{i,t} + \epsilon_{i,t} + u_i \\ &+ \beta_7 \cdot \text{NEG VALUE}_{i,t} \cdot e_{i,t}\end{aligned} \tag{3.11}$$

Table 3.5.15 lists the main effects of our independent variables in truth-telling. Negative-value projects largely and significantly increase bids' deviation from the project values. The latter effect reflects the large and significant effect of overbidding one's value in the negative value domain, detected both in our parametric (Table 3.5.9, Table 3.5.10,Table 3.5.12), and in our non-parametric results (Wilcoxon signed-rank test Z-statistic$=-2.803$, p-value$=0.005$). We find that one unit increase in the level of information search significantly decreases the deviation from the values, thus, significantly increases truth-telling. Free choice of the information search level fails significance at the 5% level, still signals a tendency for increased truth-telling relative to random assignment. Similarly, stable partnerships signal a slight tendency to decrease truth-telling. Also, partners seem to learn to truthfully bid and come to more desirable decisions with repetition, as shown by the highly significant negative coefficient of experimental rounds t of -1.129.

Since the estimation results of 3.11 show that truth-telling is strengthened with higher levels of information search, we explore each level separately (treat $e_{i,t}$ as an indicator variable). Table 3.5.16 shows how our estimation results are dispersed across information search levels. In

[1] Random effects control, once more, for the repetitive nature of our experimental study, that produces panel data (40 periods, 120 subjects).

Table 3.5.15: OLS regression results with random effects

This table reports the OLS regression results with random effects for specification (3.11). The absolute deviations of one's bid from the corresponding true value is regressed against six regressors, including $e_{i,t}$. Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

$\|Bid_{i,t} - Value_{i,t}\|$	Coeff.	Robust Std.Error	Z-stat	P-value
Intercept	19.287^{***}	3.143	6.14	0.000
NEG VALUE$_{i,t}$	2.793^{**}	1.145	2.44	0.015
ENDOGENOUS INFO$_{i,t}$	-3.434^{*}	1.867	-1.84	0.066
PARTNERS$_{i,t}$	1.380	0.850	1.62	0.104
ORDER PARTNERS$_{i,t}$	1.817	2.115	0.86	0.390
ROUND$_{i,t}$	-0.110^{***}	0.039	-2.78	0.005
INFO SEARCH$e_{i,t}$	-1.129^{***}	0.209	-5.38	0.000
Obs.=4770	Subjects=120	Wald-stat.= 58.57	p-value=0.000	

general, truth-telling is significantly larger when information search is higher. The highly significant effect of information search ranges from -7.993 to -12.126 from levels 1 to 5, respectively, and increases by the increase of one unit of information search. Table 3.5.17 shows that, investing in very high ($e_{i,t} = 5$), quite high ($e_{i,t} = 4$), medium ($e_{i,t} = 3$), and quite low ($e_{i,t} = 2$) information search, significantly increases truth-telling, relative to null value knowledge. The same holds when compared to investing in somewhat more precise value knowledge ($e_{i,t} = 1$). However, we already notice the potential for a trade-off between limited opportunism and truthful decision outcomes, induced by the fair mechanism.

Table 3.5.16: OLS regression results with random effects

This table reports the OLS regression results with random effects for specification (3.9). The absolute deviations of one's bid from the corresponding true value is regressed against five regressors with $e_{i,t}$ treated as an indicator variable. Statistical significance is indicated as follows: *** $p < 0.01,^{**}$ $p < 0.05,^{*}$ $p < 0.10$.

$\|Bid_{i,t} - Value_{i,t}\|$	Coeff.	Robust Std.Error	Z-stat	P-value
Intercept	24.288^{***}	3.00	8.07	0.000
NEG VALUE$_{i,t}$	2.837^{**}	1.162	2.44	0.015
ENDOGENOUS INFO$_{i,t}$	-3.068^{*}	1.829	-1.68	0.094
PARTNERS$_{i,t}$	1.309	0.842	1.56	0.120
ORDER PARTNERS$_{i,t}$	2.234	2.086	1.07	0.284
ROUND$_{i,t}$	-0.107^{***}	0.039	-2.74	0.006
INFO SEARCH$e_{i,t}$				
1	-7.993^{***}	1.253	-6.38	0.000
2	-10.958^{***}	1.275	-8.59	0.000
3	-11.534^{***}	1.338	-8.61	0.000
4	-12.157^{***}	1.315	-9.24	0.000
5	-12.126^{***}	1.592	-7.62	0.000
6	-7.243^{***}	1.468	-4.93	0.000
Obs.=4770	Subjects=120	Wald-stat.= 145.56	p-value=0.000	

Table 3.5.17: This table reports the relative differences of the effects in truth-telling, among the various information search levels. Values in parentheses correspond to the Wald test χ^2-stat p-values. The $H0$ of the Wald test assumes that the relative difference of the estimated impact between two different information search levels is 0. $H1$ assumes that the latter significantly differs from 0.

INFO SEARCH$e_{i,t}$	1	2	3	4	5	6
0	-7.993^{***}	-10.958^{***}	-11.534^{***}	-12.157^{***}	-12.127^{***}	-7.244^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1		-2.965^{***}	-3.541^{***}	-4.164^{***}	-4.133^{***}	0.749
		(0.004)	(0.001)	(0.001)	(0.001)	(0.542)
2			-0.576	-1.199	-1.168	3.715^{***}
			(0.613)	(0.265)	(0.360)	(0.001)
3				-0.623	-0.592	4.290^{***}
				(0.594)	(0.619)	(0.000)
4					0.031	4.914^{***}
					(0.979)	(0.000)
5						4.883^{***}
						(0.000)

The highly significant, whilst, relatively smaller increase in truth-telling with full value knowledge, equal to -7.243, may be reflecting exactly that trade-off: the significant detected pattern of underbidding and overbidding with positive and negative values, respectively. Free-choice of information search still points to reinforced truth-telling, however at the 10% level. The type of partners' matching does not seem to impact truthful bidding any further. Contrary, partners learn to come to more desirable investment outcomes with repeated decision-making ($ROUND_{i,t}$ coefficient$=-0.107$, p-value$=0.006$). We explore whether such a trade-off between limited opportunism and increased truth-telling, indeed, exists. For this purpose, we check whether efficiency implications of the mechanism by means of truth-telling, resemble between positive and negative value bidders. The interaction term coefficients in Table 3.5.18 show that,for all intermediate information search levels, there is no significant difference in the extent of truth-telling between positive and negative value bidders. However, limited opportunism dominates truth-telling in the information search levels with the highest rates of overbidding. The latter levels consider full and extinct value knowledge, as shown in Table 3.5.12. We, thus, conjecture that such a trade-off is induced by a fair mechanism. Finally, a learning effect towards truthful bidding remains highly significant.

Table 3.5.18: OLS regression results with random effects

This table reports the OLS estimation results with random effects for specification (3.11). The absolute deviations of one's bid from the corresponding true value is regressed against five regressors. $e_{i,t}$ is treated as an indicator variable and project values are interacted with information search level. Statistical significance is indicated as follows: $^{***}\ p < 0.01, ^{**}\ p < 0.05, ^{*}\ p < 0.10$.

$\lvert Bid_{i,t} - Value_{i,t}\rvert$	Coeff.	Robust Std.Error	Z-stat	P-value
Intercept	23.132***	3.170	7.30	0.000
ENDOGENOUS INFO$_{i,t}$	−3.096*	1.823	-1.70	0.089
PARTNERS$_{i,t}$	1.309	0.835	1.57	0.117
ORDER PARTNERS$_{i,t}$	2.305	2.078	1.11	0.268
ROUND$_{i,t}$	−0.105***	0.038	-2.72	0.007
NEG VALUE$_{i,t} \cdot e_{i,t}$				
0 1	−6.547***	1.451	-4.51	0.000
0 2	−9.770***	1.392	-7.02	0.000
0 3	−9.728***	1.452	-6.70	0.000
0 4	−10.778***	1.382	-7.79	0.000
0 5	−10.669***	1.748	-6.10	0.000
0 6	−7.4633***	1.536	-4.86	0.000
NEG VALUE$_{i,t} \cdot e_{i,t}$			χ^2-stat	
1 0	6.024**	2.357	6.53	0.010
1 1	1.601	2.065	0.65	0.420
1 2	2.382	2.047	2.26	0.133
1 3	0.667	2.066	0.15	0.696
1 4	1.773	2.149	0.94	0.331
1 5	1.644	2.440	0.51	0.474
1 6	6.627**	2.895	5.57	0.018
Obs.=4770	Subjects=120	Wald-stat.= 155.25	p-value=0.000	

Truth-telling

Table 3.5.19: This table reports the relative differences of the effects in truth-telling, among the various information search levels, for positive value bidders.

NEG VALUE$_{i,t} \cdot e_{i,t}$	$0 \cdot 1$	$0 \cdot 2$	$0 \cdot 3$	$0 \cdot 4$	$0 \cdot 5$	$0 \cdot 6$
$0 \cdot 0$	-6.547^{***}	-9.770^{***}	-9.728^{***}	-10.779^{***}	-10.670^{***}	-7.463^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$0 \cdot 1$		-3.223^{***}	-3.181^{**}	-4.232^{***}	-4.122^{***}	-0.916
		(0.003)	(0.015)	(0.002)	(0.009)	(0.515)
$0 \cdot 2$			0.042	-1.009	-0.899	2.307^{*}
			(0.970)	(0.330)	(0.509)	(0.066)
$0 \cdot 3$				-1.051	-0.941	2.265^{*}
				(0.389)	(0.515)	(0.090)
$0 \cdot 4$					0.109	3.316^{**}
					(0.935)	(0.016)
$0 \cdot 5$						3.206^{**}
						(0.030)

Table 3.5.20: This table reports the relative differences of the effects in truth-telling, between negative and positive value bidders, among the various information search levels.

NEG VALUE$_{i,t} \cdot e_{i,t}$	$0 \cdot 1$	$0 \cdot 2$	$0 \cdot 3$	$0 \cdot 4$	$0 \cdot 5$	$0 \cdot 6$
$0 \cdot 0$	-4.423	-3.643	-5.358^{**}	-4.251	-4.380	0.603
	(0.131)	(0.167)	(0.034)	(0.120)	(0.126)	(0.853)
$0 \cdot 1$		0.781	-0.934	0.172	0.043	5.026
		(0.734)	(0.681)	(0.943)	(0.987)	(0.103)
$0 \cdot 2$			-1.715	-0.608	-0.737	4.245
			(0.381)	(0.786)	(0.763)	(0.184)
$0 \cdot 3$				1.107	0.978	5.960^{**}
				(0.628)	(0.674)	(0.047)
$0 \cdot 4$					-0.129	4.854
					(0.959)	(0.1187)
$0 \cdot 5$						4.983^{*}
						(0.089)

3.6 Conclusion

In this study we introduce and experimentally apply a fair mechanism in group decision-making. We mainly focus on a fair mechanism that is suitable for joint ventures, and partnerships, in general where, all essential stakeholders collectively take investment decisions. Outcomes in the mechanism are determined by private bids, and the mechanism allows for veto power, equal treatment and private information search about investment values. The fair mechanism restricts partners to decide upon a bid, as costly information search, is a key realistic aspect in investment decision-making. We think that the option to decide upon investments in the form of a bid, establishes commonly accepted rules in group-decision making, and potentially, corporate governance. We introduce for the first time, ambiguous valuations, and the option to privately invest in information search about the project value. The latter features, in combination with veto power and fairness (equal treatment), offer an alternative ground for the empirical examination of decision outcomes in corporate finance.

We examine whether the fair mechanism has the potential to improve the quality of investment decision outcomes, the firm's performance and funding decisions. We particularly check whether the fair mechanism can limit potential opportunism on behalf of firm managers at the cost of shareholders' interests (Jensen and Meckling (1976), Fama and Jensen (1983)). We contribute, thus, to the literature relative to agency problems, and test the mechanism' implications. We contribute to the same research strand, also by introducing value ambiguity and allocating decision and control only to area-specific managers. In that sense, we suggest an experimental setup that allows us to investigate decision outcomes, as a function of the knowledge that is realistically required for efficient decision-making. Our experimental findings suggest that the fair mechanism limits opportunism and leads, as well, to desirable decision outcomes. We find that limited opportunism mainly stems from those partners that do not wish to prevent an overall beneficial investment from materialising. Also, the empirical investigation of the fair mechanism informs us that group decision-making with these characteristics reinforces efficiency by means of truth-telling. The fair mechanism overcomes partners' incentives to inflate costs and shade benefits, for a significant amount of projects and with intermediate information about the value. Limited opportunism, though, dominates truth-telling in the light of project value.

We also contribute to the literature on organisational design (i.e. Landier et al. (2013), Landier et al. (2013)). By proxying managers' independence and lack of congruence with veto power, private costly search and private bidding, we add another important dimension into examining group decision-making quality. We find that the experimental feature that allows for theoretical dissent, alongside fairness, indeed enhances efficiency. The latter occurs by fostering the use of objective information relative to the value in decision-making, similarly to the latter studies. We, thus, enhance our inference on the efficiency implications of the mechanism, and provide evidence for shaping a new frame in organisational design, and corporate governance.

Venture capital covenants (i.e. Cumming and Johan (2006)), that attempt to regulate the terms of venture capital relationships, significantly motivate our study. We suggest and experimentally test a mechanism, that accounts for an essential aspect of the regulatory framework in venture capital, that is veto power and control rights. We suggest the mechanism as a potential substitute of complex legal covenants in joint ventures. Finally, we overall contribute to the literature of fair mechanism implementation in collective action tasks (Güth, V.M.Levati, and Montinari (2014), Cicognani et al. (2015), Güth et al. (2014)). We experimentally test and propose a fair mechanism mostly targeted at schemes that feature joint venture characteristics. Furthermore, we experimentally test and propose a fair mechanism, that goes beyond the scope where solely one manager holds final decision rights upon investments (Alberti, Güth, Kliemt and TsuTsui (2016)).

Moreover, the mechanism, as the process of taking due account of governance considerations when making investment decisions, in the financial sector, seems a rather interesting organisational structure in view of sustainable finance. The mechanism is shown to result in more knowledge-based, and thus, more efficient, investment decision making; in the context of our results, that is, increased truth-telling. The latter result hold also for stable partnerships. We think thus, that the mechanism may be a candidate mechanism for enhancing the sustainability of economic activities and projects. The relevance of the mechanism to sustainable finance, may also attach to its governance considerations. In the European Union's policy context, sustainable finance, among others, encompasses transparency on risks related to governance factors, that may impact the financial system. In particular, it encompasses the mitigation of such risks through the appropriate governance of financial and corporate actors. We suggest and experimentally test a fair mechanism that mitigates the risk of preventing an overall beneficial project from going through (limited opportunism). In addition, as the features of fairness, veto power and equal treatment are key to the mechanism, we think that it may be a candidate mechanism also in public provision, satisfying to some extent a just economy governance structure. In that sense, the mechanism maybe viewed as a potential governance function for financial resources generation, as a complement to public money. Finally, limited opportunism and crowd in corporate identity may lead to increased longer-term investments into sustainable economic activities and projects.

Overall, our study shows that a market inspired proposal, with private information and without hierarchy, empirically tracks positive effects in financial performance and limits opportunism. The latter effects occur within a group decision-making scheme open to dissonance. Thus, our bidding proposal with private information search, renders fairness and veto power candidate key variables for improved organisational design.

Appendix

3.A Instructions

Endogenous information search

You are about to participate in an experiment on group decision making. Please switch off your mobile phones now and keep them switched off until the end. Please do not talk to anyone during the session. If you have a question, please raise your hand; a monitor will come by to answer your question.

In the experiment you participate in two related tasks. We describe the first task, and later you will be informed about the second task. In the first task, you will make decisions over 20 periods in groups of three. In each period, the other two participants of your group will be the same; that is, you play repeatedly with the same two others (the other two participants of your group will be randomly determined; it is unlikely that you play repeatedly with the same two others). The identity of the other two participants in your group will not be revealed to you at any time.

You and the other two participants simultaneously decide on the financing of a joint project. The joint project has a positive value for two group members and a negative value for one group member. Positive values are independent randomly drawn integers from the interval 1 to 64, and the negative value is an independent randomly drawn integer from the interval -1 to -64. All numbers refer to Francs, the currency we use in this experiment. At the beginning of each task you receive a lump sum payment of 10 Francs to cover potential losses.

At the beginning of each period, each of you will be informed if your individual value is positive or negative. You are able to purchase at a cost more precise information about your value. For this purpose you are endowed with 3 Francs in each period. Before you make the financing decision on the joint project, therefore, each of you chooses the precision of the information about the value. The information cost increases with the precision of the information about the value, and reduces your endowment of 3 Francs, in the following way.

Buy precision level	0	1	2	3	4	5	6
Information cost	0	0.5	1	1.5	2	2.5	3
Interval precision	64	32	16	8	4	2	1
Your endowment after cost reduction	3	2.5	2	1.5	1	0.5	0

Example: Assume your randomly drawn value is -14 Francs.

If you buy precision level	your information about your value will be
0	your value is ... between -1 and -64
1	...between -1 and -32
2	...between -1 and -16
3	...between -1 and -16
4	...between -13 and -16
5	...between -13 and -14
6	-14

Of course, at the time when you make your purchase decision about information precision you are unaware about your value, in the example of -14 Francs.

Following the revealed information about your value, you submit your financing bid. All bids must be in the interval -64 to 64.

After bidding, the average bid within your group is computed (= (bid1 + bid2 + bid3)/3). Only if the average bid in your group is positive, the project is financed.

If the project is financed, your payoff is determined as follows:

Your value – your bid + average bid of your group + (3 – your information costs).

If the average bid is negative, the project is not financed, and your payoff is as follows:

3 – your information costs.

Since the understanding of the payoffs from the project is crucial for your earnings in the experiment, we ask you to fill in an onscreen comprehension test.

You make all your decisions at the computer. You make the purchase decision on the precision of your value on the first screen. You insert your bid on the second screen.

After each period you will receive feedback information about your value, your purchase decision, your bid decision, the average bid decision in your group, and your payoff in the previous period and all earlier periods. Note that you will never learn the exact value, bids and information choices of the two other group members.

After the last period, one participant in the room will be asked to draw a chip numbered 1-20 from a bag. The drawn chip determines the payment decisive period for all participants. Your payoff in the first task of the experiment will be equal to your payment in the payment-decisive period.

Following the end of the first task you will receive further information regarding the second task in the experiment.

The cumulative earnings from both tasks will be paid out to you in private at your desk following the end of the experiment. The payment will be in Euro (including a 10 Euro participation fee). The following exchange rate applies: 1 Franc = 0.33 Euro.

Exogenous information search

You are about to participate in an experiment on group decision making. Please switch off your mobile phones now and keep them switched off until the end. Please do not talk to anyone during the session. If you have a question, please raise your hand; a monitor will come by to answer your question.

In the experiment you participate in two related tasks. We describe the first task, and later you will be informed about the second task. In the first task, you will make decisions over 20 periods in groups of three. In each period, the other two participants of your group will be the same; that is, you play repeatedly with the same two others (the other two participants of your group will be randomly determined; it is unlikely that you play repeatedly with the same two others). The identity of the other two participants in your group will not be revealed to you at any time.

You and the other two participants simultaneously decide on the financing of a joint project. The joint project has a positive value for two group members and a negative value for one group member. Positive values are independent randomly drawn integers from the interval 1 to 64, and the negative value is an independent randomly drawn integer from the interval -1 to -64. All numbers refer to Francs, the currency we use in this experiment. At the beginning of each task you receive a lump sum payment of 10 Francs to cover potential losses.

At the beginning of each period, each of you will be informed if your individual value is positive or negative. You are randomly given more precise information about your value at a cost. For this purpose you are endowed with 3 Francs in each period. Before you make the financing decision on the joint project, therefore, each of you is randomly given information about the value, which can be more or less precise. The information cost increases with the precision of the information about the value, and reduces your endowment of 3 Francs, in the following way.

Buy precision level	0	1	2	3	4	5	6
Information cost	0	0.5	1	1.5	2	2.5	3
Interval precision	64	32	16	8	4	2	1
Your endowment after cost reduction	3	2.5	2	1.5	1	0.5	0

Example: Assume your randomly drawn value is -14 Francs.

Of course, at the time when you are informed about your information precision you are unaware about your value, in the example of -14 Francs.

If you buy precision level	your information about your value will be
0	your value is ... between -1 and -64
1	...between -1 and -32
2	...between -1 and -16
3	...between -1 and -16
4	...between -13 and -16
5	...between -13 and -14
6	-14

Following the revealed information about your value, you submit your financing bid. All bids must be in the interval -64 to 64.

After bidding, the average bid within your group is computed (= (bid1 + bid2 + bid3)/3). Only if the average bid in your group is positive, the project is financed.

If the project is financed, your payoff is determined as follows:

Your value – your bid + average bid of your group + (3 – your information costs).

If the average bid is negative, the project is not financed, and your payoff is as follows:

3 – your information costs.

Since the understanding of the payoffs from the project is crucial for your earnings in the experiment, we ask you to fill in an onscreen comprehension test.

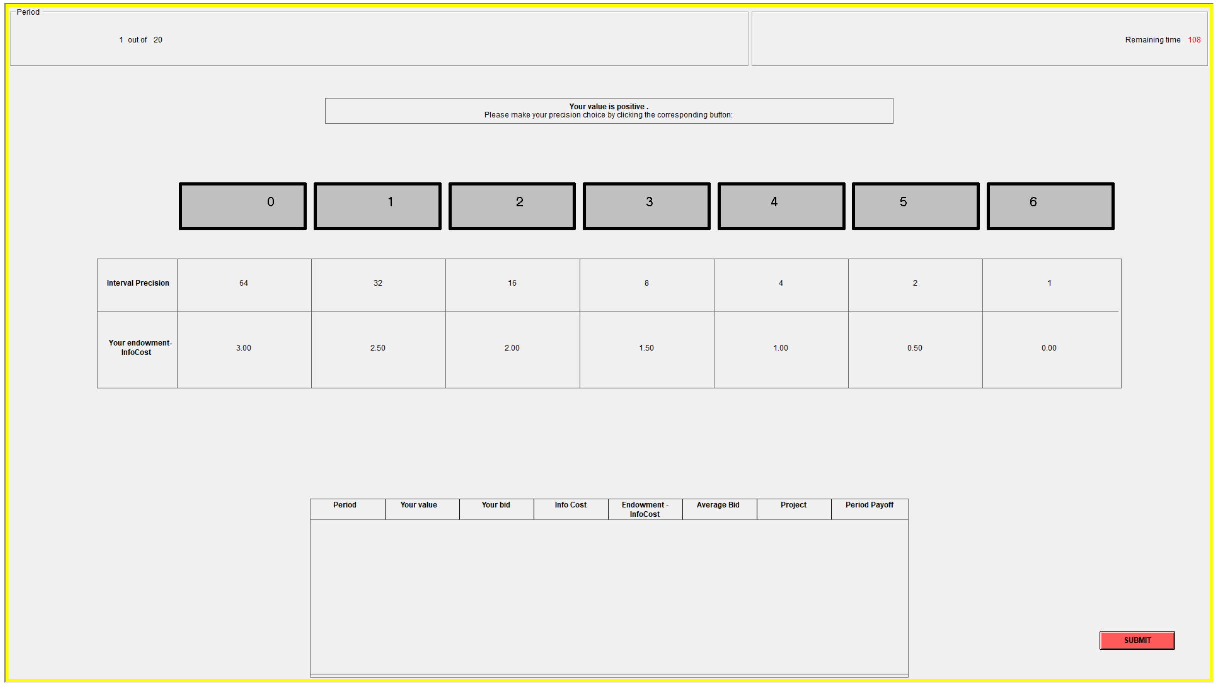
You make all your decisions at the computer. You are informed about the precision of your information on your value on the first screen. You insert your bid on the second screen.

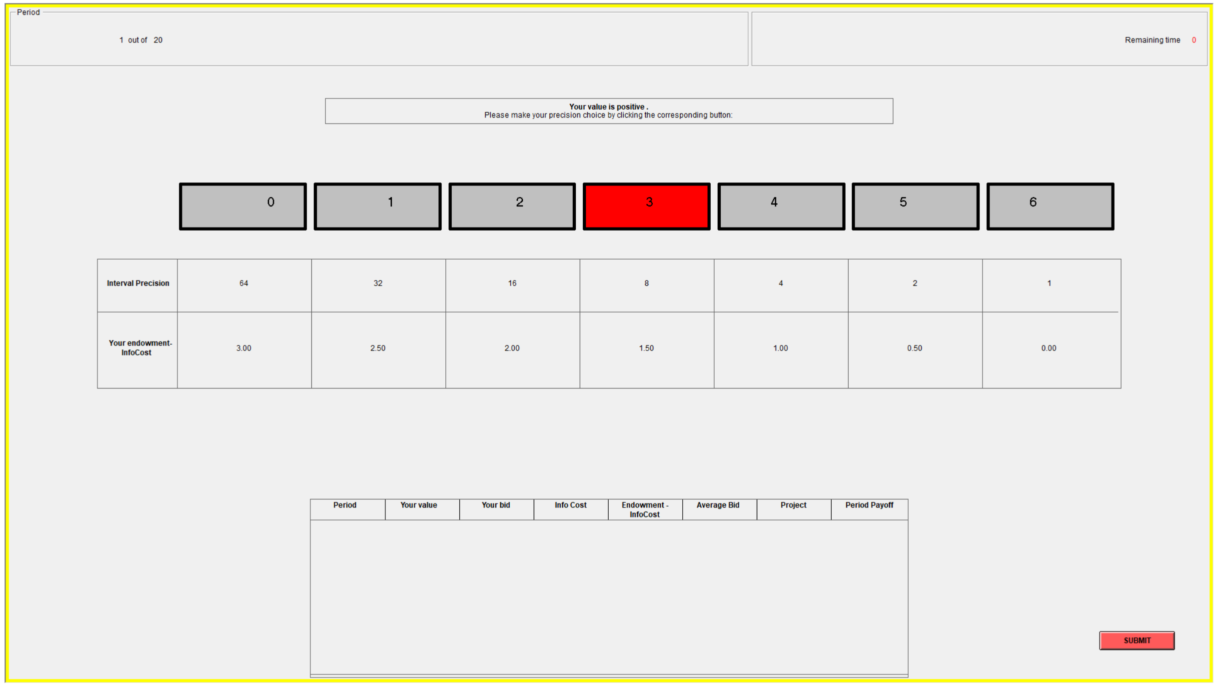
After each period you will receive feedback information about your value, your precision level, your bid decision, the average bid decision in your group, and your payoff in the previous period and all earlier periods. Note that you will never learn the exact value, bids and precision levels of the two other group members.

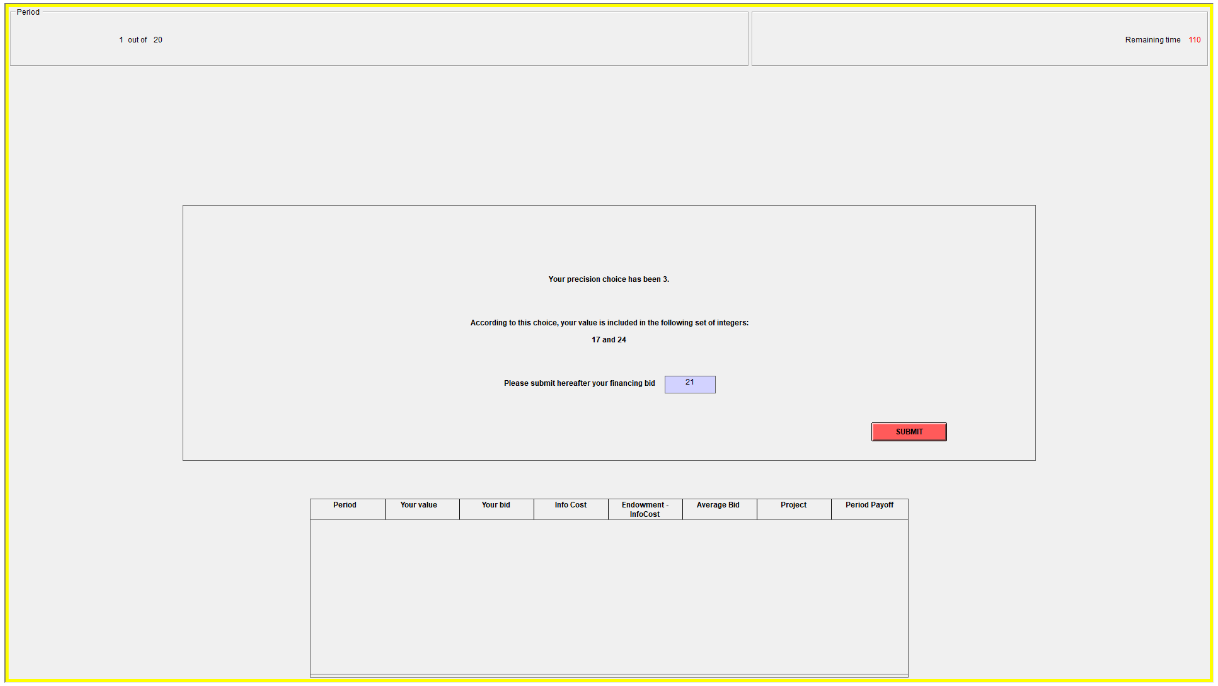
After the last period, one participant in the room will be asked to draw a chip numbered 1-20 from a bag. The drawn chip determines the payment decisive period for all participants. Your payoff in the first task of the experiment will be equal to your payment in the payment-decisive period.

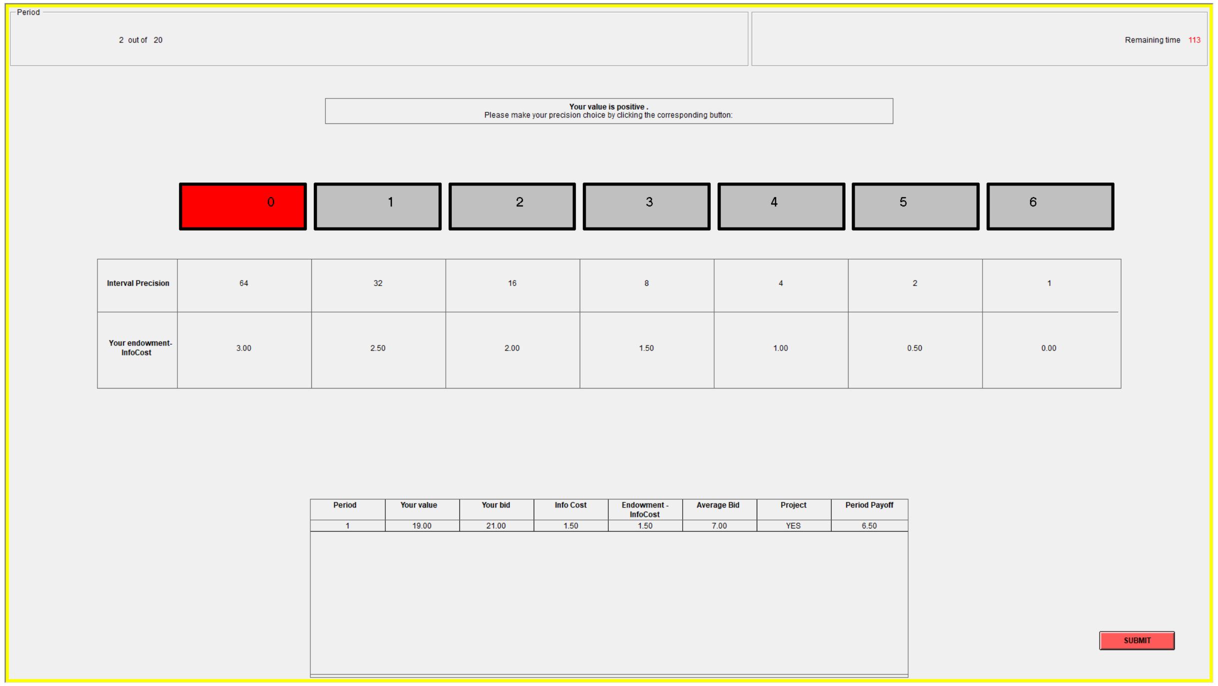
Following the end of the first task you will receive further information regarding the second task in the experiment.

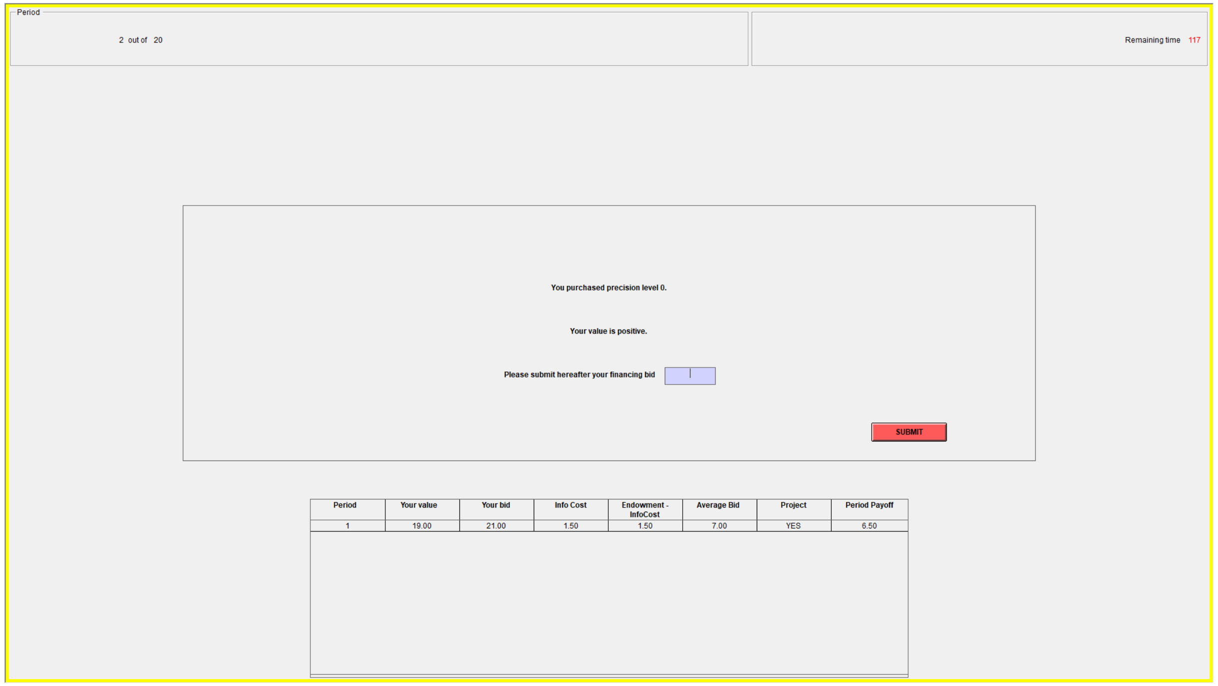
The cumulative earnings from both tasks will be paid out to you in private at your desk following the end of the experiment. The payment will be in Euro (including a 10 Euro participation fee). The following exchange rate applies: 1 Franc = 0.33 Euro.

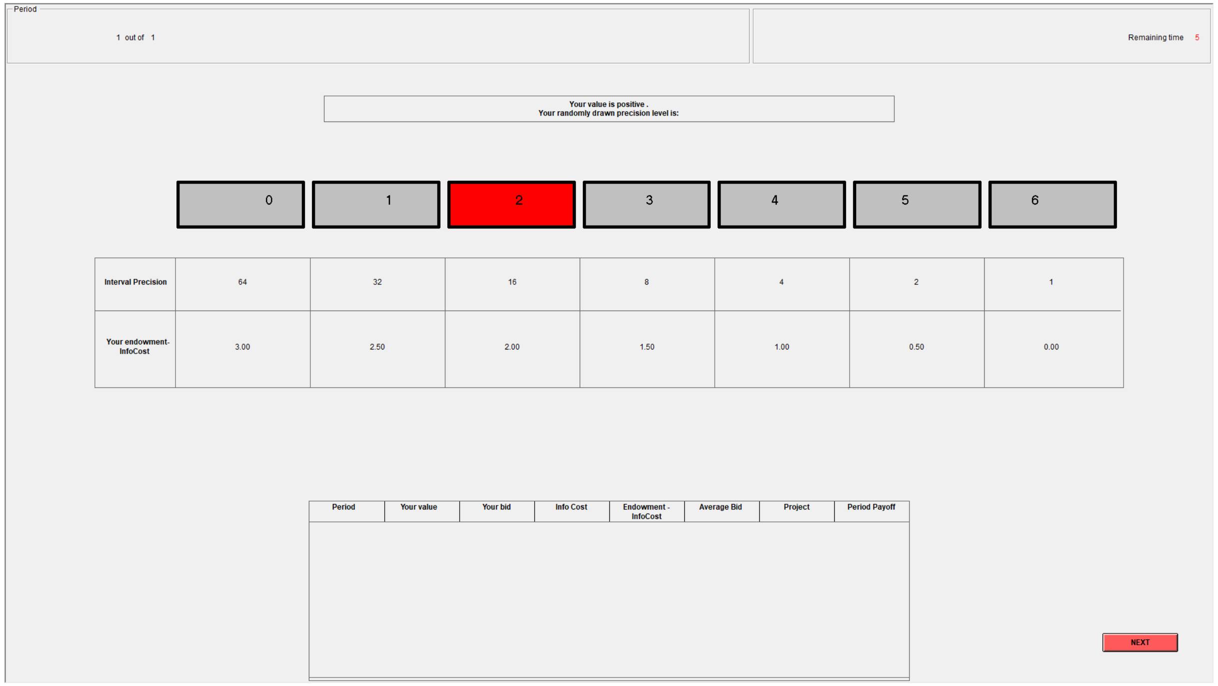

Period
1 out of 20
Remaining time 108
Your value is positive .
Please make your precision choice by clicking the corresponding button:
0
1
2
3
4
5
6
Interval Precision
64
32
16
8
4
2
1
Your endowment-InfoCost
3.00
2.50
2.00
1.50
1.00
0.50
0.00
Period
Your value
Your bid
Info Cost
Endowment - InfoCost
Average Bid
Project
Period Payoff
SUBMIT

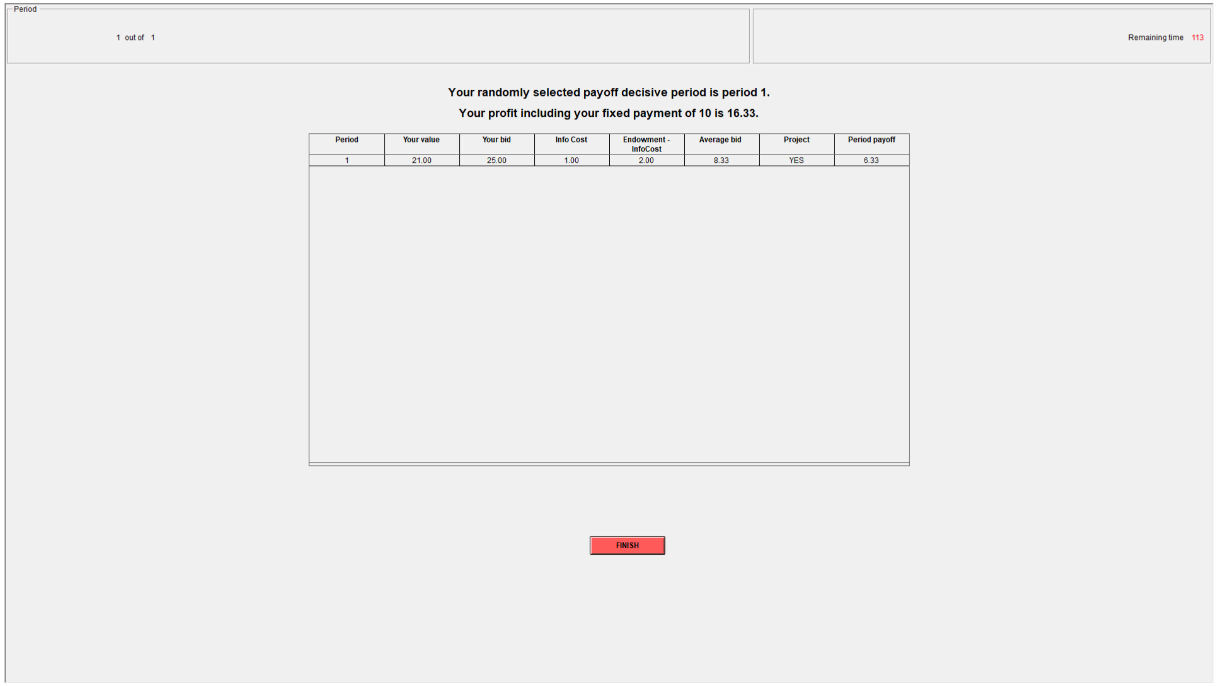

Period
1 out of 20
Remaining time 0
Your value is positive .
Please make your precision choice by clicking the corresponding button:
0
1
2
3
4
5
6
Interval Precision
64
32
16
8
4
2
1
Your endowment-InfoCost
3.00
2.50
2.00
1.50
1.00
0.50
0.00
Period
Your value
Your bid
Info Cost
Endowment - InfoCost
Average Bid
Project
Period Payoff
SUBMIT


Period
1 out of 20
Remaining time 110
Your precision choice has been 3.
According to this choice, your value is included in the following set of integers:
17 and 24
Please submit hereafter your financing bid
21
SUBMIT
Period
Your value
Your bid
Info Cost
Endowment - InfoCost
Average Bid
Project
Period Payoff


Period
2 out of 20
Remaining time 113
Your value is positive .
Please make your precision choice by clicking the corresponding button:
0
1
2
3
4
5
6
Interval Precision
64
32
16
8
4
2
1
Your endowment-InfoCost
3.00
2.50
2.00
1.50
1.00
0.50
0.00
Period
Your value
Your bid
Info Cost
Endowment - InfoCost
Average Bid
Project
Period Payoff
1
19.00
21.00
1.50
1.50
7.00
YES
6.50
SUBMIT


Period
2 out of 20
Remaining time 117
You purchased precision level 0.
Your value is positive.
Please submit hereafter your financing bid
SUBMIT
Period
Your value
Your bid
Info Cost
Endowment - InfoCost
Average Bid
Project
Period Payoff
1
19.00
21.00
1.50
1.50
7.00
YES
6.50


Period
1 out of 1
Remaining time 5
Your value is positive .
Your randomly drawn precision level is:
0
1
2
3
4
5
6
Interval Precision
64
32
16
8
4
2
1
Your endowment-InfoCost
3.00
2.50
2.00
1.50
1.00
0.50
0.00
Period
Your value
Your bid
Info Cost
Endowment - InfoCost
Average Bid
Project
Period Payoff
NEXT


Period
1 out of 1
Remaining time 113
Your randomly selected payoff decisive period is period 1.
Your profit including your fixed payment of 10 is 16.33.
Period
Your value
Your bid
Info Cost
Endowment - InfoCost
Average bid
Project
Period payoff
1
21.00
25.00
1.00
2.00
8.33
YES
6.33
FINISH

Your payoff in Task 1 (in francs)	Your payoff Task 2 (in francs)	Participation fee (in Euro)	Total earnings (in Euro)
10.01	16.33	10.00	18.77

Please write this amount on your receipt and sign the receipt.

Shortly you will receive your payment at the desk where you are seated.

Summary

The main goal of this thesis has been the exploration of individual and group decision-making in risky prospects, and its impact on the quality and nature of investment outcomes, and financial performance. We approached and extended this implicit research goal into various implications in finance.

In particular, we shifted our attention, first of all, into designing a stock market extreme events model based on duration data, and infer on predictability. Moreover, we conducted a study relative to a very interesting case of risky choice and risk preferences elicitation. Last, this thesis has extended and proposed an innovative fair bidding mechanism in organisational design. The latter mechanism incorporates considerable realistic attributes of investment decision-making, asset management and corporate governance.

Achievements

The first study, contributes to the stock market crashes prediction literature. It designates financial and macroeconomic time-varying factors, that seem to explain extreme stock market movements. It particularly examines the predictability of the aforementioned factors towards extreme market events, via a methodology that deploys, time, namely, duration data. The study formulates and tests a prediction model, that motivates from basic features of seminal work in tail and disaster risk. At the same time, it deploys a robust empirical method that has up to now remained largely unexploited in extreme events modelling in finance. It provides evidence that part of the most widely used prominent financial and macroeconomic factors, drive stock market episodes. It contributes to the literature of extreme events prediction, by interrelating these indicators to time (duration) data. In that sense, it reveals different aspects on how these indicators impact the stock market. Thus, the study extends our understanding on how and under which conditions extreme stock market movements may occur.

The second study, contributes to the literature on risk preferences elicitation, risky choice context dependence and stability of preferences in isomorphic decision environments. The study showcases isomorphism mathematically, for the experimentally employed risk tasks, namely the private value sealed bid first-price auction, and the bomb risk elicitation task. It particularly zooms at the implications of the latter in risk behaviour consistency and financial outcomes. It provides experimental evidence that favour *loss* and *gain* framing effects, and thus, context dependence in individual choices and risk preferences. Also, it tracks inconsistencies and preference reversals in individual risky choice decision-making. Finally, it presents experimental evidence that support isomorphic risk preferences with increased competition (higher market sizes).

The third study, proposes and tests a novel corporate governance (and asset management) fair mechanism. The study extends the mechanism with essential realistic features relevant to investment and group decision making. The corresponding experiment ensures that these features are apparent and applicable to individuals. It contributes to the asset management and corporate governance literature, as well as to the literature that encompasses fair mechanisms in various economic applications. This study introduces such a fair mechanism, for the first time, for joint ventures, and presents experimental data on how the mechanism performs. It particularly shows and discusses how the mechanism contributes to agency problems resolution (opportunism), to improved funding outcomes, and knowledge-based honesty in the decision-making process. Overall, the study provides evidence, that a fair corporate governance mechanism that satisfies basic market rules limits opportunism, and improves corporate performance. The latter is achieved as the mechanism enhances the quality and nature of investment decisions, while in parallel, it simulates realistic aspects of decision-making in the financial world.

Real world implications and directions for future research

The first study consists of a potential risk management empirical tool, with various financial implications. More precisely, it suggests a risk assessment tool for optimal investment allocation, relative to the stock-market. Also, it can be seen as a useful empirical tool for trading strategies formulation and regulation. To the extent that the empirical model can predict the timing and nature of stock market extreme events, in the basis of continuously updated data, it can help introducing a time-varying code of conduct for the regulatory framework. The latter framework may also touch upon financial trading rules, helping thus to eliminate the expansion of stock market crashes. It could also work as a complementary empirical tool in macro-prudential policy formulation, given its relevance to core factors of the macro economy. An extension of the project in foreign exchange markets is work-in-progress, applying the methodology to a financial field that exhibits quite different characteristics, relatively to stock markets. The latter extension targets at providing a more comprehensive view of the interrelating factors, that drive such extreme events in financial markets.

The second study provides a tool that may contribute to financial consulting, and in particular, in optimal investment allocations under risk. The corresponding experiment provides a framework for testing consistency of individuals' risk behaviour in financial decision making. Such a framework seems suitable for risk profiling in investment decisions, as it points to the anchors and decision environments, that may induce consistent risk behaviour. Also, the second study provides risk preferences elicitation measures, that may be used in other risk preferences elicitation experimental studies. In that sense, it encourages other researchers to explore and experimentally test further risk elicitation measures. Overall, this study extends our understanding about the dimensions and behavioural biases that drive risky choice and risk preferences.

Finally, the proposed corporate governance mechanism consists of a pioneering mechanism in organisational design and asset management. More precisely, the fair mechanism applies to joint ventures and other types of capital schemes (covenants) that exhibit two basic characteristics. First, all essential stakeholders are partners who collectively decide on firms' policy. Second, venture capital relationships are governed by complex regulation. The fair mechanism helps simplifying the way structural corporate and asset management decisions can be taken, and limits opportunism. At the same time, the mechanism is in line with key economic and financial theory rules and assumptions. Furthermore, the private bidding mechanism enhances egalitarian rules in financial decision making, and can be introduced as a pilot mechanism for investment outcomes evaluation, next to existing models. In that sense, the third study encourages also other researchers to identify further realistic aspects in corporate finance decision-making. An extended version of the fair bidding mechanism is work-in-progress. Overall, the study contributes to the gradual exploration and optimisation of institutional rules and procedures, in asset management and corporate finance.

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