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The impact of the aesthetic appearance of the whitepaper on the final amount raised and the probability of success of the ICO

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The ICO industry is taking more and more space in the world of finance. Indeed, this way of financing projects is becoming highly appreciated by investors. However, ICO's belong to a very unregulated environment, invaded by information asymmetries. One tool to counter this asymmetry are whitepapers which can give crucial information to investors, especially via their aesthetic appearance. We therefore decided to analyze the impact of visual aspects in the whitepaper on the amount raised by the ico. To do so, we used a database containing more than 5,200 ICO whitepapers published between 2015 and 2021. Our results show that images have a positive impact on the amount raised by the ICO. As for the graphics, which are more complicated to interpret, we can't prove any impact on the amount raised by the ICO. Concerning the presence of optimism in the text, we can demonstrate that when the text of the whitepaper is too optimistic, readers tend to be more interested in the images, which become more correlated with the amount raised, than when the presence of optimism in the text is low. Once again, we can't establish a link with graphics, considered to be complex visual aspects. In general, our results show that certain visual aspects of the whitepaper are a good indicator of ICO success.

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Abstract

The ICO industry is taking more and more space in the world of finance. Indeed, this way of financing projects is becoming highly appreciated by investors. However, ICO's belong to a very unregulated environment, invaded by information asymmetries. One tool to counter this asymmetry are whitepapers which can give crucial information to investors, especially via their aesthetic appearance. We therefore decided to analyze the impact of visual aspects in the whitepaper on the amount raised by the ico. To do so, we used a database containing more than 5,200 ICO whitepapers published between 2015 and 2021. Our results show that images have a positive impact on the amount raised by the ICO. As for the graphics, which are more complicated to interpret, we can't prove any impact on the amount raised by the ICO. Concerning the presence of optimism in the text, we can demonstrate that when the text of the whitepaper is too optimistic, readers tend to be more interested in the images, which become more correlated with the amount raised, than when the presence of optimism in the text is low. Once again, we can't establish a link with graphics, considered to be complex visual aspects. In general, our results show that certain visual aspects of the whitepaper are a good indicator of ICO success.

Keywords: ICO's, Whitepaper, aesthetic appearance, Visual Cues, Optimisme

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Contents

1. Introduction

In a world where finance is constantly evolving, Initial Coin Offerings (ICOs) are a financial innovation that has emerged in recent years. ICOs can be seen as a form of fundraising based on blockchain technology that allows companies to raise funds by issuing digital tokens (Cryptonews, 2022). They open up new fundraising opportunities for young entrepreneurs. Indeed, despite their recent nature, ICOs have become valuable funding methods. Between 2016 and 2020, more than 7,400 companies attempted to raise funds via ICOs, raising nearly $35 billion (Lyandres and al, 2022). However, ICOs represent a certain danger for potential investors. Indeed, almost 64% of ICOs fail (F. Wagner and al, 2023). It is therefore very complicated for a potential investor to avoid scams and to know if the ICO will work or if it will be a failure. The lack of regulation in the ICO industry creates large information asymmetries between sellers and investors (Fisch, 2019). The problem is that there is very little information available to investors to help them detect fraud (Shifflett and Jones, 2018). Investors are therefore left to make their own decisions about whether to invest. They must make up their own minds by finding out about the company, the founders of the ICO and finally, the whitepaper which is a collection of information describing the main objective of the project (Cryptoast, 2018). Investors must therefore navigate through a sea of information, which can be overwhelming and confusing.

It is therefore essential to study the different elements of the whitepaper that could have an impact on the probability of success of the ICO. We therefore decided to focus on the aesthetic appearance of the whitepaper and to analyze the impact of several elements present in the whitepaper on the probability of success of the ICO. We will therefore examine the behavior of investors according to the presence of these aesthetic elements in the whitepaper. When we talk about aesthetics, we are talking more precisely about visual cues, whether they are simple or complex. By simple visual cues, we refer to images, while by complex visual cues, we refer to graphics. While remaining within the framework of aesthetic appearance, we will also discuss the impact of optimism, which studies how the choice of words can influence the behavior and perception of buyers. We will also mention some theories, such as the theory of signaling, that is to say the study of positive signals that reduce information asymmetry. The behavioral bias of investors is also analyzed because a study shows that some investors have decided to invest in cryptocurrencies by simply following the decisions of other buyers without having the necessary knowledge.

Regarding the methodology used in this work, we will first conduct a literature review on ICOs, whitepapers, the visual cues and other theories related to our subject. Then, we will analyze a database containing 2500 whitepapers. Using R software, we will analyze the relationship that might exist between the number and type of visual cues present in the whitepapers and the final amount raised by the ICO. Finally, we will employ regression analysis to determine the strength and direction of this relationship.

The results of our research show that the number of images in the whitepaper has a significant impact on the final amount raised by the ICO. However, we were not able to establish a significant link between the graphics and the amount raised, probably due to their complexity of interpretation. With regard to our analysis of optimism, we observed that whitepapers with excessive optimism cause readers to focus more on the images than on the text. This suggests a correlation between text and images. However, like our first analysis, we could not establish a significant link with graphics. More detailed explanations can be found in the rest of our work.

This paper therefore makes several contributions. It provides answers as to what factors actually influence the success of an ICO, focusing in particular on investors' sensitivity to the aesthetics of whitepapers. However, many studies have already examined the elements of the whitepaper that influence the success of an ICO. For example, several authors, including Henry (2008) and Chen et al. (2020), argue that the linguistic elements of whitepapers, such as style, tone and readability, play an important role in post-ICO investment decisions. Momtaz (2020) found only a slight correlation between word count in whitepapers and ICO success.

By adding our work to the body of previous studies, we are helping to provide investors with a solid foundation to help them make their decision when considering investing in an ICO. By analyzing the aesthetics of ICO whitepapers and taking into account our analysis as well as previous analyses, potential investors will be progressively better at avoiding scams. This accumulation of knowledge will allow them to make more informed decisions and to better discern legitimate projects from scams. Secondly, whitepaper authors can use this article to understand what they should and should not add to their whitepaper. This will allow them to optimize their working time. They will be confident that what they have written is relevant and useful.

Concerning our motivations, it is evident that in recent years, cryptocurrencies have garnered significant attention within the finance world, generating numerous headlines. It is undeniable that cryptocurrency has emerged as a prominent force in the financial landscape. Indeed, with the explosion of several digital currencies such as Bitcoin or Ethereum, we can see that a growing craze is created around the virtual currency. Indeed, in 2022, the cryptocurrency market exceeded 3,000 billion dollars (Le Figaro, 2021). By comparison, Belgium's GDP is 500 bil-

lion, six times lower (Countryeconomy, 2022). The fact that this market is relatively new and rapidly developing presents a unique opportunity for exploration and analysis. This is thus the first motivation that led us to work in this sector.

Another motivation that led us to study this sector is that more and more young people, belonging to generation Y and Z like us, are interested in cryptocurrencies. Indeed, young people have experienced significant financial insecurity in recent years. This has resulted in them turning to this new type of currency. Distrust of governments is also a reason why young people prefer to turn to a decentralized monetary network (Surf Finance, 2021).

2. Literature Review

2.1 ICO and Whitepapers

There are many articles describing and understanding the term ICO. In reality, what is an ICO? According to (Jean-Marc Figuet, 2018): "Initial Coin Offering (ICO) is a new mode of crowdfunding for companies developing applications around the blockchain and/or cryptocurrencies."

2.1.1 What is a Blockchain?

According to Joo and al. (2019), a blockchain is a decentralized technology that uses a distributed digital ledger to provide a chronological and public record of transactions between two parties in an efficient, verifiable, and sustainable manner (Reid & Harrigan, 2013). The security of the ledger is maintained by the miners who manage the ledger. The main difference between blockchain and other systems is that blockchain provides a decentralized structure with no central authority. A blockchain framework is structured by a network of communicating nodes. Until the advent of blockchain technology, most successful multi-party structures required a central authority to control and access the entire system.

Blockchain offers many advantages for ICOs. Firstly, it provides increased transparency, i.e. all transactions on the blockchain are transparent, which allows tracking investment activities and better understand investment opportunities. Secondly, geographical barriers are erased, effectively making cross-border investments easier as the costs and time involved in transiting funds between different countries are reduced. Thirldy, blockchain helps to simplify transactions because it guarantees the security and integrity of data but also allows for real-time updating of balances. Fourthly, blockchain is decentralized, which means that it facilitates the management of funds because it secures transactions and allows transparency. Finally, blockchain technology helps cut out the middleman in the fundraising process, allowing companies to connect instantly with investors. This technology can lower costs for companies and increase transparency for investors (Bourse, s.d.)

2.1.2 The ICOs

According to Sapkauskienê and Visinskaitê, until the advent of ICOs, companies raised funds using traditional financing methods such as bank loans, equity, venture capital and crowdfunding. Clearly, ICOs share many similarities with other fundraising vehicles. As Barsan (2017)

points out, ICOs can be divided into initial public offerings (IPOs), where a company sells a portion of its stock on the stock market, and cloud computing, where a virtual platform raises funds from a diverse group of investors. Similar to financing. As Amsden and Schweizer (2018) noted, as ICOs become more popular, entrepreneurs are looking to invest in stocks, bonds, participatory financing, venture capital, private equity funds, and, according to Ofir and Sadeh (2018), local currency of ICOs as a hedge against volatility and geopolitical risks, distrust of the traditional banking sector after the 2008 global financial crisis, and increased media attention. The growing popularity of ICOs shows that they offer many advantages that motivate both investors and companies or entrepreneurs to choose exactly this type of fundraising or investment. In addition, one of the most important factors that increase the market risk of ICOs and complicate decision-making is information asymmetry and too little information disclosure. First, the lack of intermediary services, one of the advantages of ICOs already mentioned, can make it difficult to obtain correct information about ICOs. According to Li and Shin (2018), to overcome information asymmetries in IPOs, financial intermediaries conduct inspections to assess the value and risk of the company and the price of the shares sold, but intermediary services are not used in IPOs.

Conforming to Jean-Marc Figuet (2018), the ICO investor does not receive any title or debt. Indeed, it works with tokens. It is important to understand the fact that the value of a currency is based on the trust that people have in it. Indeed, after the subprime crisis, confidence in world currencies has declined. This is why Bitcoin was created as the first cryptocurrency. As the confidence of the population has grown since its creation, bitcoin has continued to increase in value. Since the development of the first cryptocurrency, Bitcoin, in 2009, many cryptocurrencies have been created to meet different needs and purposes. Cryptocurrencies are global digital payment systems that perform their functions online. Traditional cross-border payments traditionally use the SWIFT (Society for Worldwide Interbank Financial Telecommunication) system worldwide or the SEPA (Single Euro Payments Area) system in the European Union region. Both systems offer secure and accurate transfers. However, one of the major drawbacks of these systems is the lengthy transaction process (Joo and al, 2019).

According to the Billand and Messié website, to create an ICO, you need to make a plan called a whitepaper.

2.1.3 The Whitepaper

The whitepaper can be defined as a collection of comprehensive synthetic information. Its role is to promote a new form of cryptocurrency, the ICO. Whitepapers specify more about the technical and technological characteristics of the crypto. Whitepapers are variable and should be comparable to public offerings of financial securities. They also disclose the final objective of the project, including the developers, amounts, different currencies, characteristics of the tokens, etc. There are quotas of tokens per category of participants. Most of the time, the

number of tokens is fixed in advance, but everyone can define their number of tokens after the fundraising. Tokens do not offer any guarantee of a refund. Tokens are not a debt or property instrument.

The information given by the whitepapers is very asymmetrical. Indeed, as no information is mandatory, the investor is much less informed about the security of the whitepaper than the creator of the whitepaper. Nevertheless, these are the only documents in ICOs that contain all the information known to everyone. According to the website 'Billand and Messié', it is impossible for investors to identify the origin and identity of the issuer in more or less 30% of the whitepapers. If the origin is explained, the contacts are rarely specified. Very few whitepapers have a section dedicated to the possible risks that investors have when buying an ICO. All this proves that there is a great asymmetry of information. It is also important to know that the information revealed is not always accurate and reliable. Creators sometimes show what they want and not tell the facts. This new type of funding is both new and decentralized. Therefore, no regulation is yet established for ICOs. There are therefore various risks in this area. The buyer does not hold a real share in the company, so there is never a guarantee that the ICO in question is based on reliable foundations. In addition, there are scams like in the cryptocurrency market that are difficult to detect.

2.2 Visual Cues

Investors must choose which ICO to invest in. Unfortunately, the cryptocurrency field is plagued by information asymmetries (Kun Chen, 2019). Indeed, one must be careful not to be confronted with the many scams found in this market. As explained earlier, whitepapers are the only sources of information available when one wants to learn about an ICO. Unfortunately, they are sometimes very long and boring to read. According to the work of Chan and Park (2015), visual elements would reduce this problem. Indeed, they explain in their work "How images and color in business plans influence venture investment screening decisions", that a visual image is more easily memorized than written information because the time to recognize and interpret it is less. When information is expressed in both written and visual form, the visual impact will play a dominant role in decisions and will have the potential to override the effect of the written information.

2.2.1 Cognitive Load Theory

The heuristic theory developed by John Sweller in 1980 also explains this phenomenon. His theory is called the "cognitive load theory". In this theory, he explains that the human brain has a limited capacity to process information and that once the limit is reached, we can experience cognitive overload and thus reduce our ability to understand and retain information. The "modality effect" explains that the way in which information is presented can influence the amount of cognitive load. Visual strategies can therefore be designed to reduce this cognitive

load on readers. According to a study published in the “Journal of Experimental Psychology”(Hegarty et al. 1999) graphs and diagrams can help to make complex information much simpler and thus improve comprehension of information. Another article by Scheaf and al. (2018), entitled "Signals’ flexibility and interaction with visual cues: Insights from crowdfunding" is an article explaining as the title suggests the interaction with visual information. They point out that several theories, such as first impression bias (Barrick and al,2010), thin-slicing in judgment formation (Ambady and Rosenthal, 1992), halo effects (Nisbett and Wilson, 1977), and schema-triggered affect (Fiske, 1982), confirm that visual cues manufacture a lens that bypasses the following information. Nevertheless, other theories, such as belief updating theory, anchoring, and primacy effects maintain that visual cues act as an informational anchor in judgment creation. However, according to Feldman and Lynch (1988), causal judgment models of information processing cannot be adequately modeled because attitudes and beliefs that are aimed at creating judgment are naturally activated in the development of decision-making.

As previously explained, we will divide visual cues into two distinct categories. These are non-complex (or simple visual cues) and complex visual cues (or data visualization). Non-complex visuals are simple images while complex visuals are graphs, diagrams, maps, roadmaps,...

2.2.2 Data Visualization

Data visualization is a crucial aspect of data analysis. It consists in representing data in graphical form to make them more understandable. Representations can be descriptive, with displays of raw data and simple statistical summaries, or they can include transformed data based on more complex transformations. (Data Visualization, n.d.) Data visualization is useful for many tasks, including cleaning data, exploring data structure, detecting outliers and unusual groups, identifying trends and clusters, finding local patterns, evaluating modeling results, and presenting results. It is also essential for exploratory data analysis to check data quality and to help analysts become familiar with the structure and characteristics of the data at hand. Graphs can reveal features of the data that statistics and models may not see, such as unusual distributions, clustering, gaps, missing values, signs of rounding or accumulation, implied boundaries, and outliers. However, interpreting graphs requires experience to identify potentially interesting features and statistical knowledge to guard against the dangers of over-interpretation. (Sadiku and al., 2016) In summary, data visualization is a valuable tool for data analysis and decision-making. It allows one to represent data in an easily understandable visual form, identify interesting patterns and trends, check data quality, and explore data structure. However, interpreting graphs requires experience and statistical knowledge to avoid misinterpretation.

Visual cues can also have an impression management role, i.e. they can be used to embellish reality. Indeed, impression management is the act of influencing the perception of others about something. In the work of Korzynski, Haenlein and Rautiainen, we find that impression management techniques are used in crowdfunding. Indeed, the main idea of crowdfunding is

very similar to the functioning of ICOs. Impression management techniques allow founders to create a better image of themselves and to raise funds from potential investors (Parhankangas and Ehrlich, 2014).

Impression management can also have a downside. Indeed, there are two types of impression management (IM). There is the honest IM and the deceptive IM. According to a study in the International Journal of Selection and Assessment, which was carried out on 693 interviews (Chet, R and al, 2020), honest IM had a curvilinear effect and was therefore effective up to a certain point. Whereas deceptive MI had a linear effect on success but was negatively correlated with it. This study shows that impression management is a very effective tool to achieve a goal, but that it must be controlled and not abused so as not to cross the misinformation zone or make it an understatement.

Three main theories that we can relate to our work will be looked at in this literature review: the optimism effect, signaling theory, and investor behavioral bias. The optimism effect investigates how overconfidence can affect investors' assessments of ICO-related investment prospects. The signaling theory investigates the use of signals by ICO issuers to draw in investors and communicate details about the caliber of their project. Finally, behavioral investor bias looks at mental biases like loss aversion and the herd effect that may influence ICO investment choices. We can comprehend the elements that affect investor behavior in the particular setting of ICOs by examining these theories.

2.3 The Impact of Optimism

The paper by Loughran and McDonald (2020) focuses on financial text analysis, using a lexical and dictionary-based approach. The authors examined the language used in financial documents filed with the Securities and Exchange Commission (SEC) in the United States, including annual reports (Form 10-K) and quarterly reports (Form 10-Q). The objective was to study how word choice and tone can influence investor perception and behavior. The authors found that word choice can have a significant impact on investor perception. For example, companies that use positive words to describe their financial condition are more likely to attract investors. Similarly, companies that use negative words to describe their financial condition are more likely to experience a credit downgrade. Loughran and McDonald's article has important implications for ICO whitepapers, as these documents are often used to attract investors. Whitepapers should be written in a way that engenders confidence and interest in potential investors. The use of positive words can be helpful in getting the attention of investors and building confidence in the project.

However, excessive optimism can also be problematic. The Loughran and McDonald article points out that investors can be sensitive to cues of risk and uncertainty in financial documents.

If investors perceive excessive optimism in ICO whitepapers, it can reduce their confidence in the project and damage its credibility. In conclusion, Loughran and McDonald's article highlights the importance of word choice and tone in financial documents. Companies looking to do ICOs must be careful to maintain a balance between optimism and credibility in their whitepapers to build confidence in potential investors. The words used to describe the project should be carefully chosen to provide accurate and credible information about the financial health and performance of the project, as well as to build credibility with potential investors.

2.4 Signaling Theory

In the context of corporate fundraising via ICOs, signaling theory can be applied. There is a high degree of uncertainty in the ICO process, but also an asymmetry of information between founders and investors because founders have to bring investors along. They provide good signals for the success of the company (Spence, 2002). The key elements of the ICO process are founders, signals and investors. (Connelly et al., 2011; Spence, 1973). Founders will provide specific information, i.e. positive signals about the quality of their company and their capabilities to buyers to decrease information asymmetry and to guide investment decisions in ICO projects. Buyers decide whether to invest in ICOs by first receiving the signals and then interpreting them.

According to Boreiko and al (2018), if the fundraisers have succeeded in reaching their goals, the ICOs are generally considered successful. A great deal of research has been done to understand how founders send quality signals to decrease information asymmetry and achieve their goals. According to Fish (2019) who studied the role of voluntary disclosures, such as whitepapers, in determining whether they are valuable business signals, found that startups that hold more informative technical whitepapers and code published on GitHub are more likely to raise higher funds through ICO.

2.5 Investor Behavioral Biases

Because of the large number of irrational actions on the part of investors, due to the lack of effective information, it is possible to bring together the study of prospect theory with the cryptocurrency market. Emotions such as optimism, fear or uncertainty are traits that can be applied to the same field as the cryptocurrency market. Investors in their decision-making may take irrational actions. According to Clements (2018), After the Bitcoin Boom, many buyers were captivated due to the media and also the ease of obtaining the cryptocurrency which caused a large amount of profit for the early investors. A surge of FOMO, which is the fear of missing out, developed as future investors were afraid of not having the chance to make a large profit as well. This impatience resulted in future buyers rushing to buy cryptocurrencies (Protho,2017). This effect is called the "Bandwagon Effect" (where investors without the proper knowledge to make decisions are attracted by the rising prices of cryptocurrencies and follow the decisions of

other investors who are knowledgeable and have more wealth to get easy profits (Biggs, 2018).

Generally, it is simply not possible for people to collect and study all the data they need to make the best objective decisions. First, the amount of information available is too much to lift for individuals who are constrained by capacity and time. Second, as people lack the knowledge to interpret information correctly, they use heuristics to reduce complexity and decide whether to invest in an action (Tronnier et al., 2020).

3. Assumptions

The assumptions we have decided to prove are the following:

1) "The number of simple and complex visual cues in the whitepapers would be positively correlated with the amount raised by the ICO."

2) "The presence of optimism in the whitepapers would have an impact on the effect that visual cues have on the amount raised. This would mean that text and visual cues would be correlated."

4. Research Question

In order to better understand the impact of the presence of simple and complex visual cues in the whitepaper on the amount raised by the ICO, it is important to test it statistically. We can therefore define our first research question.

Research Question 1: What is the impact of the number of complex and simple visual cues in the whitepaper on the amount raised by the ICO ?

In view of the theory we have studied so far, our hypothesis is that the number of images and graphics in the whitepaper would be positively related to the amount raised by the ICO. We can therefore define the null hypothesis $H_0 : B_1 = 0$. This would mean that the correlation between the number of images/graphics and the amount raised would be zero. And conversely, $H_1 : B_1 \neq 0$. This would mean that the correlation between the number of images/graphs and the amount raised by the ICO would be non-zero. However, it will also be interesting to see if this effect fades as the number of images/graphs increases.

In relation to optimism, our study aims to investigate whether whitepapers with a higher level of optimism have an influence on how readers perceive the visual aspects of the whitepaper. We will explore whether a positive tone in the content affects the way individuals evaluate the visual elements present in the whitepaper. We can therefore define our second research question.

Research Question 2: What is the impact of the presence of optimism in the whitepaper on the effect that visual cues have on the final amount raised by the ICO ?

There are different possible effects of optimism. Given that the literature suggests that the presence of optimism can have a negative effect on readers' perception of the text, it is possible that a whitepaper with a high level of optimism would encourage readers to be more interested in the visual aspects of the document. On the other hand, a whitepaper with a very low presence of optimism would not necessarily arouse a particular interest in the visual aspects from the readers.

5. Data, Methodology and Empirical Results

5.1 Methodology

This work was carried out in several stages in order to test the hypotheses established above. The first step is to identify and define our database and the different variables that will be used as a basis for our analysis. A summary of all these variables can be found in Table 1.

The purpose of the second step is to present you with a comprehensive descriptive statistic of all the variables we used to test our hypotheses. You will get an overview of the mean, standard deviation, median, minimum, maximum and different quartiles. The aim is to understand the characteristics of each variable. This information can be found in table 2.A.

The third step in this work was to make a correlation matrix including all our variables. The aim is to identify the correlation between the dependent and independent variables, to find out if this correlation is significant, and to prepare for the regression analyses. You will find this correlation matrix in exhibit 3.

The last step was to run our OLS regressions and analyze them in order to test our different hypotheses based on our regression model, which is as follows

Regression Model: Amount Raised by the ICO = a_0 + β_1 Whitepaper Visual cues + β_2 Control Variables + ε

In order to better understand the impact of the presence of simple and complex visual cues in the whitepaper on the amount raised by the ICO, it is important to test it statistically. We therefore decided to run OLS regressions with the aim of estimating the parameters of a linear relationship between a dependent variable and one or more independent variables. It is a method that is considered as a reference method in economics and statistics more precisely in order to model and estimate relationships between continuous variables. However, it is important to respect several assumptions before running an OLS regression in order not to have errors in

our results. The most important assumptions are linearity, independence, homoscedasticity, normality and non-collinearity. Indeed, it is very important that the independent variables are not strongly correlated with each other and that the residuals of the regressions follow a normal distribution. We have therefore ensured that these assumptions are respected for each of our regressions.

5.2 Data

All our analyses are based on a database that we received from Mr. Thewissen. He, together with Prabal Shrestha, Wouter Torsin and Anna M. Pastwa wrote the paper "Unpacking the black box of ICO whitepapers: "A topic modeling approach". The aim of this paper is to map Initial Coin Offerings' (ICOs') whitepaper thematic content to analyze its information value to investors. Their sample is compiled from seven ICO listing websites. Namely, ICOBench.com, ICO- Holder.com, ICOMarks.com, ICORatings.com, ICODrops.com, FoundICO.com and CryptoCompare.com. This shows what a goldmine this database is, considering that most databases are often based on a single listing site. (J. Thewissen et al., 2022) More information about this database can be found in the paper mentioned above.

Variable Name	Definition
Dependent Variables	
AmountRaised	Total amount of funds raised during ICO.
LogamountRaised	Numeric Type. Logarithmic form of AmountRaised
Independent Variables: Whitepaper variables	
Lack	Number of images in the WP.
Sum	Sum of graphs, tables, flowchart. The number of complex visual cues in total.
Sum_square	is the sum square
Lack_square	is the lack square
Independent Variables: Control Variables	
WP_Readability	Gunning Fog Index Readability score of the white paper text.
WP_Sentiment	Proportion of positive minus negative words in white paper text based on the dictio- naries provided by Loughra
WP_Pages	Number of pages in the ICO white paper PDF.
WP_TopicDiversity	Diversity in white paper's topic composition based on Shannon diversity index (Shan- non and Weaver, 1963).
TaxHaven	ndicates whether the country is located in a tax haven (Hines, 2010).
Institutions	Aggregated institution score based on Worldwide Governance Indicators (Kaufmann et al., 2010).
USRestrict	Indicates if US-based investors are restricted from participating in the ICO.
Ratings	Average of the source-specific ratings in standardized values.
SocialMedia	Number of different social media channels used by the ICO project.
Video	Indicates whether the project provided a descriptive video.
Eth	ndicates whether the project blockchain is built on the Ethereum platform.
WhitelistKYC	Indicates whether the ICO implements Whitelisting and Know Your Customer (KYC) compliances.
Team	The number of members in the team behind the ICO.
TokenDist	Indicates whether the token distribution structure is specified.
MinInvest	Indicates whether a minimum investment amount is specified.
NumbCurr	The number of types of fiat and cryptocurrencies that the ICO accepts.
Fiat	Indicates whether the ICO accepts fiat currencies.
PreICO	Indicates whether a pre-ICO sale is conducted.
Hardcap	Indicates whether a soft cap is specified.
Softcap	Indicates whether a hard cap is specified.
Bonus	Indicates if a bonus scheme was offered to investors during the ICO.

Figure 5.1: :Variables Definitions

This database contained valuable information on more than 2500 ICOs using more than 225 variables. Of these 225 variables, we decided to select 26. Our dependent variable is the amount raised by the ICO. You will notice that we will use the logarithm of this variable in order to reduce the effect of extreme values, to make our distribution closer to a normal distribution and finally to facilitate the interpretation of the regression coefficients. Our dependent variables are "lack" and "sum" which are respectively the number of images and the number of graphics (of

all kinds) present in the ICO whitepaper. We also took "lacksquare" and "sumsquare" in an attempt to linearize our non-linear relationship between our dependent and independent variables. We will explain this in detail later. You will notice that we have added many control variables. This is very important as these control variables provide a more accurate estimate of the effect of our independent variables on our dependent variable. Without this, our models would be biased, as these different variables also affect the relationship. These variables are not chosen at random, they come, like the database we worked with, from the paper of J. Thewissen and al, 2022. They themselves drew on the work of Fish (2019), Adhami et al. (2018) and Amsden and Schweizer (2018) to establish this list of control variables. In order to better understand the different variables used in the models we will study later, we have prepared a statistical summary of the variables used in the models.

	N	Mean	St.Dev	Min	Max	q1	q3
Dependent Variables							
AmountRaised	1199	8721474	11695761	52761	54980000	1000000	12000000
LogamountRaised	1199	14.86	1.823	10.87	17.82	13.82	16.3
Independent Variables							
Lack	2244	22.04	27.096	0	222.02	4	29
Sum	2500	6.328	5.445	0	48.970	3	9
Sum_square	2500	69.67	145.612	0	2398.06	9	81
Lack_square	2244	1219	3668.880	0	49295	16	841
Controles Variables							
WP_Readability	2500	15.589	2.123	7.772	22.912	14.141	16.949
WP_Sentiment	2500	0.002	0.006	-0.025	0.030	-0.001	0.006
WP_Pages	2500	32.91	16.648	3	167	21	42
WP_TopicDiversity	2500	2.242	0.385	0	3.030	2.039	2.514
TaxHaven	2500	0.339	0.473	0	1	0	1
Institutions	2500	2.386	1.845	-4.326	4.448	1.667	3.708
USRestrict	2500	0.3931	0.489	0	1	0	1
Ratings	2500	-0.000309	1	-3.208	2.703	-0.736	0.712
SocialMedia	2500	6.417	2.086	0	12	5	8
Video	2500	0.7986	0.401	0	1	1	1
Eth	2500	0.855	0.352	0	1	1	1
WhitelistKYC	2500	0.6592	0.474	0	1	0	1
Team	2500	12.41	7.505	1	69	7	16
TokenDist	2500	0.9441	0.230	0	1	1	1
MinInvest	2500	0.4339	0.496	0	1	0	1
NumbCurr	2500	2.251	1.827	1	30	1	3
Fiat	2500	0.2421	0.428	0	1	0	0
PreICO	2500	0.6864	0.464	0	1	0	1
Hardcap	2500	0.8558	0.351	0	1	1	1
Softcap	2500	0.7435	0.437	0	1	0	1
Bonus	2500	0.6572	0.475	0	1	0	1

Figure 5.2: Summary statistics

There are many interesting things to analyze in this table. Firstly, we see that the average of our dependent variable "AmountRaised" is 8,721,474 for a minimum of 52,761 and a maximum of 54,980,000. Only 25% of the whitepapers have an amount raised higher than 12,000,000. This is largely why we decided to work with the logarithm of this variable in our future regressions. Indeed, there can be quite a large variability in the amount raised between smaller and larger ICOs. This extreme variability means that our curve will never follow a normal distribution. The use of the logarithm allows us to stabilize the variable "AmountRaised" and to find a

normal distribution. You will also notice that the N is smaller than for the rest of our database. Indeed, the amount collected is information that is not always available. This strongly reduces the size of our sample for our regressions, but it remains a fairly large number of observations.

Concerning our independent variables, we see that the average number of images in the whitepaper is 22.04 images, with a maximum of 222 images. The whitepaper containing 222 images is probably an extreme number and does not really represent the other whitepapers since 75% of the whitepapers contain only 29 images or fewer. As far as graphics are concerned, we notice immediately that there are far fewer of them. In fact, we find an average of 6 per whitepaper. For a maximum of 48. Again, this maximum is not very representative, given that 75% of the whitepapers have a number of graphics less than or equal to 9.

As regards the control variables, the one we are most interested in is "WP_Sentiment". As explained above, we are interested in the impact of the "WP_Sentiment" score given to the whitepaper on the final amount collected. This score reflects the proportion of net positive words. That is, the difference between the number of positive words and the number of negative words. We see in our summary statistic (figure 5.2) that this score varies between -0.025 and 0.030. The average is very close to 0 and 75% of the whitepapers have a score equal or lower than 0.006. This would mean that, on average, whitepapers are not very positive and that the number of negative words would cancel out the effect of the number of positive words. We will look at this in more detail later. For more information on all the control variables, we invite you to take a look at the paper of J. Thewissen.

We can now look at our correlation matrix.

	logAmountRaised	sum	sumsquare	lack	lacksquare	FOG	WP_Sentiment	WP_pages	TopicDiversity
logAmountRaised									
sum	0.112***								
sumsquare	0.075***	0.876***							
lack	0.158***	0.314***	0.258***						
lacksquare	0.137***	0.262***	0.246***	0.884***					
FOG	0.116***	0.060***	0.043**	0.081***	0.044**				
WP_Sentiment	-0.031	0.005	-0.004	0.051**	0.016	-0.053***			
WP_pages	0.142***	0.452***	0.336***	0.413***	0.331***	0.149***	-0.067***		
TopicDiversity	0.039	0.151***	0.085***	0.136***	0.093***	0.166***	-0.057***	0.273***	
Fin_TaxHaven	0.127***	0.089***	0.065***	0.080***	0.074***	0.079***	-0.035*	0.134***	0.105***
Fin_Institution	0.181***	0.061***	0.052***	0.038*	0.032	0.039**	-0.046**	0.073***	0.046**
Fin_USRestrict	0.051*	0.108***	0.084***	0.095***	0.058***	0.048**	-0.040**	0.139***	0.084***
Rating	0.176***	0.192***	0.126***	0.195***	0.130***	0.052***	-0.024	0.271***	0.110***
SocialMediaCount	0.024	0.132***	0.093***	0.124***	0.079***	-0.005	-0.033*	0.178***	0.078***
Fin_VideoDummy	0.087***	0.111***	0.068***	0.098***	0.067***	0.040**	0.003	0.157***	0.047**
Fin_EthereumBlockDummy	-0.004	0.072***	0.047**	0.024	0.019	-0.017	-0.079***	0.054***	0.014
Fin_WhitelistKYCDummy	0.130***	0.155***	0.110***	0.164***	0.114***	0.093***	-0.014	0.219***	0.120***
Fin_Team	0.219***	0.234***	0.165***	0.284***	0.197***	0.106***	0.017	0.373***	0.153***
Fin_TokenDistributedDummy	0.006	0.055***	0.034*	0.017	0.012	-0.018	-0.029	0.032	0.084***
MinInvest	-0.015	0.084***	0.079***	0.096***	0.070***	-0.003	-0.053***	0.093***	0.036*
NumbCurr	0.046	0.032	0.025	0.059***	0.040*	0.021	0.049**	0.081***	0.059***
Fiat	0.082***	0.066***	0.047**	0.065***	0.050**	0.054***	0.040**	0.142***	0.074***
PreICO	-0.007	0.084***	0.046**	0.051**	0.019	0.019	-0.015	0.118***	0.093***
HardCap	0.017	0.120***	0.076***	0.062***	0.045**	0.048**	-0.043**	0.128***	0.108***
SoftCap	0.006	0.102***	0.077***	0.073***	0.057***	-0.003	-0.044**	0.096***	0.046**
Bonus	0.007	0.103***	0.081***	0.063***	0.035*	-0.051**	-0.004	0.094***	0.085***

Figure 5.3: Correlation martrix

	Fin_TaxHaven	Fin_Institution	Fin_USRestrict	Rating	SocialMediaCount	Fin_VideoDummy	Fin_EthereumBlockDummy
Fin_Institution	0.313***						
Fin_USRestrict	0.136***	0.079***					
Rating	0.099***	0.080***	0.233***				
SocialMediaCount	0.047**	0.012	0.250***	0.592***			
Fin_VideoDummy	0.071***	0.029	0.131***	0.362***	0.318***		
Fin_EthereumBlockDummy	0.050**	0.033*	0.081***	0.100***	0.147***	0.070***	
Fin_WhitelistKYCDummy	0.142***	0.152***	0.280***	0.320***	0.245***	0.190***	0.061***
Fin_Team	0.133***	0.085***	0.168***	0.405***	0.297***	0.225***	0.032
Fin_TokenDistributedDummy	0.020	0.012	0.114***	0.216***	0.201***	0.073***	0.102***
MinInvest	0.032	0.020	0.230***	0.202***	0.236***	0.092***	0.132***
NumbCurr	-0.032	-0.038*	0.012	0.124***	0.095***	0.068***	-0.143***
Fiat	-0.014	0.040**	0.028	0.111***	0.098***	0.0815***	-0.000
PreICO	0.016	-0.026	0.140***	0.169***	0.186***	0.094***	0.098***
HardCap	0.082***	0.062***	0.193***	0.291***	0.249***	0.151***	0.134***
SoftCap	0.059***	0.014	0.181***	0.269***	0.252***	0.152***	0.132***
Bonus	-0.022	0.001	0.176***	0.171***	0.212***	0.118***	0.061***

	Fin_TokenDistributedDummy	MinInvest	NumbCurr	Fiat	PreICO	HardCap	SoftCap	Bonus
MinInvest	0.122***							
NumbCurr	0.046**	0.056***						
Fiat	0.024	0.074***	0.379***					
PreICO	0.158***	0.102***	0.050**	0.050**				
HardCap	0.246***	0.210***	0.071***	0.075***	0.129***			
SoftCap	0.195***	0.217***	0.076***	0.067***	0.120***	0.475***		
Bonus	0.194***	0.157***	0.115***	0.033	0.277***	0.171***	0.187***	

Figure 5.4: Correlation martrix

This correlation matrix includes all the variables that we will later insert in our different regression models. Each coefficient estimates the existing correlation by taking into account only the two variables concerned. This means that all other variables that could potentially influence this relationship are not taken into account in each coefficient. The correlation between "lack" and "logAmountRaised" is 0.158. This means that there is a positive relationship between the number of images and the amount collected. This correlation is significant at the 1% level. Indeed, we added three stars to the correlations significant at the 1% threshold, two stars for the correlations significant at the 5% threshold and only one star for those significant at the 10% threshold. This significance level means that there is a 1%, 5% or 10% chance that this coefficient is due to chance. We also notice a positive correlation between the number of graphs and the logarithm of the amount collected. We therefore note that most of our coefficients are significant at one of the three different thresholds.

A correlation matrix is also a good way to spot problems of multi-collinearity. We notice directly that the correlation between "lack" and "lacksquare", as well as between "sum" and "sumsquare" is close to 1. This makes sense given that "sumsquare" is the square of the variable sum. However, this multicollinearity is important to take into account when interpreting the results of our future regressions. Most importantly, our control variables show no sign of multicollinearity between them.

We decided to analyze the relationships between our dependent and independent variables using several regression models. Figure 5.5 shows you these 6 regression models.

5.3 Models

Modèle 1	LogAmountRaised= $\alpha + \beta_1$ lack + β_2 control variables
Modèle 2	LogAmountRaised= α+ β_1 sum + β_2 control variables
Modèle 3	LogAmountRaised= $\alpha + \beta_1$ lack + β_2 sum + β_3 control variables
Modèle 4	LogAmountRaised= $\alpha + \beta_1$ lack + β_2 lacksquare + β_3 control variables
Modèle 5	LogAmountRaised= $\alpha + \beta_1$ sum + β_2 sumsquare + β_3 control variables
Modèle 6	LogAmountRaised= $\alpha + \beta_1$ lack + β_2 lacksquare+ β_3 sum + β_4 sumsquare + β_5 control variables

Figure 5.5: Our six models of regression

Model 1 is our first regression model. Here we will simply study the impact of "lack", i.e. the number of images on the logarithm of the final amount collected. We have obviously added the control variables in order to get the most accurate result possible. Our second regression model will study the impact of the number of graphs on the amount collected in the same way as our first model. Finally, our third regression model includes both the lack and sum variables

in the same regression model, controlling for the control variables as well. This will allow us to assess their combined effect.

Our models 4, 5 and 6 add the squared values to our previous three models. Indeed, the relationships between "sum" and "lack" and "logAmountRaised" are not linear. It could be that the effect of "lack" on "logAmountRaised" changes direction or intensity as the value of "lack" increases or decreases. The relationship between the number of images and the amount collected could possibly be in the form of a parabola, i.e. after a certain number of images, the effect would be the opposite and would decrease the amount collected. By including the squared variables, we allow the model to take into account these potential non-linear relationships and to capture more complex effects between "lack" and "logAmountRaised". The same is true for the other two models.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
R^2	0.1233	0.1207	0.1235	0.1233	0.1218	0.1242
Controle Variables						
WP_Readability	0.053824**	0.063100***	0.0538883**	0.053926697 **	0.0630197***	0.054043345**
WP_Sentiment	-10.650650	-8.796801	-10.9006276	-10.554395280	-9.0475519	-10.947695837
WP_pages	0.001532	0.002621	0.0008207	0.001512277	0.0021226	0.000348447
TopicDiversity	-0.057581	-0.138648	-0.0575055	-0.055635206	-0.1480435	-0.062205117
Fin_TaxHaven	0.231393	0.170743	0.2327564	0.230697707 *	0.1690969	0.229846739
Fin_Institution	0.132517***	0.136545***	0.1321865***	0.132712720***	0.1373783***	0.133182934***
Fin_USRestrict	-0.011217	-0.007626	-0.0112330	-0.010956257	-0.0072346	-0.009124634
Rating	0.263805***	0.326460 ***	0.2627358***	0.263122135***	0.3239248***	0.259204199***
SocialMediaCount	-0.087762**	-0.112987***	-0.0875643**	-0.087319770 **	-0.1119733***	-0.086240714**
Fin_VideoDummy	0.236199	0.170890	0.2306404	0.236151895	0.1612874	0.223879812
Fin_EthereumBlockDummy	-0.024006	-0.011427	-0.0306887	-0.023780274	-0.0198630	-0.038167434
Fin_WhitelistKYCDummy	0.157601	0.155940	0.1573064	0.158294853	0.1533049	0.157904338
Fin_Team	0.036618***	0.037551***	0.0364316***	0.036708300***	0.0376998 ***	0.036648200
Fin_TokenDistributedDummy	-0.113299	-0.119442	-0.1212590	-0.114094031	-0.1258456	-0.131784163
MinInvest	-0.214476*	-0.174912*	-0.2165407*	-0.214611630	-0.1704697	-0.213110775 **
NumbCurr	0.017687	0.022406	0.0180010	0.017777010	0.0219623	0.017754821
Fiat	0.151807	0.202081	0.1542992	0.151665390	0.2015505	0.153563079
PreICO	-0.061039	-0.135605	-0.0613068	-0.059584318*	-0.1447706	-0.066471324
HardCap	-0.097320	-0.148946	-0.0961134	-0.097061845	-0.1554183	-0.100077071
SoftCap	-0.113445	-0.132107	-0.1161735	-0.113065295	-0.1366976	-0.120247286
Bonus	-0.049253	-0.067103	-0.0516994	-0.049539033	-0.0633533	-0.048696651
Independent Variables						
sum		0.012352	0.0056431		0.0342314	0.022697827
sumsquare					-0.0008689	-0.000658963
lack	0.004584**		0.0044572**	0.003943864		0.003538786
lacksquare				0.000005157		0.000007682

Figure 5.6

We will now look at which model fits us best using the Model Selection method, i.e. by gradually eliminating the variables with too high P-values. Figure 5.6 shows the results of all our coefficients for each of our regressions. The dependent variable is "logAmountRaised" for all six regressions. The sixth model is clearly the most complicated, taking into account both variables as well as the two squared variables. However, none of our independent variables are significant. The model selection method, also known as the stepwise method, suggests removing the variable with the highest p-value, i.e. the least significant variable, until we have a model with only significant p-values (Wang et al., 2007). The variable with the highest p-

value is "lacksquare" with a p-value of 0.79504. If we remove this variable from our model, we obtain a model containing the variables "lack, sum and sumsquare". It is important to note that we decided not to take into account our control variables in our stepwise selection. That is, in our search for the least significant p-value, we based our selection only on our four independent variables. We chose not to touch our control variables and to leave them in all our regressions regardless of the significance of their coefficient.

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	13.6957112	0.6617983	20.695	< 0.0000000000000002	***
lack	0.0044910	0.0021006	2.138	0.03275	*
sum	0.0222120	0.0220964	1.005	0.31502	
sumsquare	-0.0006389	0.0007410	-0.862	0.38875	
FOG	0.0538908	0.0260337	2.070	0.03869	*
WP_Sentiment	-11.0867480	8.4700256	-1.309	0.19084	
WP_pages	0.0003876	0.0040382	0.096	0.92355	
TopicDiversity	-0.0648725	0.1522878	-0.426	0.67021	
Fin_TaxHaven	0.2309468	0.1213592	1.903	0.05731	.
Fin_Institution	0.1328682	0.0312539	4.251	0.00002315	***
Fin_USRestrict	-0.0095650	0.1177469	-0.081	0.93527	
Rating	0.2602914	0.0813910	3.198	0.00142	**
SocialMediaCount	-0.0869179	0.0363514	-2.391	0.01698	*
Fin_VideoDummy	0.2241209	0.1859649	1.205	0.22841	
Fin_EthereumBlockDummy	-0.0383049	0.1724642	-0.222	0.82428	
Fin_WhitelistKYCDummy	0.1568825	0.1324327	1.185	0.23644	
Fin_Team	0.0365096	0.0076289	4.786	0.00000195	***
Fin_TokenDistributedDummy	-0.1303616	0.3609420	-0.361	0.71804	
MinInvest	-0.2130312	0.1124130	-1.895	0.05836	.
NumbCurr	0.0176337	0.0288706	0.611	0.54148	
Fiat	0.1538047	0.1322142	1.163	0.24497	
PreICO	-0.0684173	0.1244787	-0.550	0.58269	
HardCap	-0.1003222	0.2214300	-0.453	0.65060	
SoftCap	-0.1206876	0.1567492	-0.770	0.44151	
Bonus	-0.0483892	0.1307328	-0.370	0.71135	

Figure 5.7

We now see that the variable "lack" is significant, but "sum" and "sumsquare" are still not. We can therefore continue and remove the least significant variable, which is "sumsquare". The model with only "lack" and "sum" as independent variables is our model 3 which you can find in figure 5.6. However, we see again that only "lack" is significant. This means that our model 1 where we only include "lack" is the best fitting model.

An alternative way to select the best model is to use the AIC criterion. This criterion was one of the first model selection criteria to attract the attention of leading statisticians. It is now one of the most widely used criteria in practice (J. E. Cavanaugh, 2018). This criterion expresses the degree of complexity and how well our model explains our dependent variable "logAmountRaised". Our best model will be the one with the lowest AIC criterion. That is, the one that best explains our "logAmountRaised" variable and that is not too complicated either.

Akaike information criterion

Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
4265.51	4747.149	4267.236	4267.478	4747.633	4268.475

Figure 5.8: Akaike information criterion

The lowest AIC is the one of our first model. This means that the model taking into account only the number of images is the most suitable model to describe the impact on the final amount collected. Indeed, when we take into account the "lack" variable, adding the "sum" variable does not seem relevant because its p-value is way too high. The "sum" variable does not add any value and therefore has no reason to remain in the model. We can therefore deduce that when we take the number of images as well as all the control variables into account, we cannot prove that playing on the number of graphics will make a difference to the final amount collected.

For the models that take into account the squares of our variables, we might think that there would be a maximum number of images before they start to have a negative impact on the amount collected. However, as our results are not significant in our model 4, we cannot say this.

We can now interpret the results obtained in our model 1. This regression gives us a coefficient of 0.004584 for the variable "lack". This means that if the number of images increases by 1, the "logAmountRaised" will increase by 0.004584. More clearly, if we increase the number of images by 10, the final amount collected will increase by 4.7%.

5.4 The Impact of Optimism

In order to look at the impact of optimism on the effect that visual elements have on the amount collected, we decided to cut our sample in two at the level of the median of WP_sentiment which is our variable representing optimism in our whitepapers. We therefore applied our six regressions on our two databases, namely the one containing all the whitepapers with an optimism score lower than the median and the one with the whitepapers with a score higher than the median. We thus end up with two databases of about 750 ICOs each. The size of our databases is therefore quite reasonable.

Figure 5.9 and 5.10 represent, as explained above, our sample cut in half at the median of WP_Sentiment. We ran our six regressions in each of our new samples. We will continue to focus on model 1, as we did in our previous analysis, using the stepwise model selection method. In our analysis, we first examine the coefficients of our variable WP_Sentiment and find, in line with the literature, a negative correlation between optimism and the amount collected. As mentioned earlier, optimism may give the impression that the whitepaper is unreliable. However, it should be noted that this analysis should be interpreted with caution, as the coefficients do not

	Model 1 high	Model 2 high	Model 3 high	Model 4 high	Model 5 high	Model 6 high
R^2	0.1379	0.1311	0.1401	0.1379	0.1323	0.141
Controle Variables						
WP_Readability	0.093386***	0.093883***	0.091220**	0.093354606***	0.0936696 ***	0.091139950**
WP_Sentiment	-8.507406	-6.123860	-8.232876	-8.509334796	-5.5960642	-7.779218993
WP_pages	-0.000763	0.001767	-0.002772	-0.000764174	0.0009496	-0.003582095
TopicDiversity	0.284407	0.207336	0.278735	0.283440352	0.1902605	0.268575021
Fin_TaxHaven	0.265394	0.240430	0.271797	0.265419461	0.2358985	0.266764718
Fin_Institution	0.085016**	0.072969*	0.082024*	0.085064829**	0.0749953*	0.083449848*
Fin_USRestrict	-0.086901	-0.087982	-0.096688	-0.086964625	-0.0890342	-0.096753482
Rating	0.189300	0.286093	0.191679 *	0.189773962	0.2833397***	0.188582785
SocialMediaCount	-0.086547	-0.112717	-0.086745	-0.086707247 *	-0.1128700 **	-0.087192838 *
Fin_VideoDummy	0.198172	0.129294	0.168624	0.197820378	0.1193987	0.158223909
Fin_EthereumBlockDummy	-0.225586	-0.202762	-0.241515	-0.226256435	-0.2107644	-0.247872378
Fin_WhitelistKYCDummy	-0.016752	-0.029319	-0.006187	-0.016938941	-0.0257787	0.000417286
Fin_Team	0.036291***	0.032937***	0.035217***	0.036248030***	0.0332578***	0.035514895***
Fin_TokenDistributedDummy	-0.646591	-0.731453*	-0.665080	-0.646336478	-0.7276614*	-0.666465791
MinInvest	-0.079114	-0.030421	-0.084729	-0.079056968	-0.0263847	-0.081254114
NumbCurr	-0.014827	-0.012723	-0.013559	-0.014921589	-0.0131377	-0.013935822
Fiat	0.441912***	0.470076***	0.450815 **	0.441879910 **	0.4704103***	0.450800106**
PreICO	0.009131	-0.119508	-0.006845	0.009283852	-0.1242501	-0.013506916
HardCap	-0.137861	-0.103688	-0.136139	-0.137756576	-0.1232226	-0.155696880
SoftCap	0.152473	0.091734	0.150103	0.152446258	0.0908193	0.151162822
Bonus	0.025159	0.027188	0.021235	0.025213843	0.0299355	0.025892083
Independent Variables						
sum		0.022110	0.017364		0.0439532	0.035969715
sumsquare					-0.0008321	-0.000686411
lack	0.006359 **		0.006102 **	0.006646584		0.005689922
lacksquare				-0.000002456		0.000003877

Figure 5.9

	Model 1 LOW	Model 2 LOW	Model 3 LOW	Model 4 LOW	Model 5 LOW	Model 6 LOW
R^2	0.1156	0.1198	0.1144	0.1143	0.1188	0.1119
Controle Variables						
WP_Readability	0.010744	0.028265	0.009708	0.01115927	0.0280414	0.01003855
WP_Sentiment	-16.908140	-4.005230	-15.983030	-16.45988876	-4.5761790	-15.99658734
WP_pages	0.004795	0.005195	0.005933	0.00468404	0.0050259	0.00565291
TopicDiversity	-0.213144	-0.324769	-0.216930	-0.20446685	-0.3272376	-0.21055057
Fin_TaxHaven	0.228239	0.147778	0.227410	0.22342952	0.1485526	0.22232481
Fin_Institution	0.185567***	0.199215***	0.185193***	0.18728516***	0.1988833***	0.18712505***
Fin_USRestrict	0.043602	0.044938	0.040061	0.04515299	0.0455490	0.04446701
Rating	0.331580**	0.346180**	0.335031**	0.33040332**	0.3455186**	0.33231538**
SocialMediaCount	-105520*	-0.128908**	-0.106270*	-0.10367729*	-0.1273316*	-0.10215178
Fin_VideoDummy	0.249324	0.172504	0.253853	0.24568193	0.1669092	0.24724729
Fin_EthereumBlockDummy	0.210061	0.197912	0.223014	0.20402646	0.1909498	0.20767264
Fin_WhitelistKYCDummy	0.351555	0.365698_	0.356968	0.35650428	0.3594986	0.35688880
Fin_Team	0.033838**	0.038331___	0.033922**	0.03408443**	0.0383596*	0.03417877**
Fin_TokenDistributedDummy	0.681825	0.669193	0.699925	0.67448664	0.6617469***	0.67791194
MinInvest	-0.304314	-0.257123	-0.301584	-0.30459240	-0.2532736	-0.29758295
NumbCurr	0.089197	0.093436	0.089004	0.08912282	0.0933397	0.08893036
Fiat	-0.193358	-0.105203	-0.196033	-0.19756212	-0.1054419	-0.20124648
PreICO	-0.128578	-0.154290	-0.134125	-0.11658506	-0.1659823	-0.13062279
HardCap	-0.130992	-0.188176	-0.133907	-0.12901223	-0.1853704	-0.12602298
SoftCap	-0.347036	-0.341800	-0.339116	-0.34463950	-0.3458024	-0.34242463
Bonus	-0.112357	-0.105512	-0.108691	-0.11392638	-0.1033376	-0.10902803
Independent Variables						
sum		-0.003004	-0.008521		0.0128939	0.00698822
sumsquare					-0.0006576	-0.00064186
lack	0.001936		0.002170	-0.00047206		-0.00073142
lacksquare				0.00001830		0.00002255

Figure 5.10

show statistical significance.

Secondly, we find that the "lack" coefficient in model 1 is larger in our regressions that only consider WP_Sentiment variables above the median (HIGH) compared to our regressions that only consider WP_Sentiment variables below the median (LOW), with values of 0.63%** and 0.19% respectively. Furthermore, the coefficient of "lack" in the HIGH model is significant, while that of the LOW model is not. This explicitly suggests that when whitepapers have a higher average presence of optimism, readers tend to give less importance to text and more importance

to images. On the other hand, when the whitepaper does not specifically present optimism, readers are not disturbed by the text and therefore do not focus on the images, which therefore no longer have an effect on the amount raised. At least, it is not possible to prove any effect on the amount raised.

6. Conclusion

As long as the field of ICOs is not regulated, information asymmetries will always be present. The task of potential investors to distinguish promising ICOs from scams is not an easy one. ICO sellers themselves are not always able to distinguish themselves from dishonest sellers. Their only way of communicating information to potential buyers is via the ICO whitepaper. The same goes for buyers who do not use whitepapers as a source of information. We therefore tried a new approach based on simple and complex visual cues and tried to explain any link with the final amount raised from the ICO. On its own, our brief does not make much sense, but in addition to all the work already done studying the impact of visual and non-visual elements on the final amount raised or even on the probability of success of the ICO, potential buyers and sellers can have an idea of what they should be able to find in the whitepaper of a successful ICO.

We can say that there is indeed a link between the number of images in the whitepaper and the final amount raised by the ICO. As explained in the theory, visual images are easier to understand and remember than written information, which could certainly influence the buyer's decision-making. Graphics, on the other hand, are not significantly related to the amount raised. Therefore, we cannot say that they play any role in the decision-making of potential investors. Indeed, as explained in our literature review, interpreting graphs requires experience to identify the important elements. Graphs can sometimes be very or too complicated to interpret for potential buyers.

Finally, we are able to show that there is a relationship between the presence of optimism and the effect of the number of images in the whitepaper on the amount raised. Readers seem to pay more attention to images when the text has an excessive level of optimism. However, regarding our first research question, we fail to establish a significant relationship with the number of graphics, as the latter has no statistically significant effect.

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