THE POWER OF A NAME: EXPLORING THE RELATIONSHIP BETWEEN ICO NAME FLUENCY AND INVESTOR DECISION MAKING

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ABSTRACT

This study examines the impact of the fluency of Initial Coin Offering (ICO) project names on fundraising and post-ICO performance. Analyzing 8,878 ICOs from July 2012 to July 2021, we find a robust and positive correlation between name fluency (e.g., projects with succinct and English-like names) and fundraising success. Moreover, we find that this relationship is heightened for ICOs with popular names and that it influences an ICO's performance over time by increasing listing likelihood, shortening the listing time, and prolonging survival. Overall, the results of this paper align with psychological insights suggesting that fluency in stimuli enhances familiarity and memorability, which therefore, enables investors to make heuristic-based decision amidst the informationally constrained ICO landscape.

***JEL* Classification:** G15, M13, L26, D80.

Keywords: Initial coin offering; Name; Name fluency; Heuristics.

1. Introduction

Initial Coin Offerings (ICOs) have garnered significant attention from academics, investors, and regulators, with over $31 billion invested between 2016 and 2019. However, given ICOs' decentralized nature, the lack of regulation, and non-standard disclosures, investors' decision to contribute to an ICO remains a leap of faith (Werbach, 2018). We contribute to the literature by investigating whether simple heuristics based on project's name, the foremost initial point-of-reference, significantly affect the ICO fund raising and its subsequent performance.

During an ICO, a startup typically issues digital assets in the form of tokens to investors over a set period (Momtaz, 2019; Adhami et al., 2018; Fisch et al., 2021). To assess ICOs, prior research focuses on identifying complex signals in the ICO white paper, such as the use of technical topics, thematic content, white paper readability, and linguistic errors (Thewissen et al., 2022; Zhang et al., 2019; Thewissen et al., 2023). However, such signals still require a notable processing effort. Motivated by prior research in behavioral finance highlighting the importance of a stock's name on its liquidity and profitability (Chan et al., 2018; Durham and Santhanakrishnan, 2016; Alter and Oppenheimer, 2006), we argue that, in the process of screening through multiple entrepreneurial projects, investors, in fact, first rely on simple heuristics, such as the name fluency. Specifically, we examine whether the fluency of project names influences investors' decisions and affects financial outcomes in the ICO market, notable for its intense competition and scarce information.

According to prior research, in a highly uncertain environment, investors tend to simplify their investment decision by using mental shortcuts or heuristics,which aim to simplify complex tasks of assessing probabilities and predicting values through simpler judgmental operations (Tversky and Kahneman, 1974). One heuristic that can influence the decision-making process is the fluency of the name. Names are a primary cue for investors and are the first point of reference with potential investors. Prior studies in psychology show that fluency, or the ease with which information can be processed (e.g. a short and easily pronounceable name), evokes a sense of familiarity and enhances memorability (Tversky and Kahneman, 1974; Song and Schwarz, 2009) . Accordingly, studies in corporate finance show that a company's name fluency, and the consequent familiarity, sense of safety, and affinity, have supportive influences on its value, liquidity, and stock returns (e.g., Green and Jame, 2013; Alter and Oppenheimer, 2006). Furthermore, as fluent names are more recognizable, they are more memorable, making them important for investors making swift decisions amidst numerous information

(Gigerenzer and Gaissmaier, 2011; Kornell et al., 2011; Lynch et al., 1991). However, this relationship is not without contentions, as studies also suggest that name familiarity may reflect low levels of innovation, and therefore, negatively influence investors' perception (Chan et al., 2018). Given the opposing arguments, while we expect name fluency to have a significant impact on investors' decision-making, whether an ICO's name positively or negatively influences investors' decisions remains an empirical question.

ICOs provide a unique setting to examine the utility of such a heuristic. Unlike traditional public markets (e.g., IPOs), ICOs are characterized by high levels of asymmetric information and regulatory uncertainty. The fundamental information for project valuation is often restricted to the ICO whitepapers, which are unstandardized, unregulated, heterogeneous documents, known to often contain exaggerated information (Thewissen et al., 2023; Momtaz, 2021a). Furthermore, ICO projects are predominantly technology-oriented start-ups with technical details, the business and economic implications of which are obscure to most online investors (Fisch et al., 2021). Accordingly, to make investment decisions, investors are known to rely on alternative cues such as institutional strength (Shrestha et al., 2021), linguistic errors in the white paper (Thewissen et al., 2023), CEO loyalty (Momtaz, 2021b), confidence of team members perceived from pictures (Huang et al., 2021), and founder-CEO beauty (Colombo et al., 2022) to make decisions. The reliance on such non-fundamental factors to make investment decisions highlights the importance of understanding the impact of names on investors' decision-making in the ICO market.

In this study, we analyze a comprehensive sample of 8,878 ICOs that took place between July 2012 and July 2021. We focus on two fluency proxies that correlate with the ease of recognition and pronunciation. Our first measure for fluency considers the character length of the project names (*nCharacters*). We draw on the word length effect, which suggests that shorter words are better recognized and easier to pronounce, and better recalled (see e.g., Neath and Nairne, 1995; Nairne, 1990). Our second proxy is the *Englishness* defined by Travers and Olivier (1978), which assesses an expression based on the frequency with which its letter clusters appear in the English language. ICO names that are shorter in length and contain familiar English character patterns are easier to pronounce and more memorable, and thus are characterized as having greater name fluency. For example, a project name *Stellar* has a greater name fluency than the name *Crypterium.*

Our study provides strong evidence that an ICO's name fluency is positively associated with the amount of fund raising. The finding indicates that, in ICOs, investors are influenced by the project's name, as shorter and easily pronounceable names are favorable, leading to increased token purchases. Specifically, we find that a one-standard-deviation decrease (increase) in the number of characters in the ICO name (the Englishness of the ICO name) is associated with a 11.0% (8.5%) increase in the amount raised. Overall, our main results support the notion that ICOs with more fluent names can more readily attract investors.

We next turn our attention to the competitive ICO landscape, focusing specifically on how the relative popularity of an ICO's name, in comparison to its competitors, may influence the relationship between name fluency and funding decisions. As ICO names serve as the primary touch point for investors, the incorporation of market hot spots in ICO names implies a robust connection and legitimacy, a factor favorably perceived by investors (Cahill and Liu, 2021). Extensive research, such as Cahill and Liu (2021) and Thewissen et al. (2022), highlights the crowded nomenclature landscape in the ICO market. In the midst of a saturated naming environment, investors are increasingly inclined to resort to intuitive, heuristic-based methods for information processing, providing an edge to ICOs endowed with more fluent and popular names. Some ICOs exhibit popular naming trends and have highly similar names as exemplified by the cases of "bitcoinz" and "bitcoinx", "chars" and "chasyr", as well as "hyperion" and "hyperionx" (Thewissen et al., 2022). Consequently, we expect the impact of a name's fluency on a project's funding outcome to be more pronounced in situations of heightened relative name popularity. Following the methodology of Bosker (2021), we define name popularity as a string-distance-based measure (Cohen, 2011) and construct a variable for each ICO that quantifies the number of ICOs with similar names during a specified period. Our results show that during periods marked by an increase in the prevalence of similarly-named ICOs, those possessing more fluent names are more likely to achieve superior funding outcomes. This result underscores the strategic importance of individual and comparative linguistic features in navigating the challenges presented by a congested and competitive ICO landscape.

Finally, the extended performance of an ICO's name fluency hinges on its capacity to attract and retain active investors over time. We therefore examine whether the economic impact of an ICO's name is short-lived or continues to have an influence even after the ICO is completed (see, e.g., Lyandres et al., 2022; Howell et al., 2020). Building on Bettman (1979), a fluently named ICO is likely to help investors in recalling the project and fostering prolonged engagement and, as such, positively contribute to the post-ICO performance. We therefore expect a project whose name is fluent to be more memorable and to be a key factor in influencing users' retention. Consistent with our expectations, we find that an ICO's name fluency has a positive and highly significant influence on the ICO's post-performance. Specifically, we find ICOs with fluent names are more likely to be listed, take shorter time to be listed, and survive longer. This finding suggests that name fluency is not only limited to the ICO's fundraising success, but that it persistently contributes to ICO's operating performance.

This paper aims to contribute to the growing body of knowledge on the FinTech market and, particularly, the functioning of ICOs (Adhami et al., 2018; Corbet et al., 2019). Our study adds to previous research by examining the impact of a heuristic on investors' decision strategies. While prior research has highlighted various cues that influence the success of ICOs, including the attributes of ICO white papers (e.g., sentiment, readability, and thematic content), project characteristics (e.g., past venture capital funding, access to source code, and social media activity), and founder-related features (e.g., connectedness, loyalty, and attractiveness) (Zhang et al., 2019; Fisch, 2019; Samieifar and Baur, 2020; Zhang et al., 2022; Bourveau et al., 2022; Howell et al., 2020; Fisch, 2019; Lyandres et al., 2022; Amsden and Schweizer, 2018; Momtaz, 2021b; Colombo et al., 2022), our findings emphasize the importance of surface-level attributes that require little scrutiny for investor decisions. Specifically, our study suggests that a simple heuristic, such as the ICO's name fluency, plays a significant role in attracting investors during the ICO and has economic value. As such, by analyzing a comprehensive list of ICOs, we provide new evidence that complements previous research and contributes to a clearer picture of the factors that contribute to ICOs' success.

Our second contribution revolves around leveraging the distinctive context of the ICO market's intricate nomenclature landscape to highlight the correlation between a name's popularity and its ICO performance. In this context, we build upon the insights presented by Cahill and Liu (2021), who demonstrate that projects adopting monikers reminiscent of industry leaders tend to experience heightened funding success. Expanding upon their findings, our paper provides additional insights into how a name's resemblance to other concurrent ICOs influences the economic implications of its fluency. Our contribution transcends the scope of Cahill and Liu (2021) by introducing a novel measure of popularity based on the number ICOs that hold a similar name, diverging from a sole focus on copy cat projects that include, e.g., 'bit' or 'coin'. In addition, our primary focus extends beyond the direct impact of name similarity on ICO success; rather, we delve into its interaction with an ICO's name fluency. While confirming Cahill and Liu (2021)'s conclusion that a name's similarity to prior ICOs significantly increases funding success, we show that the effect of an ICO's name fluency on funding outcome is heightened when the name resonates with previously established projects. As such, our study provides comprehensive insights into the multifaceted dimensions of the naming heuristic, offering incremental evidence on its strategic significance within a congested and competitive naming environment. In summary, our research provides investors with valuable information for making informed decisions and provides strategic guidance to entrepreneurs who seek to launch successful ICOs in the fast-developing FinTech market.

Furthermore, our study provides incremental evidence that helps elucidate the influential role of names within financial markets. Whereas prior research examines the impact of a name's fluency on firm value, liquidity and returns (e.g., Green and Jame, 2013; Itzkowitz et al., 2016; Akyildirim et al., 2020), we focus on a unique market with distinct institutional background and investor resource. Diverging from traditional stock markets, ICOs operate with reduced barriers-to-entry in a less regulated environment. A significant number of ICO projects are in the early stages of business conceptualization, lacking tangible operational data and financial information for substantiation. This openness fosters increased accessibility for a diverse range of investors, including those with limited financial sophistication (Howell et al., 2020; Lyandres and Rabetti, 2023). Considering the limitations in information availability and the significant involvement of less sophisticated online investors, the direct and intuitive cues provided by a name play a considerably more significant role in shaping investors' decision-making processes. Furthermore, in this study, we show that the ICO's names play a role in fundraising, as well as in the persistent performance over an extended period after the ICO completed. Considering conflicting evidence in entrepreneurial settings (see Chan et al., 2018), where fluent names may be viewed as lacking innovativeness, our study provides evidence supporting investors' inclination toward fluent names and demonstrate the dynamic interaction between the individual characteristic of name fluency and the comparative feature of name popularity.

Together, these findings contribute to the broader literature in finance dedicated to examining the role of heuristics in investor decisions. For instance, previous studies have documented various heuristic cues, such as ICO issuing country (Shrestha et al., 2021), analyst recommendation revisions (Kliger and Kudryavtsev, 2010), and analyst consensus forecast (Hirshleifer et al., 2019). We demonstrate that in an uncertain market, the names serve as a crucial initial reference point in investors' decision-making. Furthermore, we emphasize the significance of heuristic cues in the competitive context by illustrating their interaction with relative name popularity.

2. Literature and hypothesis development

2.1. ICO market

The ICOs are a blockchain-based mode of market entrepreneurial financing, which enables startups to garner funds by selling digital assets, or tokens, to dispersed online investors (Momtaz, 2020). Startups initiate this process by publishing a detailed white paper, which outlines the ICO's objectives and technical details. Subsequently, they announce the ICO period, allowing investors to exchange funds for tokens. Following the ICO, these tokens may be listed on cryptocurrency exchanges, providing liquidity (Howell et al., 2020).

Recent research in this domain categorizes the ICO lifecycle into two main stages: the ICO phase and the post-ICO phase (Lyandres and Rabetti, 2023; Lyandres et al., 2022). The ICO phase, concluding with the fundraising's completion, involves preparations such as information disclosure (Thewissen et al., 2022; Mansouri and Momtaz, 2022), team composition analysis (Huang et al., 2021; Momtaz, 2022), and mechanism design Davydiuk et al. (2023). These elements are scrutinized for their impact on fundraising success. In contrast, the post-ICO phase focuses on the startup's subsequent evolution, including token listing (Benedetti and Nikbakht, 2021), survival performance (Cahill and Liu, 2021), and employment growth (Howell et al., 2020).

Previous studies have investigated numerous factors affecting ICO and post-ICO outcomes. These include factors, such as the content and linguistic clarity of white papers (Thewissen et al., 2022, 2023), and the team's perceived competence and appeal (Huang et al., 2021; Colombo et al., 2022), which are embedded information that require investors to make substantial processing efforts. However, in the information-constrained environment, like the ICO market, investor may often resort to heuristics—mental shortcuts and rules of thumb, simplifying complex tasks into more manageable judgments (Tversky and Kahneman, 1974; Gigerenzer and Gaissmaier, 2011).

In this study, we examine how a specific stimulus–the name of an ICO project–affects heuristics-based decision-making in the ICO market.

2.2. Name fluency as a heuristic

A project's name serves as the initial point of reference for investors, and their influence on investment decisions are known. For instance, Cooper et al. (2001) document a positive stock price reaction during the dot-com bubble period to corporate name changes adopting Internet-related names, irrespective of the company's actual involvement in internet businesses. Similarly, Akyildirim et al. (2020) discover substantial stock market premiums when companies change their names to reflect a crypto-exuberant stance. Additionally, stocks with names early in the alphabet tend to trade more due to the "alphabeticity effect" (Itzkowitz et al., 2016).

In the ICO market, the absence of standardized information and lack of regulatory oversights can have significant implications on how project names manifest and their consequent influence on investor decisions. For example, certain ICO projects adopt "newsjacking" strategies by extending the names of famous projects, such as "BitcoinZ", "Ninja Doge", and "Squid Game". Some tokens include full technical terms in their names, while others opt for short abbreviations. Furthermore, we know that "copycats", referring to ICOs incorporating "bitcoin" in their names can achieve higher valuations, yet in the long run, they encounter diminished performance due to the absence of genuine advantages (Cahill and Liu, 2021).

Accordingly, a key attribute of the project's name that can enable investors to make heuristics-based decisions is name fluency. Fluency is a processing attribute of a stimulus, which contributes to the ease of cognitive processing (Reber et al., 2004; Whittlesea et al., 1990; Jacoby et al., 1989). The concept encompasses how efficiently and smoothly the brain handles tasks like perception, attention, memory, and decision-making (Fernandez-Duque et al., 2000). Fluency functions in decision processes through two primary mechanisms: familiarity and memorability. Familiarity refers to the recognition of previously encountered stimuli, suggesting safety and affinity, while memorability deals with the ability to recall information over time. Stimuli that are easily processed gain priority in decision-making due to their enhanced recognizability and recall (Tversky and Kahneman, 1974; Green and Jame, 2013; Westerman, 2008; Song and Schwarz, 2009).

In ICOs, often involving distant project founders presenting obscure technologies, name fluency may evoke familiarity, leading to a sense of assurance. Similarly, fluent names can help initial recognition and support recall, especially when investors are rapidly screening numerous projects. Especially during boom period, when the market is inundated with thousands of projects simultaneously fundraising, these cues enable investors to sift through the crowd. Furthermore, as many ICO projects are still in the conceptual phase, actual product or even a business plan is often missing, which compounds investors' difficulty in identifying potential projects. In such a complex informational environment, investors can opt for the first "acceptable" choice rather than the optimal one. Consequently, ICO projects with names that are recognizable and memorable may benefit from a greater favorability among investors. Therefore, we hypothesize:

Hypothesis 1: The fluency of ICO project name has a positive impact on its funding outcome.

2.2.1. The context of name popularity.

Functioning as the initial point of reference in investors' screening processes, ICO names possess not only individual characteristics but also comparative features when juxtaposed with other projects. While the ICO market lacks a standardized naming convention, project names in the market exhibits certain patterns. For example, many projects mimic successful predecessors like Bitcoin, exploiting the name's popularity to enhance fundraising. Cahill and Liu (2021) document that more than half of ICOs preceding mid-2017 imitated the name "bitcoin", even when having no substantive commonalities with the trailblazer. Moreover, during Thewissen et al. (2022)'s comprehensive ICO data collection, they find considerable overlap in ICO names. Examples include the similarities between "aeron" and "aerum", "chars" and "chasyr", "chronobank" and "chronobase", along with "hyperion" and "hyperionx". The adoption of similar name strategies reflects specific trends in periods when certain names are more popular. Given the contextual name popularity in the market, we examine whether the popularity of an ICO name has an interaction effect on the impact of its fluency.

Accordingly, we hypothesize that beyond investors' preference for fluent ICO names, the positive impact of fluency is likely to be further enhanced if the name is popular in the fund raising period. Several studies have documented the substantial impact that the adoption of popular names can have on investor perception in uncertain environments, as observed during periods like the Dot-Com bubble and instances of blockchain-related company name changes (e.g., Cooper et al., 2001; Akyildirim et al., 2020). The inclusion of market hot spots in ICO names suggest a stronger connection and legitimacy, which is viewed favorably by investors (Cahill and Liu, 2021). A fluent name therefore enhances investors' appeal by establishing a clear and easily understandable first impression. When this fluency is combined with popularity, a reinforcing effect occurs, capturing broader attention and instilling confidence among investors. Essentially, the fluency and popularity of an ICO name forms a potent combination that not only distinguishes itself in a competitive market, but also leverages the psychological impact of familiarity and recognition, which, in turn, increases the probability of attracting significant funds.

Hypothesis 2: The impact of ICO name fluency on its funding outcome is amplified if there are more similar named ICOs in the market.

2.2.2. Name fluency and post-ICO performance

In addition to its impact on fundraising performance, the fluency of the project's name can have a more lasting effect, reflected on the project's post-ICO performances. A unique attribute of ICO projects is that investors often double as users for the online services offered by the projects (Momtaz, 2020). Furthermore, the value of ICO tokens and the sustainability of the ICO project is largely contingent on building and maintaining a robust user network, rather than solely on realization of financial profits (Roosenboom et al., 2020). Therefore, the long-term performance of an ICO is highly correlated with its ability to attract and retain active users and investors over an extended period.

We hypothesize that a project's name fluency plays a significant role in its post-ICO success, primarily through the lens of recognition memory. Drawing from the insights of Bettman (1979), we propose that a fluent name aids in long-term investor and user engagement. A fluent name is easier to recall, increasing the likelihood of ongoing engagements with the project. This ongoing engagement is crucial, as sustained users' and investors' persistent interest directly contributes to the project's post-ICO performance. By maintaining a memorable presence in the minds of initial investors and future token holders, fluently named projects may enjoy longer and more stable performance much after the culmination of the ICO and token issuance.

Hypothesis 3: The fluency of ICO project name has a positive impact on its long-term performance.

3. Data and method

3.1. Variable construction

3.1.1. Measure of ICO name fluency

In accordance with Green and Jame (2013), we formulate two distinct measurements of name fluency—one based on structural attributes and the other on linguistic characteristics. As we consider the names of the ICOs as they are mentioned on the source platforms, in cases of inconsistencies across platforms, we take the most popular version of the name. For instance, if only one source refers to a project as 'WAX' but three other sources record it as 'Worldwide Asset Exchange', we adopt the project name 'Worldwide Asset Exchange'. However, in cases where there are multiple modal names, we consider the shorter name or the one that comes first alphabetically. For the given example, we would choose the project name 'WAX' if an equal number of sources recorded both versions of the name. We exclude expressions such as tm, Ltd, and LLC, if they are the last expression in the company name.

The first fluency measure accounts for the structural complexity of the project names, i.e. the number of characters apart from the inter-word spacings (*nCharacters*). [1] Cognitive science research has identified a "word-length" effect, indicating that the recognition and recall of longer words take more time than their shorter counterparts (Hulme et al., 2004; Baddeley et al., 1975). As the number of characters increases, the structural complexity rises, resulting in decreased fluency of ICO names. Consistently, Green and Jame (2013) observed that investors tend to favor shorter company names, leading to better valuation outcomes.

The second measure relies on the linguistic algorithm developed by Travers and Olivier (1978) to estimate the "Englishness" of a given sequence of characters. *Englishness* is defined as a product of a series of conditional probabilities of the tri-grams in the character sequence. In accordance with Travers and Olivier (1978), we operationalize the measure through two-fold transformations. First, we replace each probability with ratios of relative frequencies of tri-grams and bi-grams. Second, we perform a natural-logarithmic transformation of the product of relative frequencies. This calculation creates fluency values that are increasing in the degree of Englishness, the calculation of which is as follows:

$$Englishness = logF(\#L_1L_2) + log[\frac{F(L_1L_2L_3)}{F(L_1L_2)}] + log[\frac{F(L_2L_3L_4)}{F(L_2L_3)}] + ... + log[\frac{F(L_{n-1}L_n\#)}{F(L_{n-1}L_n)}], \quad (1)$$

where $\#$ denotes space and L_i denotes the letter in the ith position in the $n-$letter string. We estimate the frequencies of given tri- and bi-grams relying on the data from the Corpus of Contemporary American English (COCA), which provides detailed estimates of the frequency of English words from over 500,000 texts from 1990 to 2019. Note, if the name has more than one word, we focus on the word with the lowest Englishness score because a highly non-English word could substantially reduce

[1] Note that in our regression analysis, we employ the negative form of *nCharacters*, denoted as *nCharacters* * (-1). The tranformation facilitates the interpretation of coefficients, where a shorter value corresponds to increased fluency.

the name's fluency. In instances where the name includes punctuations, we replace the punctuations with spaces, and we do not consider names with numerical characters. The name fluency measures are winsorized at one and 99 percent levels to avoid potential estimation bias caused by extreme values.

3.1.2. Measure of ICO naming popularity.

To measure the naming popularity in ICO campaigns, we establish a metric using a fuzzy string matching technique to calculate pairwise ICO name similarity. Intuitively, when there are more similarly named ICOs for a specific ICO in a given period, there is heightened popularity for such naming pattern. Specifically, we use the FuzzyWuzzy package in Python to assess the partial similarity ratio between the ICO name and those of the preceding months from the ICO issuance. The similarity ratio use the Levenshtein distance to calculate the difference between strings and output a score ranging from 0 to 100 (Cohen, 2011). The FuzzyWuzzy package has been applied in previous studies (e.g., Gaur et al., 2021; Rao et al., 2022).[2]

Given that an ICO's fundraising duration typically takes months, and online promotion commences several weeks before the ICO launch, we designate the preceding six months as the timeframe during which similarly named ICOs are likely to coexist in the market. To quantify the portion of similarly named ICOs for a specific ICO in a given period, we calculate the percentage by dividing the count of ICOs with similar names to an ICO in the preceding six months by the total number of ICOs within the same period (*NamePopularity*). The metric yields a percentage measure indicating the prevalence of similarly named ICOs in the market and is specified as follows:

$$NamePopularity_{i,t} = \frac{Number\ of\ similar\ named\ ICO_{i,t}}{Number\ of\ total\ ICO_{i,t}} * 100 \tag{2}$$

where i refers to a specific ICO project and t represents the retrospective period (in months) when other ICO projects may appear in the market simultaneously. $Number\ of\ similar\ named\ ICO_{i,t}$ represents the count of ICOs with a name similar to that of project i issued in the preceding t months from the issuance month of project i. In our analysis, two ICO names are considered "similar" if their string partial fuzzy ratio is equal to or higher than 90 and t takes the value of 6.[3]

[2]The partial ratio function in the FuzzyWuzzy package conducts substring matching by taking the shortest string and comparing it with all substrings of the same length. This mechanism enhances our ability to accurately measure the similarity between ICO names that are inherently similar but differ in length, exemplified by cases like "bitcoinz" and "bitcoin zebra." Using full string matching in such instances would result in a significantly lower similarity score.

[3]We also explore alternative parameter specifications, specifically using a preceding 3-month period and setting the threshold at

3.1.3. ICO and post-ICO performance

Leveraging the distinctive mechanism of ICOs, we follow prior research methodologies and construct variables encompassing ICO fund-raising, listing, and survival performance, which enables a comprehensive assessment of the ICO life cycle, covering both ICO and post-ICO periods (Momtaz, 2021a; Howell et al., 2020; Lyandres et al., 2022; Cahill and Liu, 2021; Shrestha et al., 2021).

We use the natural logarithm of the US dollar raised during the ICO as a measure of ICO performance (*AmountRaised*). Given that not all ICOs achieve successful fund-raising, and some may opt not to disclose the amount raised, observations with missing fund-raising data are excluded from the respective empirical models.

To evaluate post-ICO performance, we follow Amsden and Schweizer (2018) and use an indicator variable to identify successful ICOs as those that subsequently trade their tokens on a secondary exchange (*TokenTraded*) (also see Bourveau et al., 2022). We retrieve listing information from Coinmarketcap.com, which monitors tokens listed across major cryptocurrency exchanges. Once a token is listed on any of the major exchanges, Coinmarketcap proceeds to gather and compile its relevant data. Additionally, we adopt two time variables: *TimeToListing*, measuring the duration from ICO issuance to listing, and *SurvivalTime*, which tracks the time from ICO issuance to its delisting. Delisting information is available on Coinmarketcap.com, where a token is removed if all its trading pairs are no longer active on any of the major exchanges. [4]

Being listed on an exchange provides ICO tokens with substantial liquidity, playing a pivotal role for both early investors and issuers (Momtaz, 2020). Cryptocurrency exchanges typically require certain qualifications to approve a listing. The listing process typically spans several months post-ICO. The variable *TimeToListing* captures the efficiency and quality of an ICO project in meeting listing standards, serving as an indicator of post-ICO operational performance. A prompt listing after the ICO correlates with more efficient post-fundraising operations.

In such a highly volatile market, ICO survival is crucial as it reflects the viability and sustainability of the project (Lyandres et al., 2022). A longer survival time indicates that the project has overcome initial challenges and is operating over an extended period. Therefore, *SurvivalTime* serves as an indicator of the long-term sustainable performance.

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a 95 similarity score. The results are robust and are not reported in the analysis.

[4]For ICOs that have not been listed or delisted on an exchange, we calculate the duration between the ICO issuance date and the time of data collection for the survival analysis.

3.1.4. Other variables

To obtain unbiased estimates of the effect of ICO names on their success, we include a number of control variables. The list of control variables included largely varies across studies, and a consensus in this regard has yet to be found. Nonetheless, we draw inspiration from the works of Fisch (2019), Adhami et al. (2018), and Amsden and Schweizer (2018) in selecting a list of prominent ICO-level and country-level control variables.

First, we control for three country-level attributes to consider key characteristics of the ICO's country-of-origin. We include a dummy variable indicating whether the ICO originated from a country classified as a tax haven (*TaxHaven*). We also account for the institutional strength of the country (*Institutions*) as per (see, e.g., Shrestha et al., 2021). Additionally, we incorporate a variable (*Regulated*) to control for the presence of ICO-specific regulatory frameworks announced by the ICO's country-of-origin at the time of ICO issuance, aiming to address potential regulatory impacts on ICO performance (Shrestha et al., 2021; Bellavitis et al., 2022; Xia et al., 2023).

Furthermore, we control for ICO types to account for potential variations in performance caused by differing ICO issuance forms, namely Security Token Offering and Initial Exchange Offering. These types deviate from regular ICOs in terms of their structural characteristics and regulatory implications (Lambert et al., 2021). We construct a dummy variable, which takes the value of one if the ICO is a common utility token offering and zero otherwise (*ICO*).

Finally, we include a broad array of ICO-specific attributes used in prior empirical literature. These encompass a dummy variable indicating whether the project provides a white paper (*WhitePaper*), the expert rating from ICO aggregators (*Rating*), the number of social media channels used (*SocialMedia*), the average Bitcoin price during the ICO period (*PriceBit*), the number of known team members (*Team*), the number of currencies accepted (*NumbCurr*), and dummy variables indicating if the ICO restricts US-based investors from participating (*USRestrict*), whether the project is built on the Ethereum platform (*Eth*), whether the token distribution structure is specified (*TokenDist*), if a minimum investment amount is required (*MinInvest*), if fiat currencies are accepted as payment (*Fiat*), whether a pre-ICO sale is conducted (*PreICO*), whether a hard/soft cap is specified (*HardCap/SoftCap*), and if a bonus scheme was offered to investors during the ICO (*Bonus*). Variable definitions are summarized in Table 1.

[Insert Table 1 here]

3.2. Empirical methods

3.2.1. Main models

To test Hypothesis 1, we use Equation 3 to test the association between ICOs' name fluency and fund raising performance:

$$AmountRaised_i = \alpha + \beta_1 \cdot NameFluency_i + \sum_{j=1}^{J} \beta_{j+1} \cdot Controls_{j,i} + \varepsilon_i \tag{3}$$

where ε are Newey West standard errors, corrected for heteroskedasticity and autocorrelation. The equation is estimated using linear Ordinary Least Squared (OLS) model.

To test Hypothesis 2, we involve an interaction term:

$$\begin{aligned} AmountRaised_i = \alpha + \beta_1 \cdot NameFluency_i + \beta_2 \cdot NamePopularity_i + \\ \beta_3 \cdot NamePopularity_i \cdot NameFluency_i + \\ \sum_{j=1}^{J} \beta_{j+3} \cdot Controls_{j,i} + \varepsilon_i \end{aligned} \tag{4}$$

where ε are Newey West standard errors, corrected for heteroskedasticity and autocorrelation. The equation is estimated using linear Ordinary Least Squared (OLS) model.

To examine the association between ICO name fluency and Post-ICO performances, we estimate the following equation:

$$PostICOPerformance_i = \alpha + \beta_1 \cdot NameFluency_i + \sum_{j=1}^{J} \beta_{j+1} \cdot Controls_{j,i} + \varepsilon_i \tag{5}$$

where ε are Newey West standard errors, corrected for heteroskedasticity and autocorrelation. Post-ICO performance is measured through *TokenTraded*, *TimeToListing*, and *SurvivalTime*. A Logit model is employed when *TokenTraded* is the dependent variable. For *TimeToListing* and *SurvivalTime*, which involve time-related impacts, the Cox Proportional Hazard model is applied to capture the duration until listing and survival, respectively.

3.2.2. Econometrics approach

Our empirical focus centers on estimating the impact of name fluency on ICO performance. However, potential endogeneity concerns arise due to information deficiencies in the ICO market, leading to unobservable variables, such as CEO characteristics (Momtaz, 2022; Colombo et al., 2022; Xia et al., 2023), and regulatory factors (Bellavitis et al., 2022; Huang et al., 2020; Shrestha et al., 2021), which may be correlated with ICO performance. To address the omitted variable concern, we employ two approaches to tackle endogeneity: entropy balancing (EB) and restricted control function (rCF). These methods enhance the robustness of our estimations in the presence of potential confounding factors.

Entropy balancing We follow the methodology outlined by Hainmueller (2012) and employ the entropy balancing method to achieve covariate balance through the re-weighting of observations. This technique ensures covariate balance by addressing a constrained optimization problem, facilitating an exact match on the covariate distributions between the treatment and control groups (Hainmueller, 2012). The resulting balanced sample contributes to mitigating model dependence, enhancing the precision of our treatment effect estimation.

We categorize ICOs into treatment and control groups based on the 75th percentile of the sample. The treatment group includes ICOs with high name fluency, while the control group comprises ICOs with low name fluency. We achieve balance in the sample by aligning the first, second, and third order moments of the covariates between the groups. Following this, we conduct a weighted ordinary least squares regression, using the weights derived from the balancing process. This approach ensures that the estimation is conducted with due consideration to the balanced distribution of covariates, enhancing the robustness of our results.

Restricted control function (rCF) We follow Fisch and Momtaz (2020) and Mansouri and Momtaz (2022) to implement a restricted control function (rCF) approach to address unobserved endogeneity. Using generalized residuals as instrument variables for name fluency, we mitigate the potential endogeneity arising from spurious correlations (Gourieroux et al., 1987). In contrast to matching methods, rCF models account for omitted variables, and the generalized residuals from the first stage serve as a explicit test for endogeneity (Heckman and Navarro-Lozano, 2004; Thewissen et al., 2023). This approach enhances the robustness of our analysis by explicitly addressing concerns related to unobserved endogeneity.

We adopt a two-stage approach to ascertain the impact of name fluency on ICO performance (Mansouri and Momtaz, 2022). To address potential endogeneity arising from the correlation between name fluency and error terms, we model the selection of ICO companies based on their name fluency. Specifically, we employ a Probit model to estimate the likelihood that a given ICO exhibits high name fluency. The binary indicator, *hiFluency*, is defined as one when the ICO's name fluency is equal to or exceeds the 75th percentile and zero otherwise. The probability is modeled as a function of exogenous control variables that may influence the selection mechanism, denoted as Ω_i^c, in the following equation:

$$hiFluency_i = \Omega_i^c \delta + \xi_i \tag{6}$$

where $hiFluency_i$ denotes the dummies derived from our independent variables. Consistent with Gourieroux et al. (1987) and Mansouri and Momtaz (2022), we then construct the generalized residuals as the following :

$$GENRES_i = hiFluency_i \times \frac{\phi(-\Omega_i^c \delta)}{1 - \Phi(-\Omega_i^c \delta)} + (1 - hiFluency_i) \times \frac{-\phi(\Omega_i^c \delta)}{\Phi(-\Omega_i^c \delta)} \tag{7}$$

where $\phi(.)$ represents the probability density and $\Phi(.)$ is the cumulative density functions of the standard normal distribution. We then add $GENRES$ to our main models as an control for unobserved endogeneity and re-estimate these models.

3.3. Sample Description

To construct the sample, we follow the methodology adopted by Thewissen et al. (2022) and manually compile an extensive dataset of 8,878 ICOs launched between July 2012 and July 2021, relying on seven prominent ICO-listing websites, namely ICOBench.com, ICOHolder.com, ICOMarks.com, ICORatings.com, ICODrops.com, FoundICO.com and CryptoCompare.com. Benefiting from multiple sources, we capture a substantial portion of the ICO population, and also cross-verify ICO details when there are inconsistencies between sources, relying on methods outlined in Lyandres et al. (2022). The dataset is then supplemented with token-listing data from CoinMarketCap.com, the leading price-tracking platform for cryptocurrencies and ICO tokens. Observations with insufficient control variables or invalid ICO names are removed.[5]

As our analysis involves models with various dependent variables, namely *AmountRaised*, *Token-*

[5]ICO names that include multiple special symbols, numbers, emojis, or non-English characters are excluded from sample, as their presence could introduce bias to the variable construction related to name fluency measures.

Traded, *TimeToListing*, and *SurvivalTime* as measures of ICO and Post-ICO performance, the sample size changes with the available data for the respective models. Therefore, while we consider the entire sample for models with *TokenTraded* and *TimetoListing*, the *AmountRaised* (*Survival*) model is limited to the sample with 3,056 (1,787) observations.

4. Results

4.1. Descriptive statistics

Table 3 shows the descriptive statistics of our sample. An average ICO token has a likelihood of 20% of being traded in an exchange, of raising over USD$ 9.92 million. On average, an ICO requires 17 months to attain token listing and exhibits a survival duration of 3 years. Regarding the ICO's name fluency, the mean length of project names is 8.0 characters, ranging between 3 to 22 characters. The average Englishness score of the sample names is -14.2, ranging between -46.8 and 6.7, which implies substantial variability in fluency among ICO project names. To illustrate the type of names provided to ICO tokens and their associated fluency, Figure 1 provides a word cloud of ICO names in our sample, while Table 2 includes examples of ICO names based on varying levels of *Englishness* and *nCharacters*.

[Insert Table 3 here]

[Insert Figure 1 here]

[Insert Table 2 here]

Table 4 presents the correlations among our primary variables. We observe significant correlations between the name fluency measures and the amount raised during the ICO, providing initial support for our hypothesis. In line with the argument that ICOs with shorter and easier-to-pronounce names being more likely to be traded on secondary exchanges, we find that name fluency is positively correlated with the likelihood of a token being traded. Our control variables are significantly correlated with the ICO and post-ICO performance variables, which indicates that multivariate regressions are appropriate.

[Insert Table 4 here]

4.2. Multivariate analysis

4.2.1. ICO name fluency and amount raised

We employ multivariate analysis to test Hypothesis 1. Table 5 presents the OLS regression results of Equation 3. In model (1) and (4), we find significant (p-values < 0.05) and positive relationships between the project's name fluency measures and the funding outcome. In term of economic significance, a one-standard-deviation increase in *NameFluency* (corresponds to 3.77 characters decrease in *nCharacters* and 11.38 score increase in Englishness) is associated with a 11.0% and 8.5% increase in the logarithm of amount raised, respectively.

Regarding control variables, we observe that *WhitelistKYC*, *Fiat*, and *ETH* are positively and significantly correlated with the funding outcome. This is consistent with previous literature, suggesting that these funding mechanisms serve as signals of legitimacy (e.g., Momtaz, 2020; Howell et al., 2020). We also find the coefficient of *Rating* to be positive and significant, indicating that ICO rating plays an important role in signaling ICO quality (Florysiak and Schandlbauer, 2022). In line with Shrestha et al. (2021), whether the ICO is issued in a "tax haven" country and a country with strong institutional strength is positively and significantly related to ICO funding success.

Model (2) and (5) report regression results with entropy balancing observations. The coefficients of *NameFluency* remain consistent with the baseline regressions, signifying the robustness of our results to model dependence concerns. In Model (3) and (6), we introduce the generalized residuals (*GENRE*) as an explicit test for spurious correlations. The estimation results maintain similar levels of significance and magnitude to the baseline. Overall, our results show that after controlling for a number of relevant factors and addressing endogeneity concerns, the fluency of ICO names has a significantly positive effect on the amount raised in ICOs.

[Insert Table 5 here]

4.2.2. The moderating role of naming popularity

We then turn our attention to testing Hypothesis 2 and identifying the underlying mechanism by examining the empirical relationship between ICO name fluency and funding outcome in a naming popularity context. Table 6 shows the results of interaction effects of naming popularity and name fluency in the ICO market. In Model (1) and (3), the interaction terms between *NamePopularity* and *NameFluency* are positive and significant (p-values < 0.05), indicating a magnified effect when naming popularity is high is the fund raising period. A one unit increase (1%) in *NamePopularity* leads to an 6.9% and 2.1% increase in the effect of *nCharacters* and *Englishness* on *AmountRaised*, respectively. Model (2) and (4) show that the results are robust to endogeneity concerns. In our analysis, we set the threshold for potential overlapping periods and similarity at the previous six months and a 90 fuzzy ratio. Our empirical findings remain robust to alternative specifications, specifically using three months and a 95 fuzzy ratio.[6] This result supports Hypothesis 2, indicating that the positive impact of ICO name fluency is further enhanced when the ICO's name is popular during the funding period. This result further underscores the dynamic interaction mechanism between name fluency and popularity and contributes to our understanding of the interplay between individual name characteristics and comparative features among other market participants.

[Insert Table 6 here]

4.2.3. Post-ICO performance and name fluency

We further explore the enduring effects of an ICO's name by exploring its influence on the token's performance, post ICO. We adopt three post-ICO performance measures: (i) whether the ICO is subsequently listed on an exchange, (ii) the time from ICO to its listing, and (iii) the time from ICO to its delisting. These measures capture the long-term operating performance after the ICO event (Thewissen et al., 2022; Cahill and Liu, 2021; Lyandres et al., 2022).

Table 7 presents the results of the impact of an ICO's name fluency and its post-ICO performances. In Model (1) and (4), the coefficients of *NameFluency* are positive and significant at a 99% confidence interval, indicating that ICOs with a fluent name are more likely to be listed on an exchange. Specifically, an one-standard-deviation increase in *NameFluency* (corresponds to 3.77 characters decrease in *nCharacter* and 11.38 score increase in *Englishness*) is associated with a 19.2% and 13.7% increase in the logarithm of the odds ratio of being traded, respectively. Model (2) and (5) reports the Cox Propotional Hazard estimate of the effect of *NameFluency* on *TimeToListing*. The coefficients are positive and significant at a 99% confidence interval, indicating that, as *NameFluency* increases, the hazard increases, while *TimeToListing* decreases. This suggests a promoting effect of the ICO's name on the duration from ICO to listing. Specifically, an one-standard-deviation increase in *NameFluency* (corresponding to a 3.77 characters decrease in *nCharacters* and a 11.38 score increase in Englishness) is associated with a 15.1% and 8.0% increase in the expected logarithm of the hazard ratio,

[6] The results are available upon request.

respectively. Model (3) and (6) present the result of applying Cox Propotional Hazard model on the relationship between *NameFluency* and *SurvivalTime*. The coefficients are negative and significant at a 90% confidence interval, indicating that as *NameFluency* increases, the hazard of survival decreases, while the time of survival increases. This suggests a protection effect of *NameFluency* on the duration between ICO to its "death", i.e., delisting.

In summary, *ceteris paribus*, an ICO endowed with a more fluent name demonstrates a higher probability of listing, a shorter time to be listed, and a longer survival period. The results support our third hypothesis, indicating a positive association between ICO name fluency and post-ICO performance.

[Insert Table 7 here]

4.3. Robustness tests

To ensure the robustness of our main findings, we conduct two robustness tests. Similar to stocks, ICOs usually define a ticker for their token, which is an abbreviation containing several characters to facilitate trading. Head et al. (2009) find that stocks with a fluent and memorable ticker have a higher daily return than for the overall market on average as such ticker is appealing to investors. To account for the potential omitting effect of ticker fluency on ICO investor decisions, we control for *TickerFluency* by constructing two variables: *Tic.nCharacters* and *Tic.Englishness* with the same method introduced in Section 2. Furthermore, in the cryptocurrency market, Cahill and Liu (2021) show that copycats, which are defined as cryptocurrencies with a name that includes the words associated with Bitcoin or Ethereum, earn higher returns because investors interpret the name as a signal of quality. We, therefore, construct a dummy *CopyCat*, which equals one if the name of the ICO project contains at least one of the following keywords: Bitcoin, BTC, Ethereum, and ETH.

Model (1) and (3) of Table 9 reports the results of regressing ICO success measures on ICO name with the two additional control variables, *TickerFluency*, and *CopyCat*. We find that the coefficient of *NameFluency* remains similar to our main results. The ticker's fluency, on the contrary, has no apparent correlation with the amount raised. Furthermore, unlike Cahill and Liu (2021), we find no significant relationship between ICOs that have similar names to Bitcoin or Ethereum and our ICO performance metrics. Note that the significance and magnitude of *NameFluency* remain quantitatively similar compared to our main results, indicating that our findings are robust to additional controls.

As a second robustness test, we account for the effects of common words used in ICO names. Many

ICO names contain words such as coin, token, and crypto which do not aid in project identification but are naming conventions. We remove such recurring words and re-calculate the *NameFluency* for the cleaned names.[7] Model(2) and (4) Table 9 provides the regression results for the ICO success measures with fluency measures of the cleaned ICO names. The results are similar to our main findings, suggesting that our findings are robust.

[Insert Table 9 here]

5. Conclusion

Building on the psychology literature that demonstrates fluent stimuli appear more familiar (Travers and Olivier, 1978; Alter and Oppenheimer, 2006) and memorable (Gigerenzer and Gaissmaier, 2011; Kornell et al., 2011; Lynch et al., 1991), we find that ICOs with more fluent names are more likely to achieve funding success, especially when the name is popular in the market. The effect of name fluency is enduring after the ICO event.

Our result complements prior literature on the signals of ICO success (e.g., Amsden and Schweizer, 2018; Fisch, 2019; Samieifar and Baur, 2020) and highlights a relatively low-cost method for improving investor recognition and increasing ICO success. The finding suggests that investors rely on heuristics such as the names of the ICOs to make their investment decisions, possibly because it allows investors to screen through numerous ICOs with little cost, before expending the effort to adequately evaluate the selected project's future cash flows or the white paper content.

Our study incrementally contributes to understanding the influence of names in financial markets, particularly in the context of innovative and information-scarce markets. While previous literature has explored various mechanisms of how names impact investor decisions, our focus on a highly competitive market with limited information highlights the crucial role of naming heuristics and introduce a new mechanism of memorability and demonstrate that the impact of name fluency is heightened in periods of increased naming popularity. Our research also contributes to the broader field of heuristic studies in finance, shedding light on the significance of ICO names as an initial reference point in investor decision-making within uncertain markets, with this effect persisting over an extended period.

[7] We remove the following words in ICO names if they appear at the end and are included as separate words: coin, token, crypto, chain, cash, network, net, money, .io, currency, fund, protocol, foundation, platform, exchange, finance, bank, dao, swap, wallet, ledger, project, enterprise, global and capital. We shortlist these words based on word frequencies in our sample of ICO names.

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Table 1.: Variable Definitions.

This table summarizes the definitions of variables. For Team and NumbCurr, missing observations are filled with one. For Institutions and Rating, missing observations are filled with the sample mean. The estimation results that exclude ICOs with incomplete control observations are robust (not reported).

Dependent variables	
AmountRaised	The natural logarithm of the amount raised during the ICO in US dollars.
TokenTraded	Indicates whether the token is eventually traded on a currency exchange (Coinmarketcap).
TimeToListing	The number of days from the ICO issuance to the listing of the issued token on an exchange platform.
SurvivalTime	The number of days from the ICO issuance to the delisting from all exchanges (Coinmarketcap).
Independent variables	
nCharacters	The number of characters in the ICO project name.
Englishness	A word fluency measure based on conditional probabilities of constituting tri-grams in character sequences (Travers and Olivier, 1978) .
Other variables	
NamePopularity	The percentage of ICO names exhibiting a fuzzy partial ratio greater than 90, indicating similarity to the ICO name, in the six months leading up to the ICO issuance.
ICO	Indicates whether the project is a utility token type ICO.
PreICO	Indicates whether a pre-ICO sale is conducted.
WhitelistKYC	Indicates whether the ICO implements Whitelisting and Know Your Customer (KYC) compliances.
SocialMedia	Number of different social media channels used by the ICO project.
WhitePaper	Indicates if a white paper was issued.
USRestrict	Indicates if US-based investors are restricted from participating in 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.
HardCap	Indicates whether a hard cap is specified.
SoftCap	Indicates whether a soft cap is specified.
Bonus	Indicates if a bonus scheme was offered to investors during the ICO.
Rating	Average of the source-specific ratings in standardized values.
Eth	Indicates whether the project blockchain is built on the Ethereum platform.
Team	The number of members in the team behind the ICO.
TaxHaven	Indicates whether the country is located in a tax haven (Hines, 2010).
Institutions	Aggregated institution score based on Worldwide Governance Indicators (Kaufmann et al., 2010).
Regulated	Indicates whether the ICO is issued in a country that has established ICO-specific regulation framework.
PriceBit	The natural logarithm of the average Bitcoin price in the duration of the ICO.

Figure 1.: Word cloud of ICO names.

The figure displays a word cloud of random-selected ICO names. As names are mostly unique, the size of word is random and does not represent word frequency.

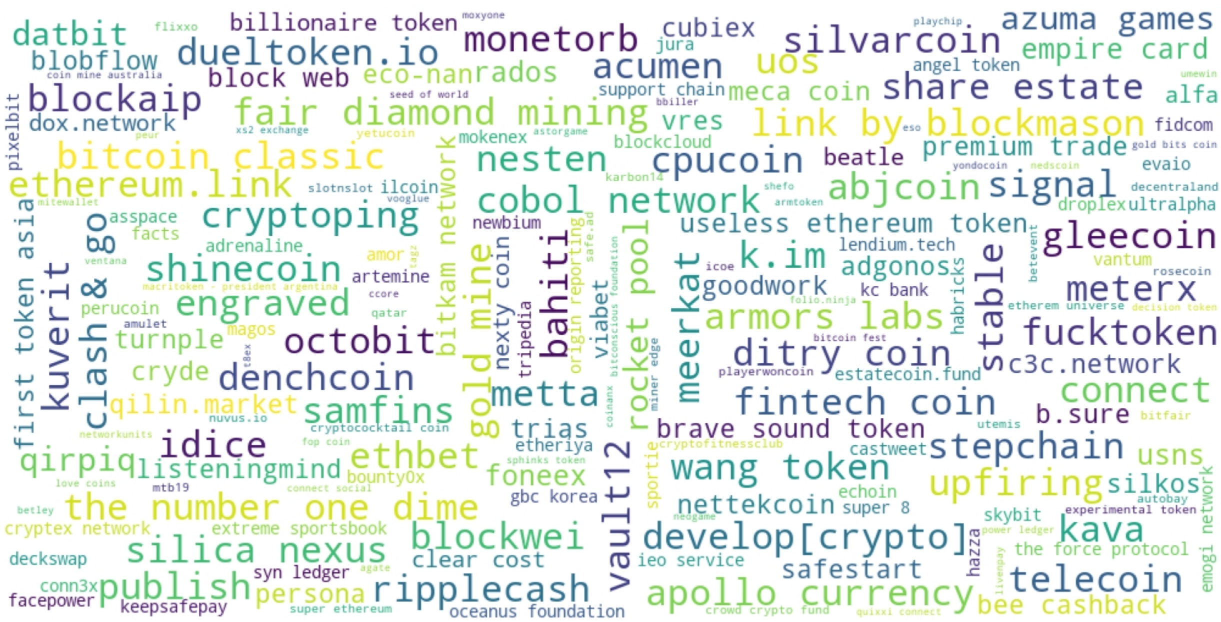

Table 2.: Examples of ICO names in cross-sectional groups of name fluency quintiles.

This table presents examples of ICO names categorized into distinct quintiles based on *Englishness* and *nCharacters*. The provided names include punctuations and numbers, which are excluded during measurement.

Group	**1 (lowest Englishness)**	**2**	**3**	**4**	**5 (highest Englishness)**
1 (lowest n-characters)	tezos jinbi helbiz	tatatu hdac tzero	gcbib qash dcoin	eos petro dragon	grid+ bancor u.cash
2	odyssey celsius jio coin	dfinity dacplay wawllet	nebulas tradove elastos	kinesis pumapay alchemy	bankera stellar current
3	flashmoni swissborg domraider	bitfinex polymath polkadot	mobilego coinpoker lead coin	file coin sirin labs baal coin	smart city ingot coin uservice
4	huobi token hybrid block crypto bank	trak invest zen protocol consentium	neuromation block stack crypterium	centrality echarge.work social good	six network orch network brain space
5 (highest n-characters)	karatgold coin crypto solartech ins ecosystem	hedera hashgraph bitbon system kyber network	worldwide asset exchange london football exchange quantum intelligence	telegram open network tron game global thunder token	one meet one love gold bits coin raiden network

Table 3.: Summary Statistics.

The table presents summary statistics for the key variables employed in the empirical analysis. Variable definitions can be found in Table 1. For *AmountRaised*, ICOs that did not disclose their raised amount are excluded, and the natural logarithm is utilized in our regression analysis. Regarding *TimeToListing*, only statistics for listed ICOs are reported in this table. In subsequent Cox Proportional-Hazard models, for ICOs lacking listing information, we populate *TimeToListing* with the number of days between ICO issuance and our data collection date.

	N	Mean	SD	Min	Median	Max
Main variables:						
AmountRaised (in million USD)	3056	9.92	17.59	0	3.29	118
TokenTraded	8878	0.20	0.40	0	0	1
TimeToListing (among listed)	1787	512.35	550.65	0	224	2942
SurvivalTime	1787	1071.2	408.65	74	1169	2923
nCharacters	8878	8.89	3.77	3	8	22
Englishness	8878	-14.22	11.38	-46.79	-12.82	6.67
Other variables:						
NamePopularity	8878	0.023	0.15	0	0	10
ICO	8878	0.93	0.25	0	1	1
PreICO	8878	0.48	0.50	0	0	1
WhitelistKYC	8878	0.46	0.50	0	0	1
SocialMedia	8878	5.18	2.44	0	5	12
WhitePaper	8878	0.75	0.43	0	1	1
USRestrict	8878	0.21	0.41	0	0	1
TokenDist	8878	0.72	0.45	0	1	1
MinInvest	8878	0.29	0.45	0	0	1
NumbCurr	8878	1.92	1.63	1	1	30
Fiat	8878	0.16	0.37	0	0	1
HardCap	8878	0.6	0.49	0	1	1
SoftCap	8878	0.55	0.50	0	1	1
Bonus	8878	0.42	0.49	0	0	1
Rating	8878	-0.11	0.80	-3.49	-0.11	2.98
Eth	8878	0.65	0.48	0	1	1
Team	8878	8.69	7.78	1	7	75
TaxHaven	8878	0.23	0.42	0	0	1
Institutions	8878	2.33	1.60	-4.8	2.33	4.57
Regulated	8878	0.33	0.47	0	0	1
PriceBit	8878	8.47	6.24	0.1	7.39	63.31

Table 4.: Pairwise Correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) AmountRaised	1.00													
(2) TokenTraded	0.201***	1.00												
(3) TimeToListing	-0.167***	-0.538***	1.00											
(4) SurvivalTime	0.142***	.	0.388***	1.00										
(5) nCharacters*(-1)	0.051***	0.088***	-0.019*	0.126***	1.00									
(6) Englishness	0.034*	0.064***	-0.022**	0.040*	0.241***	1.00								
(7) NamePopularity	-0.00	0.00	0.01	0.02	0.01	0.01	1.00							
(8) ICO	0.02	-0.106***	0.291***	0.400***	0.01	0.00	0.01	1.00						
(9) PreICO	-0.01	-0.050***	0.024**	0.039*	0.022**	0.017*	-0.022**	0.051***	1.00					
(10) WhitelistKYC	0.074***	0.134***	-0.202***	-0.232***	0.045***	0.024**	-0.026**	-0.076***	0.260***	1.00				
(11) SocialMedia	-0.01	0.121***	-0.084***	0.105***	0.059***	0.01	-0.033***	-0.00	0.330***	0.370***	1.00			
(12) WhitePaper	0.063***	0.098***	-0.101***	-0.03	0.063***	0.020*	-0.024**	-0.01	0.191***	0.233***	0.294***	1.00		
(13) USRestrict	-0.01	0.063***	-0.081***	-0.01	0.049***	0.01	-0.021**	-0.01	0.252***	0.370***	0.369***	0.179***	1.00	
(14) TokenDist	0.01	0.108***	-0.100***	0.072***	0.055***	0.01	-0.00	-0.067***	0.332***	0.354***	0.383***	0.246***	0.283***	1.00
(15) MinInvest	-0.01	0.067***	-0.119***	-0.071***	0.01	0.01	-0.01	-0.028***	0.188***	0.282***	0.317***	0.126***	0.319***	0.302***
(16) NumbCurr	0.02	-0.00	-0.048***	-0.098***	-0.01	-0.01	-0.01	-0.088***	0.134***	0.175***	0.176***	0.110***	0.118***	0.213***
(17) Fiat	0.035*	0.01	-0.079***	-0.134***	0.00	-0.00	-0.01	-0.113***	0.133***	0.227***	0.166***	0.113***	0.124***	0.183***
(18) HardCap	0.03	0.060***	-0.092***	0.121***	0.039***	0.019*	-0.02	-0.046***	0.327***	0.356***	0.398***	0.231***	0.315***	0.522***
(19) SoftCap	-0.01	0.113***	-0.163***	-0.122***	0.024**	0.021**	-0.019*	-0.044***	0.251***	0.351***	0.357***	0.195***	0.279***	0.408***
(20) Bonus	0.01	0.040***	-0.01	0.132***	0.042***	0.01	-0.00	-0.01	0.393***	0.292***	0.379***	0.243***	0.304***	0.455***
(21) Rating	0.110***	0.237***	-0.246***	0.01	0.049***	0.040***	0.00	-0.061***	0.209***	0.345***	0.501***	0.188***	0.284***	0.201***
(22) Eth	0.02	0.122***	-0.123***	-0.110***	0.037***	0.01	-0.019*	-0.064***	0.230***	0.289***	0.318***	0.170***	0.229***	0.480***
(23) Team	0.092***	0.116***	-0.073***	0.121***	0.074***	0.044***	-0.034***	-0.018*	0.266***	0.343***	0.454***	0.222***	0.289***	0.266***
(24) TaxHaven	0.065***	0.081***	-0.077***	0.04	0.044***	0.01	-0.02	-0.036***	0.121***	0.228***	0.190***	0.114***	0.235***	0.194***
(25) Institutions	0.093***	0.053***	-0.045***	0.01	0.023**	0.038***	-0.019*	-0.031***	-0.01	0.110***	0.023**	0.01	0.072***	0.01
(26) Regulated	0.041**	0.00	-0.121***	-0.173***	0.02	-0.01	-0.02	-0.106***	0.122***	0.233***	0.179***	0.114***	0.162***	0.198***
(27) PriceBit	0.01	0.044***	-0.303***	-0.548***	-0.049***	-0.026**	-0.01	-0.137***	-0.065***	-0.074***	-0.143***	-0.037***	-0.086***	-0.040***

	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
(15) MinInvest	1.00												
(16) NumbCurr	0.154***	1.00											
(17) Fiat	0.152***	0.408***	1.00										
(18) HardCap	0.336***	0.200***	0.189***	1.00									
(19) SoftCap	0.356***	0.175***	0.163***	0.621***	1.00								
(20) Bonus	0.253***	0.197***	0.144***	0.392***	0.330***	1.00							
(21) Rating	0.231***	0.123***	0.148***	0.278***	0.273***	0.231***	1.00						
(22) Eth	0.294***	0.059***	0.119***	0.430***	0.391***	0.277***	0.141***	1.00					
(23) Team	0.207***	0.129***	0.180***	0.316***	0.256***	0.258***	0.388***	0.268***	1.00				
(24) TaxHaven	0.142***	0.059***	0.069***	0.215***	0.162***	0.121***	0.153***	0.194***	0.249***	1.00			
(25) Institutions	0.01	-0.01	0.039***	0.019*	-0.00	0.02	0.072***	0.01	0.081***	0.277***	1.00		
(26) Regulated	0.178***	0.095***	0.140***	0.220***	0.168***	0.130***	0.112***	0.209***	0.185***	0.340***	0.447***	1.00	
(27) PriceBit	-0.01	-0.01	-0.01	-0.069***	-0.01	-0.070***	-0.067***	0.029***	-0.127***	-0.053***	-0.01	0.023**	1.00

Table 5.: Fund raising and name fluency.

The table presents the results of Ordinary Least Square (OLS) regression for the impact of ICO name fluency on fund-raising performance. The variable definitions can be found in Table 1. Model (3) reports the regression results with the entropy balanced sample, while Model (4) incorporates GENRE as the generalized residual to control for endogeneity. Time fixed effect is controlled at quarter-year level. Robust standard errors are reported in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

	Panel A - NameFluency: nCharacters*(-1)			Panel B - NameFluency: Englishness		
	Baseline	EB	rCF	Baseline	EB	rCF
	(1)	(2)	(3)	(4)	(5)	(6)
	AmountRaised	AmountRaised	AmountRaised	AmountRaised	AmountRaised	AmountRaised
NameFluency	0.0292**	0.0292**	0.0320***	0.00743**	0.00763**	0.00890**
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
ICO	-0.0302	-0.0998	-0.0444	-0.0467	-0.0996	-0.0443
	(0.20)	(0.23)	(0.20)	(0.20)	(0.21)	(0.20)
PreICO	-0.119	-0.0635	-0.119	-0.126	-0.122	-0.131
	(0.10)	(0.11)	(0.10)	(0.10)	(0.11)	(0.10)
WhitelistKYC	0.728***	0.625***	0.738***	0.733***	0.735***	0.720***
	(0.10)	(0.12)	(0.10)	(0.10)	(0.11)	(0.10)
SocialMedia	-0.116***	-0.112***	-0.117***	-0.114***	-0.120***	-0.113***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
WhitePaper	0.191	0.0760	0.167	0.201	0.234*	0.195
	(0.12)	(0.14)	(0.13)	(0.12)	(0.13)	(0.12)
USRestrict	0.0978	0.0518	0.0961	0.101	0.116	0.103
	(0.09)	(0.11)	(0.09)	(0.09)	(0.09)	(0.09)
TokenDist	0.0890	-0.0225	0.0782	0.0944	0.148	0.0943
	(0.18)	(0.20)	(0.18)	(0.18)	(0.20)	(0.18)
MinInvest	-0.0731	-0.0293	-0.0646	-0.0725	-0.0730	-0.0733
	(0.09)	(0.11)	(0.09)	(0.09)	(0.10)	(0.09)
NumbCurr	0.0120	0.0251	0.0132	0.0125	0.0258	0.0140
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Fiat	0.240**	0.238*	0.250**	0.239**	0.234**	0.232**
	(0.10)	(0.12)	(0.10)	(0.10)	(0.11)	(0.10)
HardCap	0.121	0.220	0.131	0.116	0.0353	0.118
	(0.13)	(0.16)	(0.14)	(0.14)	(0.15)	(0.14)
SoftCap	0.0161	0.0178	0.00836	0.0141	0.0747	0.0117
	(0.11)	(0.14)	(0.11)	(0.11)	(0.13)	(0.11)
Bonus	-0.154	-0.126	-0.158*	-0.145	-0.206**	-0.138
	(0.09)	(0.11)	(0.09)	(0.09)	(0.10)	(0.09)
Rating	0.625***	0.638***	0.624***	0.627***	0.609***	0.624***
	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)
Eth	0.265**	0.375**	0.261**	0.266**	0.283**	0.264**
	(0.13)	(0.15)	(0.13)	(0.13)	(0.13)	(0.13)
Team	0.0349***	0.0330***	0.0340***	0.0348***	0.0317***	0.0345***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
TaxHaven	0.272***	0.281***	0.265***	0.276***	0.349***	0.273***
	(0.09)	(0.10)	(0.09)	(0.09)	(0.09)	(0.09)
Institutions	0.154***	0.191***	0.152***	0.152***	0.122***	0.148***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Regulated	0.0780	-0.0466	0.0845	0.0798	0.0618	0.0919
	(0.10)	(0.12)	(0.10)	(0.10)	(0.11)	(0.10)
PriceBit	0.0285	0.0338	0.0300	0.0304	0.0680***	0.0304
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Quarter-year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
GENRE	No	No	Yes	No	No	Yes
Observations	3056	3056	3056	3056	3056	3056
Adjusted R^2	0.161	0.151	0.161	0.160	0.163	0.160

Table 6.: The moderating role of similar ICO names.

The table presents the results of OLS regression for the interaction effect between ICO name fluency and the percentage of similarly named ICOs in the previous 6 months. Variable definitions can be found in Table 1. Time fixed effect is controlled at quarter-year level. Robust standard errors are reported in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

	Panel A - NameFluency: nCharacters*(-1)		Panel B - NameFluency: Englishness	
	(1)	(2)	(3)	(4)
	AmountRaised	AmountRaised	AmountRaised	AmountRaised
NameFluency	0.0259**	0.0286**	0.00652*	0.00811*
	(0.01)	(0.01)	(0.00)	(0.00)
NamePopularity	1.197***	1.197***	0.977***	0.984***
	(0.33)	(0.33)	(0.26)	(0.26)
NameFluency * NamePopularity	0.0689**	0.0690**	0.0213***	0.0214***
	(0.03)	(0.03)	(0.01)	(0.01)
ICO	-0.0395	-0.0533	-0.0542	-0.0517
	(0.20)	(0.20)	(0.20)	(0.20)
PreICO	-0.120	-0.120	-0.129	-0.135
	(0.10)	(0.10)	(0.10)	(0.10)
WhitelistKYC	0.735***	0.745***	0.740***	0.726***
	(0.10)	(0.10)	(0.10)	(0.10)
SocialMedia	-0.117***	-0.118***	-0.114***	-0.112***
	(0.02)	(0.02)	(0.02)	(0.02)
WhitePaper	0.197	0.174	0.207*	0.200
	(0.12)	(0.13)	(0.12)	(0.12)
USRestrict	0.101	0.0996	0.103	0.106
	(0.09)	(0.09)	(0.09)	(0.09)
TokenDist	0.0985	0.0881	0.107	0.107
	(0.18)	(0.18)	(0.18)	(0.18)
MinInvest	-0.0707	-0.0624	-0.0700	-0.0708
	(0.09)	(0.09)	(0.09)	(0.09)
NumbCurr	0.0127	0.0138	0.0130	0.0146
	(0.03)	(0.03)	(0.03)	(0.03)
Fiat	0.240**	0.250**	0.239**	0.232**
	(0.10)	(0.10)	(0.10)	(0.10)
HardCap	0.117	0.126	0.104	0.106
	(0.13)	(0.13)	(0.14)	(0.14)
SoftCap	0.0210	0.0135	0.0176	0.0150
	(0.11)	(0.11)	(0.11)	(0.11)
Bonus	-0.161*	-0.164*	-0.147	-0.140
	(0.09)	(0.09)	(0.09)	(0.09)
Rating	0.622***	0.621***	0.622***	0.620***
	(0.07)	(0.07)	(0.07)	(0.07)
Eth	0.278**	0.274**	0.273**	0.271**
	(0.13)	(0.13)	(0.13)	(0.13)
Team	0.0354***	0.0345***	0.0355***	0.0351***
	(0.00)	(0.01)	(0.00)	(0.01)
TaxHaven	0.273***	0.266***	0.276***	0.273***
	(0.09)	(0.09)	(0.09)	(0.09)
Institutions	0.156***	0.154***	0.153***	0.149***
	(0.03)	(0.03)	(0.03)	(0.03)
Regulated	0.0712	0.0775	0.0764	0.0895
	(0.10)	(0.10)	(0.10)	(0.10)
PriceBit	0.0283	0.0298	0.0301	0.0300
	(0.02)	(0.02)	(0.02)	(0.02)
Quarter-year fixed effect	Yes	Yes	Yes	Yes
GENRE	No	Yes	No	Yes
Observations	3056	3056	3056	3056
Adjusted R^2	0.163	0.163	0.162	0.162

Table 7.: Post-ICO performance and name fluency.

The table presents the results for ICO name fluency and post-ICO performance. Variable definitions are provided in Table 1. Models (1) and (4) employ Logistic regression, while Models (2), (3), (5), and (6) use the Cox Proportional Hazards model. The time origin for the latter models is defined as the quarter when the ICO is issued. Time fixed effect is controlled at quarter-year level. Robust standard errors are reported in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

	Panel A - NameFluency: nCharacters*(-1)			Panel B - NameFluency: Englishness		
	Logit	Cox.P.Hazard	Cox.P.Hazard	Logit	Cox.P.Hazard	Cox.P.Hazard
	(1)	(2)	(3)	(4)	(5)	(6)
	TokenTraded	TimeToListing	SurvivalTime	TokenTraded	TimeToListing	SurvivalTime
NameFluency	0.051***	0.040***	-0.036***	0.012***	0.007***	-0.008*
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
ICO	-0.767***	-0.851***	-1.992***	-0.767***	-0.846***	-1.981***
	(0.13)	(0.09)	(0.27)	(0.13)	(0.09)	(0.27)
PreICO	-0.460***	-0.362***	0.350***	-0.471***	-0.368***	0.368***
	(0.07)	(0.06)	(0.11)	(0.07)	(0.06)	(0.11)
WhitelistKYC	0.548***	0.329***	0.113	0.550***	0.328***	0.114
	(0.08)	(0.07)	(0.11)	(0.08)	(0.07)	(0.11)
SocialMedia	0.000	0.018	0.091***	0.002	0.019	0.089***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
WhitePaper	0.580***	0.471***	-0.088	0.591***	0.485***	-0.088
	(0.08)	(0.08)	(0.12)	(0.08)	(0.08)	(0.12)
USRestrict	0.072	0.013	0.169	0.082	0.020	0.156
	(0.08)	(0.07)	(0.13)	(0.08)	(0.07)	(0.13)
TokenDist	0.141	0.140	-0.220	0.147	0.143	-0.250*
	(0.10)	(0.10)	(0.14)	(0.10)	(0.10)	(0.14)
MinInvest	0.097	0.070	0.016	0.093	0.065	0.011
	(0.07)	(0.06)	(0.12)	(0.07)	(0.06)	(0.11)
NumbCurr	-0.057**	-0.016	0.040	-0.059***	-0.016	0.040
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Fiat	-0.199**	-0.144*	0.335**	-0.196**	-0.144*	0.344***
	(0.09)	(0.08)	(0.13)	(0.09)	(0.08)	(0.13)
HardCap	-0.320***	-0.161*	-0.233**	-0.319***	-0.162*	-0.229**
	(0.09)	(0.08)	(0.11)	(0.09)	(0.08)	(0.11)
SoftCap	0.404***	0.242***	-0.026	0.395***	0.237***	-0.020
	(0.08)	(0.07)	(0.12)	(0.08)	(0.07)	(0.12)
Bonus	-0.227***	-0.084	0.060	-0.222***	-0.076	0.064
	(0.07)	(0.06)	(0.10)	(0.07)	(0.06)	(0.11)
Rating	0.875***	0.644***	-0.225***	0.879***	0.649***	-0.243***
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)
Eth	0.316***	0.319***	0.014	0.318***	0.319***	0.014
	(0.08)	(0.08)	(0.12)	(0.08)	(0.08)	(0.13)
Team	0.016***	0.014***	-0.006	0.016***	0.014***	-0.006
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
TaxHaven	0.271***	0.173***	-0.057	0.277***	0.180***	-0.056
	(0.07)	(0.06)	(0.11)	(0.07)	(0.06)	(0.12)
Institutions	0.066***	0.037**	-0.087***	0.063***	0.035*	-0.083***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Regulated	-0.196**	-0.054	0.760***	-0.189**	-0.049	0.753***
	(0.08)	(0.07)	(0.13)	(0.08)	(0.07)	(0.13)
PriceBit	-0.006	0.038***	0.103***	-0.005	0.038***	0.103***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
Quarter-year fixed effect	Yes	No	No	Yes	No	No
Observations	8860	8577	1787	8860	8577	1787
Adj./Pseudo R^2	0.199	0.044	0.047	0.197	0.044	0.047

Table 8.: Addtional analysis: ICO scam and name fluency.

The table presents logistic regression results. Robust standard errors are reported in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

	Panel A - NameFluency: nCharacters*(-1)	Panel B - NameFluency: Englishness
	Logit	Logit
	(1)	(2)
	Scam	Scam
NameFluency	0.080***	0.005**
	(0.01)	(0.00)
ICO	0.033	0.025
	(0.20)	(0.20)
PreICO	0.332***	0.320***
	(0.06)	(0.06)
WhitelistKYC	-0.030	-0.031
	(0.07)	(0.07)
SocialMedia	0.032**	0.033**
	(0.02)	(0.02)
WhitePaper	0.215***	0.247***
	(0.07)	(0.07)
USRestrict	-0.000	0.007
	(0.07)	(0.07)
TokenDist	0.173*	0.189**
	(0.09)	(0.09)
MinInvest	-0.015	-0.022
	(0.07)	(0.07)
NumbCurr	0.016	0.013
	(0.02)	(0.02)
Fiat	0.071	0.060
	(0.08)	(0.08)
HardCap	0.212***	0.204**
	(0.08)	(0.08)
SoftCap	0.063	0.063
	(0.07)	(0.07)
Bonus	0.207***	0.206***
	(0.06)	(0.06)
Rating	-0.031	-0.028
	(0.04)	(0.04)
Eth	0.115	0.121*
	(0.07)	(0.07)
Team	0.006	0.007*
	(0.00)	(0.00)
TaxHaven	-0.094	-0.079
	(0.07)	(0.07)
Institutions	0.018	0.018
	(0.02)	(0.02)
Regulated	-0.007	-0.002
	(0.07)	(0.07)
PriceBit	-0.020	-0.019
	(0.02)	(0.02)
Quarter-year fixed effect	Yes	Yes
Observations	8850	8850
Adj./Pseudo R^2	0.139	0.128

Table 9.: Robustness checks: Ticker, CopyCats, and cleaned names.

The table presents the results of OLS regression for the robustness checks. A cleaned ICO name is formed by eliminating commonly used and non-identifiable words in ICO names, including 'coin,' 'token,' 'crypto,' 'network,' '.io,' 'currency,' 'fund,' 'protocol,' 'foundation,' 'platform,' 'exchange,' 'finance,' 'project,' 'enterprise,' 'global,' and 'capital.' The construction of the word list is based on word frequency sorts and manual inspection. Variables are defined in Table 1. Robust standard errors are reported in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

	Panel A - Name/Tic.Fluency: nCharacters*(-1)		Panel B - Name/Tic.Fluency: Englishness	
	(1)	(2)	(3)	(4)
	AmountRaised	AmountRaised	AmountRaised	AmountRaised
NameFluency	0.030**		0.007*	
	(0.01)		(0.00)	
NameFluency (Cleaned)		0.040***		0.006*
		(0.01)		(0.00)
TickerFluency	-0.027		0.003	
	(0.02)		(0.01)	
CopyCat	-0.506		-0.547	
	(0.37)		(0.38)	
ICO	-0.037	-0.032	-0.053	-0.048
	(0.20)	(0.20)	(0.20)	(0.20)
PreICO	-0.123	-0.112	-0.129	-0.127
	(0.10)	(0.10)	(0.10)	(0.10)
WhitelistKYC	0.722***	0.725***	0.727***	0.738***
	(0.10)	(0.10)	(0.10)	(0.10)
SocialMedia	-0.115***	-0.114***	-0.112***	-0.115***
	(0.02)	(0.02)	(0.02)	(0.02)
WhitePaper	0.184	0.197	0.195	0.206*
	(0.12)	(0.12)	(0.12)	(0.12)
USRestrict	0.102	0.096	0.103	0.103
	(0.09)	(0.09)	(0.09)	(0.09)
TokenDist	0.093	0.084	0.090	0.093
	(0.18)	(0.18)	(0.18)	(0.18)
MinInvest	-0.069	-0.077	-0.071	-0.073
	(0.09)	(0.09)	(0.09)	(0.09)
NumbCurr	0.011	0.012	0.011	0.012
	(0.03)	(0.03)	(0.03)	(0.03)
Fiat	0.240**	0.244**	0.237**	0.238**
	(0.10)	(0.10)	(0.10)	(0.10)
HardCap	0.131	0.122	0.122	0.119
	(0.14)	(0.13)	(0.14)	(0.14)
SoftCap	0.017	0.016	0.012	0.011
	(0.11)	(0.11)	(0.11)	(0.11)
Bonus	-0.150	-0.149	-0.144	-0.144
	(0.09)	(0.09)	(0.09)	(0.09)
Rating	0.623***	0.624***	0.622***	0.629***
	(0.07)	(0.07)	(0.07)	(0.07)
Eth	0.273**	0.262**	0.269**	0.267**
	(0.13)	(0.13)	(0.13)	(0.13)
Team	0.034***	0.035***	0.035***	0.035***
	(0.00)	(0.00)	(0.00)	(0.00)
TaxHaven	0.273***	0.271***	0.275***	0.277***
	(0.09)	(0.09)	(0.09)	(0.09)
Institutions	0.153***	0.153***	0.152***	0.152***
	(0.03)	(0.03)	(0.03)	(0.03)
Regulated	0.076	0.077	0.081	0.079
	(0.10)	(0.10)	(0.10)	(0.10)
PriceBit	0.029	0.029	0.030	0.030
	(0.02)	(0.02)	(0.02)	(0.02)
Quarter-year fixed effect	Yes	Yes	Yes	Yes
Observations	3056	3056	3056	3056
Adjusted R^2	0.161	0.161	0.162	0.162

The Power of a Name: Exploring the Relationship Between ICO Name Fluency and Investor Decision Making

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The Power of a Name: Exploring the Relationship Between ICO Name Fluency and Investor Decision Making

- We find a robust and positive correlation between ICO token name fluency and fundraising success.
- This relationship is heightened for ICOs with popular names and that it influences an ICO's performance over time by increasing listing likelihood, shortening the listing time, and prolonging survival.
- The results of this paper align with psychological insights suggesting that fluency in stimuli enhances familiarity and memorability.

Journal Pre-proof

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