This is a ``preproof'' accepted article for *Journal of Financial and Quantitative Analysis*.
This version may be subject to change during the production process.
DOI: 10.1017/S0022109024000681

https://doi.org/10.1017/S0022109024000681 Published online by Cambridge University Press

Gambling on Crypto Tokens?

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September 26, 2024

Abstract

We proxy retail investor attention through Google Trends and find that fungible and non-fungible crypto tokens generate greater attention from high–gambling propensity regions. Crypto attention is higher during bubble-like episodes in the crypto market and for more lottery-like tokens. Moreover, retail crypto attention decreases after sports gambling is legalized. Higher token attention is associated with more contributors and higher fundraising. However, consumer credit default rates spike after periods of high crypto attention, but solely in the subprime segment. Overall, our findings suggest that gambling preferences strongly predict retail investor interest in the crypto market.

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I. Introduction

The crypto market has experienced tremendous growth since Bitcoin's introduction in 2009. During this time, thousands of crypto tokens – digital assets created on a blockchain, a decentralized and distributed digital ledger – have been introduced. These tokens can represent various assets and utilities. Prominent examples like Bitcoin and Ethereum are primarily used as a medium of exchange or a store of value. However, crypto tokens can also serve other purposes, such as granting access to specific products or services on a blockchain platform or representing ownership of physical and digital items. Consumer interest has surged alongside this growth, with over 20% of U.S. adults having invested in, traded, or used a crypto token (CNBC (2022)), and an estimated 580 million crypto investors worldwide (Crypto.com (2024)).

The retail crypto investor base has grown significantly, but due to the anonymous nature of blockchain, there is little direct evidence about the characteristics of these investors. However, at the same time, this rapid increase in crypto investors has raised concerns among policymakers, especially given the extreme volatility of the crypto market.[1] Specifically, crypto tokens offer returns that are highly positively skewed, meaning there is a small chance of extremely large gains (Liu and Tsyvinski (2021), Liu, Tsyvinski and Wu (2022)). These payoffs resemble those of lottery products and are especially appealing to investors with strong gambling preferences (Kumar (2009)). Accordingly, in this paper, we explore whether gambling preferences can predict

[1]For example, the combined market capitalization of all crypto tokens hit almost $2.8 trillion in November 2021, before falling to $1.2 trillion in June 2022, and then recovering to $2.6 trillion in May 2024 (Forbes (2024)). Such large swings in crypto market valuations raise concerns that retail investors may not fully understand the complexities and risks associated with crypto tokens.

retail investor interest in the crypto market. Understanding if retail investors perceive crypto tokens as similar to lottery products could aid policymakers in determining the appropriate disclosures, standards, and regulations for crypto assets.[2]

In the absence of direct data on crypto investors, we follow Da, Engelberg and Gao (2011) and proxy for retail investor attention through Google search attention. Specifically, we study the regional variation in Google search attention towards two salient types of crypto tokens – initial coin offerings and non-fungible token collections. Initial coin offerings (ICOs) are a popular fundraising method for startups in the crypto industry, where investors receive crypto tokens that provide a stake in the product or service being developed, though not an equity stake in the company itself. Non-fungible tokens (NFTs), on the other hand, are blockchain-based assets that represent ownership of digital items, typically unique digital artworks sold as part of themed collections.[3] Unlike other crypto tokens, which often serve as a medium of exchange or store of value, ICOs and NFTs are more specialized, with ICOs focusing on project-specific investments and NFTs on digital ownership and collectibles.

Consistent with the notion that gambling preferences predict retail crypto interest, we find that crypto tokens generate significantly higher attention from regions with higher lottery sales per capita. We explore the robustness of this finding to alternative measures of regional gambling preferences. Specifically, we consider all the demographic characteristics associated with strong

[2]For instance, a recent legislative proposal, the Lummis-Gillibrand Responsible Financial Innovation Act, aims to provide a comprehensive framework for regulating crypto assets. The proposal emphasizes consumer protection, especially concerning disclosure standards for crypto assets. For more details, see Lummins and Gillibrand (2023).

[3]For example, the popular NFT collection, *Bored Ape Yacht Club*, includes 10,000 NFTs that involve the image of an ape but with slight variations in features and accessories.

gambling preferences as identified in Kumar (2009) and Kumar, Page and Spalt (2011), and find that retail crypto attention is higher in areas where such demographic characteristics dominate.

One important concern with our analysis is that crypto *attention* may not necessarily translate into crypto *investment*. We mitigate this concern by documenting that crypto-wallets (which are needed to participate in ICOs and NFTs) also experience a surge in attention around token offering dates. Moreover, we also find that higher token attention is associated with higher fundraising and more contributors. In addition, we attempt to rule out channels other than gambling propensities that could explain our findings. We find that regional variation in crypto product advertising, risk-taking preferences, or distrust in institutions do not explain our findings.

Next, we explore the various crypto token–level factors that affect the gambling-driven attention received by crypto tokens. Firstly, we find that the timing of token introduction influences retail investor attention. Specifically, we note that ICOs and NFT collections introduced during bubble-like episodes in the crypto market generate significantly higher retail attention from high–gambling propensity regions. Secondly, in the ICO market, we document that tokens with low first-day opening prices (i.e., tokens with more "lottery-like" features) generate relatively more attention from high–gambling propensity regions. Furthermore, we also note that ICOs that have characteristics similar to cryptocurrencies popularly targeted for pump-and-dump schemes generate relatively higher attention from high–gambling propensity regions.[4] Li, Shin and Wang (2021) document that pumped cryptocurrencies have weak "know-your-customer"

[4]Broadly, pump-and-dump schemes are a form of price manipulation, in which market manipulators artificially "pump" asset prices and then sell the previously cheaply purchased asset for large gains. Prices typically revert to pre-manipulation levels when the manipulators "dump" the assets. Despite the potential for large investor losses, the countervailing potential for large short-run returns can attract gambling attention.

https://doi.org/10.1017/S0022109024000681 Published online by Cambridge University Press

(KYC) protocols, and consistently, we find that ICOs that lack the KYC protocol experience higher interest from high–gambling propensity regions.

We find that gambling-driven retail crypto attention is also affected by the advent of sports gambling in the U.S. Using the staggered legalization of sports gambling across different states as a natural experiment, we find that token offerings receive relatively less attention from high–gambling propensity regions after the residents of these regions are allowed to place legal sports bets. Thus, it appears that the provision of an alternate outlet for the gambling appetite of the residents of a region detracts from the attention that crypto tokens receive from that particular region. Moreover, the analysis further suggests that crypto tokens and traditional gambling products are seen as substitutes by a significant portion of retail crypto investors.

Existing research generally indicates that retail investors are relatively unsophisticated and perform poorly in the traditional stock market (Barber and Odean (2000), Barber, Huang, Odean and Schwarz (2022)). Thus, retail investors may also face financial distress if they fare similarly poorly in the crypto market. To investigate this, we gather data from Equifax to study the relationship between retail crypto attention and subsequent consumer credit outcomes. Our results indicate that higher retail crypto attention is associated with higher subsequent consumer default rates in regions with high gambling propensities. Importantly, these increased incidences of defaults are concentrated in the more financially-constrained subprime segment of the population. Lastly, through a lead-lag analysis, we further document that higher attention precedes the uptick in default rates, and not vice versa. However, we refrain from making strong inferences from these findings. Given that we do not have access to retail crypto investor–level data, we are restricted to conducting our analysis at an aggregate level. And thus, we interpret this last set of results as being more suggestive in nature.

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Our paper contributes to several strands of the literature. First, our paper adds to the literature on the ICO market. The theoretical strand of the literature explores the potential and pitfalls of ICOs vis-à-vis traditional forms of financing in terms of their ability to improve outcomes (Li and Mann (2024), Lee and Parlour (2021), Cong, Li and Wang (2021), Cong, Li and Wang (2022)). The empirical ICO literature has primarily explored the determinants of ICO success.[5] We contribute to this literature by shedding light on the characteristics and motivations of retail crypto investors.

Our paper also contributes to the growing literature on NFTs. One strand of this literature explores the asset pricing characteristics of NFTs. Kong and Lin (2021) study the returns on CryptoPunks, one of the earliest NFT collections. Using a more comprehensive dataset of NFT transactions, Borri, Liu and Tsyvinski (2022) create indices of NFTs, and document that NFT market returns are significantly exposed to the cryptocurrency market, but that a large amount of NFT return variation is unexplained by factors from both the traditional asset and cryptocurrency markets. More generally, Oh, Rosen and Zhang (2023) find that NFTs are comparable to luxury fashion goods in the sense that social factors heavily influence consumers' value for NFTs. The authors thus posit that NFTs can be characterized as digital Veblen goods. Moreover, Oh et al. (2023) also explore the factors associated with the success of NFT collections in the primary

[5]Some factors that have been shown to impact ICO success include voluntary disclosures through white papers, GitHub repositories, and token pre-sales, the quality of such disclosures, governance mechanisms, team size and quality, credible commitments towards project completion, higher token retention, and favorable ratings by large, diverse groups of analysts. More information on the determinants of ICO success can be found in Bourveau, De George, Ellahie and Macciocchi (2022), Howell, Niessner and Yermack (2020), Davydiuk, Gupta and Rosen (2023), Hu, Parlour and Rajan (2019), Lee, Li and Shin (2022), and Lyandres, Palazzo and Rabetti (2022), among many other papers.

market. We contribute to this literature by uncovering a positive association between the retail attention generated by NFT collections and their primary market outcomes, and more generally documenting that gambling preferences predict retail investor interest in NFTs.

Our paper is also related to the literature on gambling preferences and their effects on the prices and trading volume of financial products. Using a theoretical model, Barberis and Huang (2008) document that investors' skewness preference can result in stocks with highly-skewed returns being overpriced and having negative expected long-run returns. Bali, Cakici and Whitelaw (2011) find complementary results in an empirical setting. Kumar (2009) examines the demographic characteristics of state lottery participants, and finds that the same demographics also predict participation in lottery stocks. Moreover, Kumar et al. (2011) and Chen, Kumar and Zhang (2021) document that investor participation in lottery-like stocks is impacted by cross-sectional regional variation in religious attitudes towards gambling and time-variation in gambling sentiment, respectively. Similarly, gambling sentiment has been shown to affect the IPO market (Green and Hwang (2012)) and options markets (Blau, Bowles and Whitby (2016)), and has also been documented to be a primary determinant of various market anomalies (Kumar, Motahari and Taffler (2023)). We contribute to this literature by providing evidence that suggests that gambling preferences explain retail investor interest in crypto tokens, and exploring the relationship between such preferences and crypto tokens' primary market outcomes.

Importantly, our paper also connects to the literature on retail investors. Our results suggest that investors are attracted to attention-grabbing financial assets and events, which is broadly consistent with the findings of Grinblatt and Keloharju (2001) and Barber and Odean (2008). In seminal work exploring the performance of retail investors, Barber and Odean (2000) find that individual investors have high trading levels and poor performance. However, more

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recent evidence is mixed. Using data on Robinhood investors, both Welch (2022) and Fedyk (2022) document that the average portfolio of Robinhood investors outperforms the market. In contrast, Eaton, Green, Roseman and Wu (2022) document that a sizeable fraction of Robinhood users are noise traders, while Barber et al. (2022) find that Robinhood users are more susceptible to purchase herding episodes, and thus, experience large subsequent losses. We contribute to this literature by analyzing the factors that motivate retail investors' interest in crypto tokens.

Our paper also adds to the nascent literature that explores the characteristics of crypto investors. Dhawan and Putniņš (2023) document that time-variation in gambling sentiment explains investor participation in cryptocurrency pump-and-dump schemes. Using data from a German bank, Hackethal, Hanspal, Lammer and Rink (2022) find that Bitcoin investors are more likely to trade penny stocks and lottery-like stocks than non-crypto investors. Kogan, Makarov, Niessner and Schoar (2024) use proprietary data to compare the positions taken by retail investors in traditional stocks versus crypto assets. In addition, the literature documents that factors such as wealth and risk attitudes (Aiello, Baker, Balyuk, Di Maggio, Johnson and Kotter (2023)), past return experience (Pursiainen and Toczynski (2022)), and the disbursement of COVID-19 stimulus checks (Divakaruni and Zimmerman (2024)) are predictive of future retail crypto investment. Moreover, Sun (2023) documents that NFT investors who randomly receive more valuable NFTs in the primary market are subsequently significantly more likely to participate in both the NFT and cryptocurrency markets. We contribute to this literature by providing evidence that suggests that gambling preferences strongly predict retail investor interest in the crypto market. Finally, we also explore the relationship between gambling-driven retail crypto attention and subsequent consumer credit outcomes.

https://doi.org/10.1017/S0022109024000681 Published online by Cambridge University Press

II. Data and Summary Statistics

In this section, we present our data sources and the descriptive statistics for all the variables used in our regression analysis.

A. Data Sources

1. Retail Investor Attention

In this paper, we use online attention toward a particular crypto token as a proxy for the actual investment in the token. We gather data on the online attention towards these tokens from Google Trends. Google Trends data works well for our purposes because it is a reasonable proxy for retail investor attention (Da et al. (2011)). One relative advantage of Google Trends data is that it plausibly captures what investors do in private.

The search results on Google Trends are normalized to the time and location of the query. Thus, Google Trends compares the search activity for a particular phrase on a particular date to the search activity for the same phrase in the specified geography and time range, which helps capture the *relative* popularity of the phrase. The resulting value, which is called the Google Search Volume Index (SVI), is then scaled on a range of 0–100, where 100 represents the highest relative attention received by the search phrase for the specified search parameters.

We are interested in studying the regional variation in the attention generated by crypto tokens. Google Trends can provide attention data for search terms at the disaggregated geography level in the U.S. Currently, it is possible to gather Google Trends data for all 50 states, for all 209 designated market areas (DMAs), and for select cities. Thus, we gather data at the DMA level given the higher level of granularity and completeness. As a result, for each ICO or NFT collection, we gather the regional variation in the retail attention across DMAs toward the *same* ICO or NFT collection, respectively. Moreover, the attention data is scaled on a range of 0–100, with the DMA generating the largest interest towards a particular crypto product receiving a value of 100.

2. *Initial Coin Offerings*

An initial coin offering (ICO) is a fundraising method used by startups in the blockchain or cryptocurrency space to raise capital for entrepreneurial projects. In an ICO, the company issues digital tokens (or coins) to investors, usually in exchange for other cryptocurrencies like Bitcoin or Ethereum. However, unlike a traditional initial public offering (IPO), these digital tokens do not represent an ownership stake in the issuing startup. Instead, these tokens represent some form of utility within the financed project's ecosystem, such as a stake in the product or service created by the company. More details are provided in the appendix.

We construct our sample of coin offerings through various publicly-available online sources. We gather data on coin offerings from two major ICO aggregator websites – ICOBench.io and ICOMarks.com. We restrict our sample to ICOs that meet their minimum funding target (i.e., their "soft cap"), thus allowing the fundraisers to launch their projects.[6] Moreover, we only consider ICOs that are accessible to U.S. investors. In total, we identify 937 completed ICOs that meet these criteria between January 2016 and December 2018.

The two aggregator websites provide data on the funds raised by each ICO as well as the

[6]In contrast, if ICOs fail to meet their minimum funding target, all raised funds are generally returned to investors. For ICOs that do not report their soft cap, we only include those that are listed and traded on cryptocurrency exchange platforms after the ICO process.

ICO whitepapers. ICO whitepapers provide important ICO information, such as the size of the development teams behind a given ICO and the length of the ICO. Moreover, about 24% of ICO white papers list their ICO wallet address. Following Lyandres et al. (2022) and Fahlenbrach and Frattaroli (2021), we look up each of these ICO wallet addresses on Etherscan.io and infer the number of unique wallet addresses that contribute toward any particular ICO wallet address as the number of contributors to that ICO.

3. *Non-Fungible Tokens*

Non-fungible tokens (NFTs) are a type of digital asset that represent ownership or proof of authenticity of a unique item or piece of content, typically stored on a blockchain. NFTs typically represent digital artwork. They are often bought and sold in online marketplaces using cryptocurrency, with ownership and transaction history recorded on a blockchain to ensure transparency. Moreover, similar to pieces of art, individual NFTs are usually packaged together as part of a larger collection, where each NFT in a collection shares a common theme. Additional details about NFT collections are provided in the appendix.

We gather data on NFT collections from OpenSea, the largest NFT trading platform. Due to data limitations in the Google Trends attention measure, we focus on the top one hundred NFT collections based on trading volume from 2017–2022.[7] For each NFT collection, we gather data on the total number of tokens available for "minting" – i.e., offered for sale in the primary market. In addition, we also identify whether each collection has a presence on Twitter or Discord.

[7]Specifically, we find that Google Trends reports a lot of values of 0 attention (i.e., no attention) toward NFT collections with low trading volumes. As a result, we cannot measure the regional variation in retail attention toward such collections.

Further, we gather data on the funds raised in the primary market and the number of primary market buyers (identified through the number of unique crypto wallets during the minting stage) from Etherscan. Finally, we also identify whether the NFT collection creator advertises the presence of rare items as part of the collection.

We restrict our sample to NFT collections with less than 10,000 tokens. Moreover, we omit NFT collections with a median mint price of 0 across all the tokens of the collection. As a result, we focus on NFT collections where investors have to actively participate to invest in the collection (as opposed to receiving a token for free). Overall, we find 46 NFT collections between 2017 and 2022 that meet these criteria.

4. *Regional Demographic Characteristics*

We gather data on demographic information from a variety of data sources. We proxy for regional gambling propensities using per-capita lottery sales. We hand-collect annual lottery sales data from the lottery administrations of various states. At present, 45 states and the District of Columbia have state-wide lotteries. The lottery sales data is available at the county level. To remain consistent with the granularity of the Google SVI data described earlier, we aggregate this data to the DMA level, and exclude DMAs with zero lottery sales. In total, we identify 197 DMAs with strictly positive lottery sales data. Finally, we scale DMA–level lottery sales by the DMAs' adult population to create a per-capita lottery sales measure. To avoid concerns of look-ahead bias, we gather all the demographic data described in this section as of 2015. Moreover, this construction method helps capture static, cross-sectional differences across DMAs in various demographic attributes.

https://doi.org/10.1017/S0022109024000681 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109024000681 Published online by Cambridge University Press

5. *Consumer Credit Characteristics*

Lastly, we also gather data on consumer defaults from Equifax. Consumers who are more than ninety days past due on any debt payment are considered to be in default. Given that we do not have direct data on crypto investors, we conduct our consumer defaults analysis by computing the consumer default rates at the DMA–year-month level.[8] Moreover, we also study how consumer default rates vary depending on ex-ante consumer credit constraints. We proxy for credit constraints through two broad consumer credit score categories – subprime (credit scores $<$ 620) and non-subprime ($\geq$ 620).

B. Descriptive Statistics

In this section, we discuss the descriptive statistics of our data. We begin by discussing DMA–level geographic characteristics, which are presented in Table 1, Panel A. We focus on the 197 DMAs with strictly positive lottery sales data. We first study the variation in the gambling propensities of the residents of the different regions in the U.S. We find that the average annual lottery sales per adult capita is $199. However, this average masks the large variation in gambling propensities across different DMAs, with annual per capita lottery sales ranging from a low of under $1 to a high of above $800.

[Table 1 here]

In Panel B, we study ICO–level characteristics. We find that, on average, project entrepreneurs retain approximately 47% of the tokens involved in an ICO. Moreover, consistent with Davydiuk et al. (2023), we also find that there is wide variation in token retention in ICOs,

[8]Equifax's credit files report consumers' 5-digit ZIP codes. We map these ZIP codes to DMAs.

ranging from a low of 0% to a high of 87%. We also find that 36% of the ICOs in our sample require their contributors to pass know-your-customer (KYC) verification before purchasing tokens. KYC standards help protect financial institutions from fraud, offer project entrepreneurs the opportunity to gather important details about investors, and help investors differentiate between legitimate and fraudulent projects. Moreover, approximately 57% of the ICOs in our sample make their code available on GitHub, which signals both transparency (Amsden and Schweizer (2019), Howell et al. (2020)) and an advanced level of progress in the development of the final product (Davydiuk et al. (2023)).

Moreover, we find that ICOs raise an average of $26.3 million in funds. The descriptive statistics also reveal that, on average, ICOs raise approximately 40% of the maximum amount of funds the development teams are willing to collect (i.e., the ICO "hard cap"). For approximately 24% of the ICO sample, we can infer the number of ICO contributors, and observe an average of 4,485 ICO contributors in this subsample.

Panel C reports the descriptive statistics for our sample of NFT collections. We find that at the time of the collection introduction, the median collection in our sample offers nearly 9,200 tokens for sale. Moreover, at the time of collection release, 93% (89%) have a presence on Twitter (Discord). Lastly, we find that approximately 85% of the collections in our sample advertise rare items as being part of the initial token supply for sale in the primary market.

There is wide variation in the funds raised by NFT collections in the primary market, with some collections raising negligible amounts and others raising approximately $58 million. Similarly, during the collection minting (i.e., primary market purchase) period, there is wide variation in the number of wallet addresses, which we refer to as minting wallets. Lastly, we note that there is wide variation in the amount of time it takes to mint at least 99% of the initial token supply – while some collections reach this milestone in a few minutes, other collections can have large portions of their initial supply of NFTs unminted.

In Figure 1, we display the distribution of lottery sales per capita (top panel) and retail attention toward ICOs and NFT collections (middle and bottom panels, respectively) across different DMAs of the U.S. The maps indicate that regions that display higher attention toward ICOs and NFTs also tend to have higher lottery sales per capita.

[Figure 1 here]

III. Regional Gambling Propensities and Retail Crypto Attention

We study how the regional variation in gambling propensities influences the attention received by crypto tokens by estimating regression specifications of the following general form:

$$SVI_{i,d} = \beta_1 LotterySalesPC_d + f(\mathbf{X}_d) + \gamma_i + \epsilon_{i,d} \quad (1)$$

where $SVI_{i,d}$ represents the attention received by ICO/NFT collection *i* in DMA *d* at the time of the offering. The coefficient of interest, β_1, identifies the impact of DMA–level gambling propensities on the attention received by crypto tokens. We proxy regional gambling propensities through per-capita lottery sales, and restrict our analysis to DMAs with strictly positive lottery sales data. $f(\mathbf{X}_d)$ represents a vector of DMA–level controls that could influence ICO or NFT collection attention. γ_i represents a vector of ICO/NFT collection fixed effects, which helps us compare the attention received by the *same* ICO/NFT collection across different regions varying in their gambling propensities. When studying the regional variation in the attention generated by

ICOs (NFT collections), we double-cluster the standard errors of this specification at the ICO and DMA (NFT collection and DMA) levels.

[Table 2 here]

The results of this analysis are presented in Table 2. Panel A reports results for ICOs. We study the total attention received by ICOs in the two-week window after the initial offering dates ($SVI_{[0,+14]}$), and only consider ICO–DMA observations with strictly positive retail attention data. We regress $SVI_{[0,+14]}$ on the standardized lottery sales per capita measure without any controls, and report our results in Column (1). The coefficient estimate is 6.9 (statistically significant at the 1% level), which suggests that ICOs receive approximately 12.8% higher attention from DMAs with one standard deviation higher gambling propensities.[9] We find that our inferences remain unchanged if include DMA–level or ICO–level controls that could potentially influence ICO attention (Columns (2)–(3)). Finally, in Column (4), we include ICO fixed effects to study the regional variation in the attention received by the *same* ICO, and document that DMAs with one standard deviation higher gambling propensities generate 11.7% higher attention toward ICOs.

In Panel B, we study the regional variation in retail attention toward NFT collections between their introduction dates and February 2023. Importantly, retail attention toward NFT collections is concentrated in fewer DMAs compared to ICOs, which generate retail attention from all over the country. In Column (1), we regress regional retail NFT collection attention on the lottery sales per capita measure and find a statistically significant positive estimate. The economic magnitude of the estimate is not meaningfully impacted by the inclusion of demographic controls

[9]The mean of $SVI_{[0,+14]}$ for ICOs is approximately 54.1. Thus, regions with one standard deviation higher gambling propensities generate $6.9/54.1 \approx 12.8\%$ higher attention toward ICOs.

(Column (2)), NFT collection controls (Column (3)), or NFT collection fixed effects (Column (4)). The mean of the NFT collection–DMA SVI is approximately 46. Thus, the estimate in Column (4) suggests that regions with one standard deviation higher gambling propensities generate approximately 20% ($\approx 9.2/46$) higher attention towards NFT collections.[10]

A. Robustness Check: Alternate Proxies for Regional Gambling Preferences

In this section, we explore the robustness of the findings presented in the previous section to alternative measures of regional gambling propensities. Kumar (2009) provides a near-comprehensive list of socioeconomic characteristics associated with strong gambling preferences. Specifically, Kumar (2009) documents that men and minorities display stronger gambling preferences relative to women and non-minorities, respectively. Furthermore, gambling preferences are also relatively stronger among low-income, unmarried, younger, and less-educated individuals, as well as in regions with higher income inequality and higher unemployment. Finally, Kumar et al. (2011) document stronger gambling preferences in areas with a higher Catholic-to-Protestant ratio. The logic underpinning the Catholic-to-Protestant ratio measure derives from several lottery and gambling studies that find that Catholics display tolerant attitudes toward gambling, while Protestants largely view gambling as a sinful activity.

We replace the lottery sales per capita measure in equation (1) with each of the above-mentioned demographic measures in separate specifications and study ICO attention in the

[10]We choose to consider a longer window for the NFT collection analysis because it can take some NFT collections a substantial amount of time to sell their entire initial set of tokens. However, our inferences remain unchanged if we instead consider the attention generated by NFT collections in the [0,+14] day window in relation to the NFT collection introduction date. We present these results in Table **??**.

two-week window immediately after the offering dates. We report the associated coefficients of interest in Table 3, Column (1). Consistent with the hypothesis of Kumar (2009), we find that ICO attention is higher in regions with a higher Catholic-Protestant ratio, higher income inequality, higher unemployment, and a higher share of minorities. In contrast, ICO attention is lower in regions with higher fractions of college-educated residents and married residents, as well as in regions with higher median incomes. We document mostly similar results for NFT collections (Table 3, Column (2)). Thus, overall, we document that our findings are robust to the use of alternative measures of regional gambling preferences.

[Table 3 here]

B. External Validation: Does Attention Equal Investment?

An implicit assumption in our empirical tests is that online token attention proxies for actual token investment. In this section, we conduct two tests to help validate this mechanism.

1. Attention to Crypto Wallets

Investors can only participate in ICOs using cryptocurrencies (such as Bitcoin, Ethereum, or Tether), and not through traditional fiat money. Thus, prospective ICO investors need to first register with a cryptocurrency exchange, and then transfer fiat money from their bank accounts to the newly-created cryptocurrency exchange account. At this juncture, investors convert their fiat money into the cryptocurrency of their choice. These crypto tokens are then sent to an online crypto-wallet offered by the exchange. However, these exchange-provided crypto-wallets restrict the free transfer of crypto tokens and can also limit investor participation in the token sales of

ICOs that are not explicitly registered with the crypto-exchange in question. Thus, investors often prefer to transfer their crypto-tokens to personal crypto-wallets that offer greater flexibility.

Importantly, given the above discussion, accessing such personal crypto-wallets can be viewed as a strong signal of investor interest in an ICO. Thus, we now study whether crypto-wallets generate relatively higher attention in regions with higher gambling propensities around ICO dates. For every ICO in our sample, we explore the regional variation in the attention received by three popular personal crypto-wallets – MetaMask, MyEtherWallet, and Coinbase Wallet – in the two-week window immediately after the ICO dates. Equivalently for NFT collections, we consider the attention generated by MetaMask and Coinbase Wallet, as well as the NFT trading platform, OpenSea. We then average this crypto-wallet attention measure across the crypto-wallets considered for the ICO and NFT collection samples. We regress this crypto-wallet attention measure on our regional lottery sales per capita measure and report our results in Table 4, Panel A. Our findings indicate that crypto-wallets receive higher attention from regions with higher gambling propensities around ICO and NFT collection introduction dates.

[Table 4 here]

2. Crypto Token Primary Market Outcomes

In this section, we compare the retail attention generated by different crypto tokens to study whether there is any association between the retail attention toward crypto tokens and their primary market fundraising outcomes. However, it is important to note that Google Trends does not report the raw search count data for any crypto tokens. Instead, Google Trends reports a "relative" measure scaled from 0 to 100 that corresponds to the parameters provided in the Google Trends query.

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As an illustrative example, consider *ICO X* and *ICO Y*, both of which are offered on the same date. *ICO X* generates a daily maximum of one million searches, while *ICO Y* generates a daily maximum of only one thousand searches. If we had access to raw search count data, *ICO X* would be correctly classified as being more popular compared to *ICO Y*. However, if we were to search for the terms "ICO X" and "ICO Y" separately on Google Trends, the days on which *ICO X* and *ICO Y* generate their maximum daily search volume would both be scaled to 100, thus rendering any comparison between the two attention data series meaningless. One approach could be to include both *ICO X* and *ICO Y* in the same search query, which would then accurately capture the former's relatively higher popularity. However, the Google Trends query "payload" only allows for searching five terms at a time. As a result, this approach does not work if there are more than five ICOs taking place during a particular time window. And lastly, there is wide variation in ICO dates, which further complicates comparisons across ICO attention data series.

Given these data limitations, we rely on an "anchor" token to facilitate comparisons between two crypto tokens. Our approach is best described in Figure 2 using an example of two ICOs. The top panel plots the weekly Google SVI from January 2016 – December 2018 for the token, Paragon Coin. The bottom panel displays the same for Merculet. Importantly, in both panels, CoinPoker serves as the anchor token. The dashed vertical lines specify the ICO dates for each token. In both panels, the Google search attention measures for both the anchor token (CoinPoker) and the tokens of interest spike during the weeks of their respective offerings. In the example in Figure 2, Paragon Coin attracts more attention during its ICO window than CoinPoker, and thus, Paragon Coin has its SVI valued at 100. On the other hand, Merculet attracts less investor attention during its ICO window than CoinPoker. Thus, in the bottom panel, CoinPoker's SVI is valued at 100.

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[Figure 2 here]

Since Google Trends calculates SVI based on raw search counts of a specific search term, the attention received by CoinPoker is the same in both the top and bottom panels. Thus, the relative Google attention calculated as $SVI_{Paragon}/SVI_{CoinPoker}$ and $SVI_{Merculet}/SVI_{CoinPoker}$ should facilitate a direct comparison between the attention received by Paragon Coin and Merculet. We average the attention received by each token in the two-week window after its offering date, and then scale it by the two-week average of the attention received by CoinPoker after its ICO date. We implement a similar approach to compare the retail attention generated by different NFT collections.

We use this measure to estimate specifications of the following general form:

$$Y_i = \beta_1 SVI_i + f(\mathbf{X}_i) + \epsilon_i \tag{2}$$

where Y_i represents the outcome for ICO or NFT i. SVI_i identifies the attention received by token i. Thus, β_1 captures the association between higher token attention and token fundraising outcomes. $f(\mathbf{X}_i)$ represents a vector of ICO– or NFT–level controls.

We report our results in Table 4, Panel B. For the ICO analysis, we identify the year-quarter of introduction and the geographic region of origination for all the ICOs in our sample. We include ICO geographic region $\times$ year-quarter fixed effects in equation (2) and double-cluster our standard errors at the ICO geographic region and year-quarter levels. In Column (1), we find that higher ICO attention is associated with higher fundraising during the ICO process. Moreover, higher ICO attention is associated with a higher amount of funds being raised as a percentage of the hard cap (Column (2)). Lastly, we find that high-attention ICOs are associated with a higher number of first-day contributors (Column (3)).

For the NFT collection analysis, we include year-quarter fixed effects in equation (2) and cluster our standard errors at the year-quarter level. We find that high-attention NFT collections raise relatively higher funds (Column (4)) and are associated with a relatively higher number of minting wallets (Column (5)). Moreover, high-attention NFT collections take considerably less time for at least 99% of their initial supply to be minted. Our estimate in Column (6) suggests that NFT collections with one standard deviation higher retail attention take approximately 71 fewer days for at least 99% of the initial collection supply to be minted. Thus, taken together, the findings in this section suggest that there is a positive association between the retail attention generated by crypto tokens and their primary market fundraising outcomes.

C. Ruling Out Alternative Channels

In this section, we examine whether characteristics other than gambling propensities could potentially explain our results.

1. Regional Distrust in Financial Institutions

Given the nature of decentralization and anonymity associated with the crypto market, one could expect crypto tokens to attract people with either an anti-establishment libertarian ideology or a general distrust of institutions. We use two measures to gauge these alternative channels. First, we use the vote share from each DMA for Libertarian party candidates in the 2016 U.S. Senate election. Second, following Hayes, Jiang and Pan (2021), we use DMA–level complaints per thousand residents to the Consumer Financial Protection Bureau (CFPB) as an alternate

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measure. We include both measures as control variables in equation (1) to test this alternative channel and report our findings in Table 5, with Panel A focusing on ICOs and Panel B focusing on NFT collections. The results reported in Columns (1) and (2) of both panels suggest that neither control significantly impacts the estimate on the baseline regional gambling propensities measure.

[Table 5 here]

2. *Regional Risk-Taking Preferences*

We also explore whether general risk-taking preferences explain our findings. We measure risk-taking using survey data from Falk, Becker, Dohmen, Enke, Huffman and Sunde (2018) and Falk, Becker, Dohmen, Huffman and Sunde (2023).[11] We find that including the regional risk-taking preference measure in equation (1) does not subsume the effect of the baseline gambling propensities measure for either ICOs or NFT collections (Column (3) for Panels A and B of Table 5).

3. *Regional Crypto Advertising*

Lastly, we examine whether regional variation in the advertising of crypto products explains our findings. We gather advertising data at the DMA level from Vivvix (formerly known

[11]The survey data in Falk et al. (2018) and Falk et al. (2023) is at the individual level from all over the world. We first restrict the sample to individuals from the U.S. Next, we average the risk-taking preference variable at the state level, which is the narrowest regional-level classification available in the data. Finally, we merge this state-level variable with our crypto token–DMA–level data. For DMAs that span across state borders, we use the average weighted by the population that the DMA has in the bordering states.

as Ad$pender). Importantly, Vivvix does not report advertising expenses for specific ICOs or NFT collections or even a broad "crypto" category. Moreover, the advertising data is only available for 2021 and 2022.

Given these data limitations, we measure the DMA–level variation in total advertising expenses (measured in dollars) in 2021 and 2022 by three major cryptocurrency exchanges: FTX Trading Ltd., Coinbase, and Binance. We assume that there are no advertising expenses in DMAs with missing data. We scale these expenses by the DMA–level population to create a per-capita measure. We conduct this analysis only on the NFT collection sample since our ICO sample period precedes the advertising data availability period. We find that controlling for this expense measure does not subsume the effect of our baseline gambling propensities measure for NFT collections (Column (4) for Panel B of Table 5).

IV. Factors Influencing Gambling-Driven Token Attention

In this section, we explore various factors that moderate the gambling-driven retail investor attention toward crypto tokens.

A. Token Characteristics

In this section, we explore token characteristics that can potentially influence retail crypto attention. Kumar (2009) identifies low prices as one of the key characteristics of lottery-style stocks. Thus, we expect that ICOs with relatively lower first-day opening prices will generate significantly more attention from regions with higher gambling propensities than ICOs with higher opening prices. To test this hypothesis, we create an indicator variable that equals 1 for

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ICOs with below-median first-day opening prices and 0 otherwise. To account for the possibility that ICO opening prices change over time, we construct this above/below-median measure at the quarterly frequency. We then modify equation (1) by including this indicator variable and its interaction with the lottery sales per capita measure, and report our findings in Panel A, Column (1) of Table 6.[12]

[Table 6 here]

We find that the coefficient on the lottery sales per capita measure is strongly significant at the 1% level, which indicates that even high-priced ICOs generate higher attention from regions with higher gambling propensities. In addition, the coefficient on the interaction term is also strongly significant. In terms of economic magnitude, this interaction term coefficient indicates that low-priced ICOs generate approximately 5% (0.3/6.1) higher attention from regions with higher gambling propensities.[13]

Next, we examine whether the characteristics that make certain cryptocurrencies susceptible to pump-and-dump (P&D) schemes also influence the attention received by ICOs. Broadly, P&D schemes are price manipulations where market manipulators artificially inflate asset prices before selling the cheaply purchased asset for large gains. In a typical P&D scheme, prices fall drastically once the market manipulators dump the assets. Such P&D schemes are pervasive in cryptocurrency markets (Li et al. (2021), Dhawan and Putniņš (2023)). Despite the potential for large investor losses, pumped cryptocurrencies experience large returns in the

[12]By definition, this analysis can only be conducted on ICOs listed on exchanges.

[13]Our specification includes ICO fixed effects. Thus, the baseline indicator variable that identifies low-price ICOs is absorbed.

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short-term horizon, which can potentially attract investors with gambling preferences. Pumped cryptocurrencies typically have weak KYC protocols (Li et al. (2021)). Consistently, we find that ICOs without KYC protocols generate significantly greater attention from high–gambling propensity regions (Column (2)).

Importantly, the ICO market experienced a boom between mid-2017 and early 2018 (e.g., see Zerocap (2024)). Between July 2017 and January 2018, the total market capitalization of the ICO market increased from roughly $11 billion to nearly $835 billion. Thus, it is highly likely that this rapid run-up in the ICO market attracted the attention of retail investors with strong gambling preferences. To test this hypothesis, we create an indicator variable that equals 1 for "boom-period" ICOs that occur between July 1, 2017 and January 31, 2018, and 0 otherwise. We then include the interaction between our lottery sales per capita measure and this boom-period ICO indicator to our baseline specification, and report our findings in Column (3). The positive and statistically significant coefficient on the interaction term suggests that gambling-driven retail crypto interest was significantly higher during the ICO boom period.

The NFT market also experienced several price run-ups in 2021 and 2022. For example, Barbon and Ranaldo (2023) document several price run-ups in the NFT market between January 2021 and August 2021, while other news sources identify another NFT bubble between December 2021 and mid-January 2022.[14] Accordingly, we create an indicator variable that equals 1 for NFT collections introduced during these price run-up events, and 0 otherwise. We find that

[14]For example, CNBC (2021) discussed a looming NFT bubble in December 2021, while CoinGecko (2023) documented that the total market capitalization of the NFT market declined significantly after mid-January 2022. While the precise factors driving these NFT bubbles are unknown, there is significant evidence of wash trading in the NFT market (Song, Liu, Shah and Chava (2023)).

high–gambling propensity regions generate 23% ($\approx 1.9/8.4$) more attention toward such boom-period NFT collections compared to non–boom-period collections (Column (4)).

B. Legalization of Sports Gambling

In this section, we conduct a natural experiment that involves analyzing the impact of the legalization of sports gambling across different states on the attention received by crypto tokens. If crypto attention is indeed driven by gambling preferences, one would expect that the provision of an alternate outlet for the gambling appetite of the residents in legalizing states would reduce the attention received by crypto tokens from such regions.

Between 2016 and 2018, nine U.S. states legalized sports gambling in a staggered fashion.[15] In most states, the law change took place immediately.[16] Given that the staggered legalization of sports gambling across states only overlaps with the time period of our ICO sample, the analysis in this section is restricted to ICOs. To study how the introduction of legalized sports gambling affects the DMA–level attention received by ICOs, we create an indicator variable, $PostSG_{d,t}$, that equals 1 for ICO–DMA observations where the ICO occurs after the legalization of sports gambling in the state containing DMA d, and 0 otherwise.[17]

[15]The complete list of states that legalized sports gambling, along with their legalization dates, is presented in Table **??**.

[16]The one exception is the state of New York, which legalized sports gambling in 2013, but only allowed for sports bets to be placed starting from March 1, 2018. Thus, we use this latter date as the relevant date on which the law change came into effect in New York.

[17]In some instances, DMAs can cover regions across state borders. In such cases, we set $PostSG_{d,t}$ to 1 if the DMA covers regions in a state that has legalized sports gambling.

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We estimate the following specification:

$$SVI_{i,d,t} = \beta_1 PostSG_{d,t} + \gamma_d + \delta_t + f(\mathbf{X}_i) + \epsilon_{i,d,t} \tag{3}$$

where $SVI_{i,d,t}$ is attention generated by ICO *i* (occurring on date *t*) in DMA *d*. $f(\mathbf{X}_i)$ represents a vector of ICO–level controls. γ_d and δ_t represent vectors of DMA and ICO date fixed effects, respectively. Thus, β_1 measures the attention generated by ICOs in DMAs after the legalization of sports gambling relative to the pre-legalization period, compared to a control group of DMAs where sports gambling is not legal. The standard errors are double-clustered at the DMA and ICO levels.

[Table 7 here]

We report the results of this specification in Table 7, Column (1). We find that the coefficient on $PostSG_{d,t}$ is negative and significant. However, it is important to note that the legalization of sports gambling is expected to have a stronger impact on high–gambling propensity DMAs. Thus, we include the interaction of $PostSG_{d,t}$ and our DMA–level lottery sales measure to equation (3), and report our findings in Column (2). We find that the coefficient on the interaction term is negative and strongly significant, which suggests that ICO attention is considerably lower in high–gambling propensity DMAs where sports gambling is legal relative to non-legalizing states. In Column (3), we include ICO–fixed effects to capture all observed and unobserved ICO characteristics, and find that our inferences remain unchanged. Overall, we conclude that the legalization of sports gambling reduces the attention received by ICOs from high–gambling propensity regions, thus suggesting that crypto tokens and traditional gambling

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products are viewed as potential substitutes for one another by the residents of high–gambling propensity regions.

V. Retail Crypto Attention and Consumer Credit Outcomes

Barber and Odean (2000) and Barber et al. (2022) find that retail investors often perform poorly in the traditional stock market. Retail investors may face financial distress if they fare similarly poorly in the crypto market. Thus, in this section, we study the association between retail crypto attention and subsequent consumer credit outcomes, and how these vary depending on ex-ante consumer credit constraints. We proxy credit constraints through consumer credit scores, and focus on two broad consumer credit score categories – subprime (credit scores < 620) and non-subprime (≥ 620). Given the relative comprehensiveness of the ICO sample compared to the NFT collection sample, we only study the relationship between retail ICO attention and subsequent consumer default rates.

Given that we do not have access to direct data on crypto investors, we conduct our analysis in an aggregated fashion to compute consumer default rates. For each DMA in any given year-month, we compute the average consumer default rates separately for the subprime and non-subprime segments of consumers. Next, we use our ICO–DMA–level attention data, and compute the average retail attention received by ICOs at the DMA–year-month level. We then

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estimate our regressions at the DMA–credit segment–year-month level:

$$
\begin{aligned}
(4) \qquad \Delta Defaults_{d,c}^{t+6,t} = {} & \beta_1 LotterySalesPC_d + \beta_2 HighSVI_{d,t} + \beta_3 Subprime_c \\
& + \beta_4 LotterySalesPC_d \times HighSVI_{d,t} \\
& + \beta_5 LotterySalesPC_d \times Subprime_c \\
& + \beta_6 HighSVI_{d,t} \times Subprime_c \\
& + \beta_7 LotterySalesPC_d \times HighSVI_{d,t} \times Subprime_c \\
& + f(\mathbf{X}_{d,c,t}) + \gamma_{d,c} + \delta_{d,t} + \epsilon_{d,c,t}
\end{aligned}
$$

where the subscripts *d*, *c*, and *t* identify DMA, credit score segment (i.e., subprime/non-subprime), and year-month, respectively. The dependent variable is the change in default rates for a given DMA–credit segment bin between the current month, *t*, and six months in the future ($t + 6$). $LotterySalesPC_d$ is defined as in equation (1). $HighSVI_{d,t}$ is an indicator variable that identifies the top tercile of the attention distribution in any given month, while $Subprime_c$ is an indicator variable that equals one for the subprime credit score segment, and zero otherwise. $f(\mathbf{X}_{d,c,t})$ represents a vector of control variables, which includes average credit scores, delinquency rates, and utilization ratios, all of which are computed at the DMA–credit segment–year-month level. In our most stringent specifications, we include $\gamma_{d,c}$ and $\delta_{d,t}$, which are vectors of fixed effects that help capture all time-invariant characteristics at the DMA–credit

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segment level and time-varying trends within DMAs, respectively.[18] We double-cluster our standard errors at the DMA and year-month levels.

[Table 8 here]

We report our results in Table 8. In Column (1), we regress the change-in-defaults measure on the lottery sales measure, the indicator variable identifying high attention, and the interaction of the two terms. The coefficient on $LotterySalesPC$ is positive, but insignificant. However, the coefficient on the interaction term is positive and strongly significant at the 1% level, suggesting that areas with both high gambling propensities and high ICO attention in a particular year-month subsequently experience significantly larger default rates. In Column (2), we include an indicator variable for the subprime consumer segment and all relevant interaction terms involving this subprime indicator variable, and find that the increase in subsequent defaults in regions with both high gambling propensities and high ICO attention is driven entirely by the subprime segment of consumers. Our inferences remain unchanged when we include DMA– and year-month fixed effects (Column (3)).

Lastly, in Column (4), we include fixed effects at the DMA–credit segment and DMA–year-month levels, and continue to find evidence suggesting that the subprime segment of consumers in regions with both high gambling propensities and high ICO attention experiences large increases in subsequent default rates. The mean default rate for the subprime segment is approximately 8.6%. Thus, in terms of economic magnitude, our estimate indicates that following

[18] It is important to note that the inclusion of $\gamma_{d,c}$ results in the coefficients associated with β_1, β_3, and β_5 being absorbed. Moreover, the inclusion of $\delta_{d,t}$ results in the further absorption of the coefficients associated with β_2 and β_4.

periods of high retail crypto attention in high–gambling propensity regions, the subprime default rate increases by approximately 2.3% ($\approx \frac{0.2}{8.6}$).

Next, we examine if there are any pre-trends in default rates. For any focal month *t*, we compute the difference in default rates between month *t* and *every* month in the range $[t-6, t+6]$, and regress it on the DMA–level lottery sales measure ($LotterySalesPC_d$), the indicator for high ICO attention ($HighSVI_{d,t}$), and the interaction of the two variables. For ease of exposition, we conduct this analysis separately for the subprime and non-subprime segments of consumers. Moreover, we include both year-month and DMA fixed effects in our specifications. The inclusion of DMA–fixed effects helps us control for time-invariant DMA–specific characteristics, but results in the absorption of the coefficient associated with $LotterySalesPC_d$. As a result, the interaction term helps capture the differential impact of higher ICO attention in high–gambling propensity regions versus low–gambling propensity regions on consumer default rates. We plot these interaction term estimates in Figure 3.

[Figure 3 here]

The interaction term estimates for the subprime segment are reported as circles, while those for the non-subprime segment are reported as triangles. The vertical bars represent the 95% confidence intervals associated with the estimates. For the subprime segment, we find that the interaction term coefficient is insignificant in the pre-period. However, we document positive and significant coefficients in the post-period. In contrast, for the non-subprime segment, the interaction term coefficient is insignificant in both the pre- and post- periods.

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VI. Conclusion

In this paper, we present evidence that suggests that gambling preferences explain retail investor interest in the crypto market. Using data from Google Trends, we show that high–gambling propensity regions exhibit higher attention toward two salient events in the crypto market – initial coin offerings (ICOs) and the introductions of non-fungible token (NFT) collections. We further validate that crypto attention is associated with actual crypto investment in two important ways. First, we find that crypto wallets (i.e., the means to invest in ICOs and NFT collections) experience higher retail attention from high–gambling propensity regions around ICO and NFT collection introduction dates. Second, we observe a strongly positive correlation between the retail attention generated by crypto tokens and their fundraising outcomes in the primary market.

We also explore the factors that moderate the gambling-driven attention generated by crypto tokens. We find that crypto tokens introduced during bubble-like episodes in the crypto market experience significantly higher retail attention from high–gambling propensity regions. In the cross-section, tokens with more lottery-like features and those more prone to episodes of price manipulations generate relatively greater attention from regions with higher gambling propensities. Moreover, by employing the staggered legalization of sports gambling across states as a natural experiment, we find that tokens generate significantly lower attention from high–gambling propensity regions after sports betting is legalized. These findings imply that the residents of high–gambling propensity regions view traditional gambling products and crypto tokens as substitutes.

Lastly, we study the relationship between retail crypto attention and subsequent consumer credit outcomes. Using unique credit bureau data from Equifax, we document that regions with high levels of retail crypto attention experience higher subsequent consumer credit default rates. Moreover, we document that this effect is driven entirely by the subprime segment of consumers. Thus, taken together, our paper sheds light on the characteristics and motivations of retail crypto investors, and provides suggestive evidence of the relationship between retail crypto attention and subsequent consumer creditworthiness.

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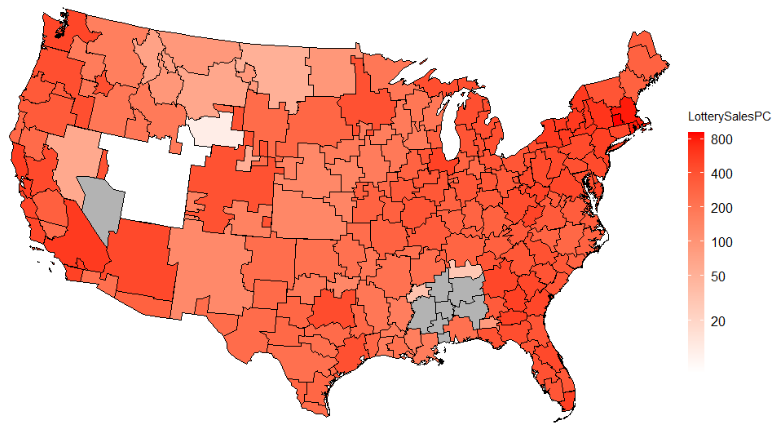
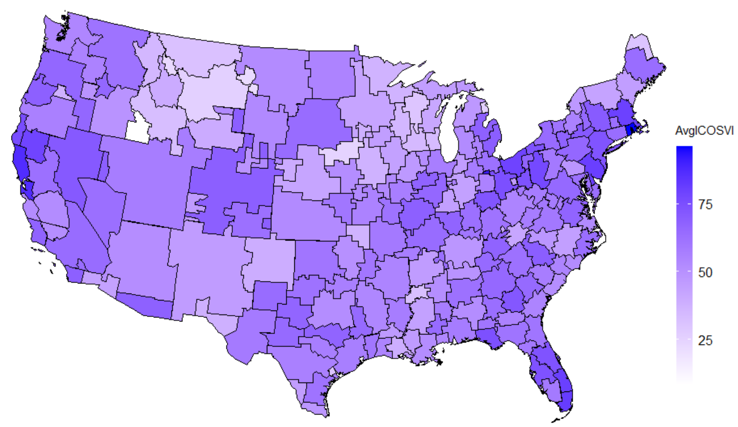
FIGURE 1

Regional Variation in Lottery Sales and Retail Crypto Attention

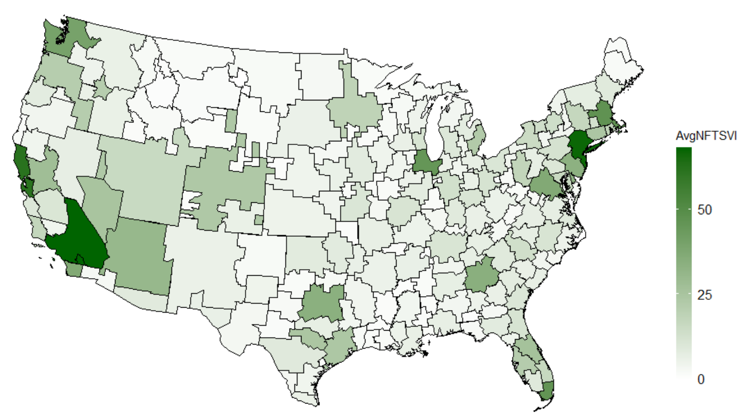
This figure displays the DMA–level distribution of gambling propensities and retail investor attention toward initial coin offerings (ICOs) and non-fungible token (NFT) collections. The top panel displays the lottery sales per capita across DMAs. The middle and bottom panels display the regional variation in retail investor attention toward ICOs and NFT collections, respectively.



Lottery Sales Per Capita across DMAs



Average ICO Attention (Google SVI) across DMAs



Average NFT Attention (Google SVI) across DMAs

https://doi.org/10.1017/S0022109024000681 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109024000681 Published online by Cambridge University Press

FIGURE 2

An Illustration of Creating the ICO–Level Attention Measure

This figure describes the creation of the ICO–level attention measure. The ICO of interest in the top (bottom) panel is Paragon Coin (Merculet). CoinPoker serves as the anchor ICO, which facilitates a comparison between the two ICOs of interest.

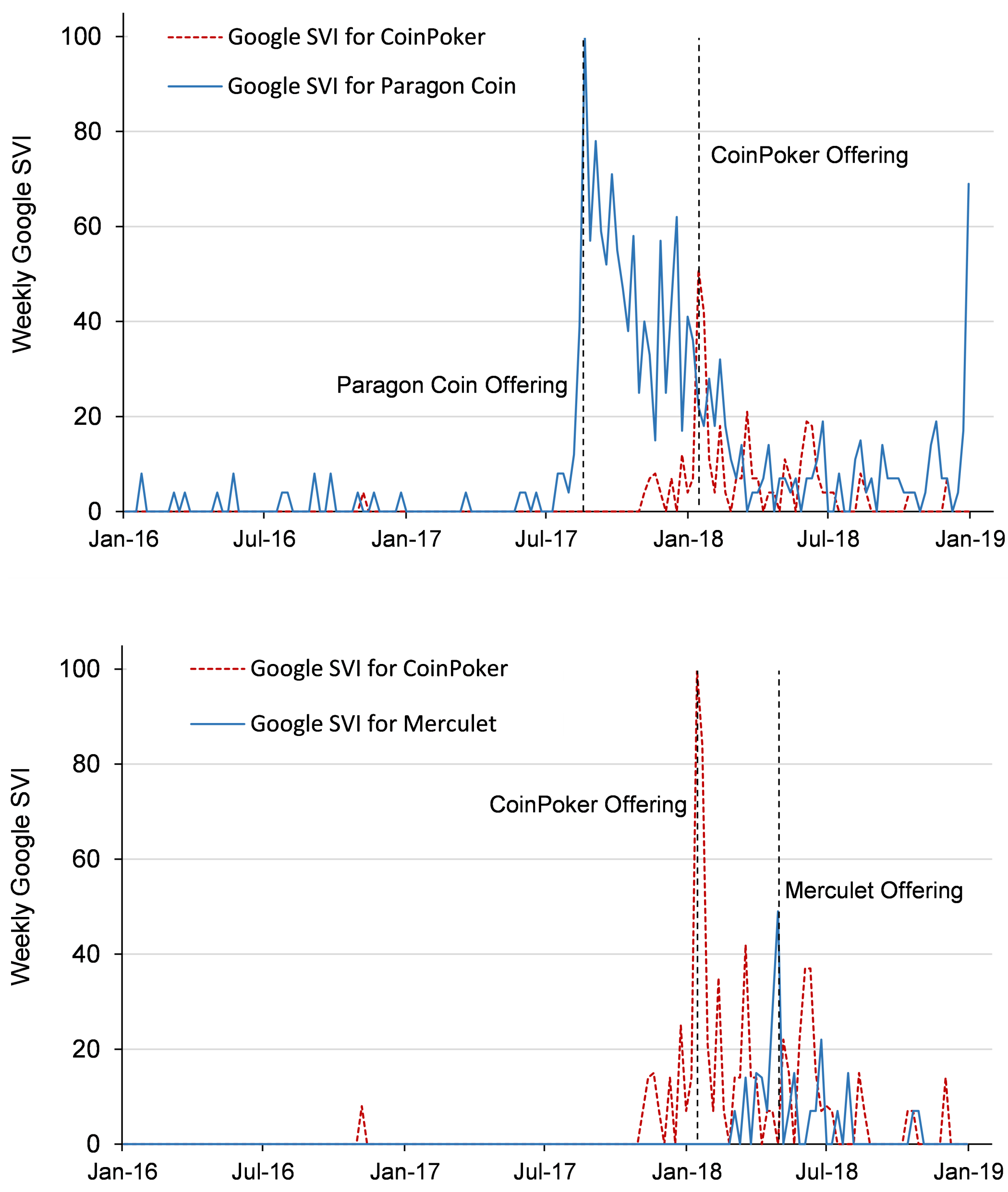


FIGURE 3

Regional Retail Crypto Attention and Consumer Credit Default Rates

This figure displays the relationship between retail investor attention toward ICOs and credit default rates. The analysis is conducted at the DMA–year-month level. The point estimates document the effect of the attention received by ICOs in any given DMA during a particular month t on the credit default rates of the same DMA for *every* month in the range $[t-6, t+6]$. The circles represent point estimates for the subprime (< 620) segment of the population, while the triangles represent point estimates for the non-subprime (≥ 620) segment of the population. The vertical lines represent 95% confidence intervals.

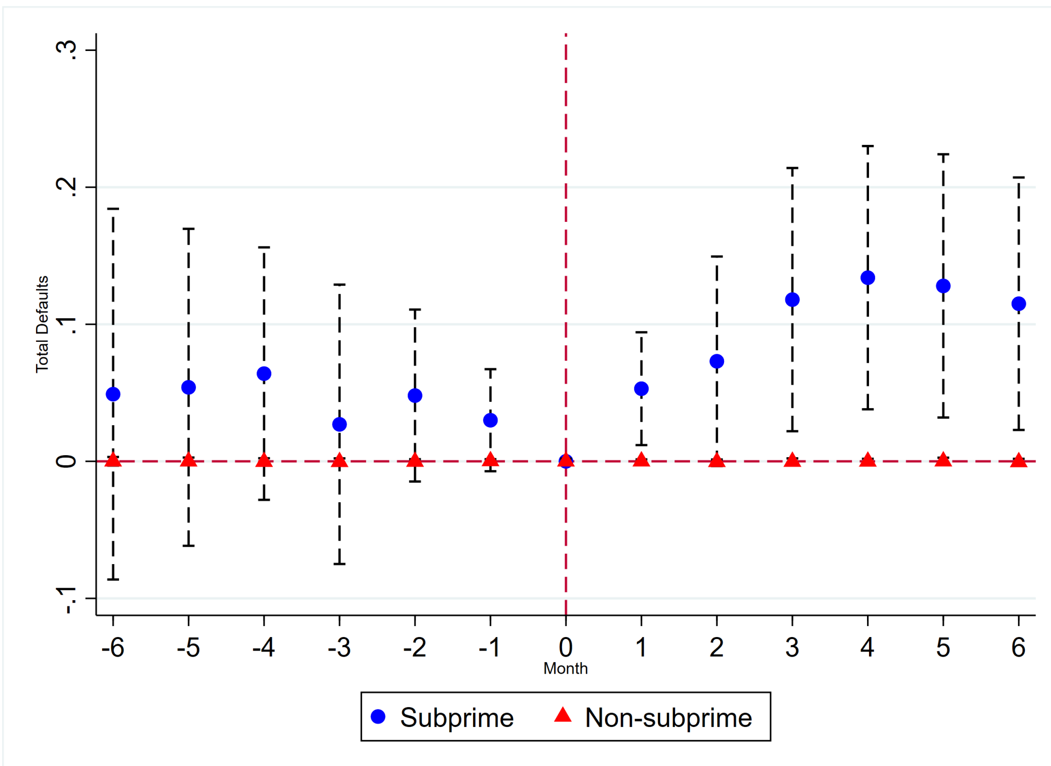


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TABLE 1

Descriptive Statistics

This table reports the descriptive statistics of all the variables considered for the regression analysis samples. Panel A reports the descriptive statistics of Designated Market Area (DMA)–level characteristics, while Panel B and Panel C report the descriptive statistics of the characteristics of initial coin offerings (ICOs) and non-fungible token (NFT) collections, respectively. All variables are described in the appendix.

Panel A: DMA–Level Characteristics

	# Obs	Mean	Median	S.D.	Min	Max
Lottery sales ($ per capita)	197	199.21	172.55	130.64	0.77	822.84
Median income ($ thousands)	197	48.21	46.69	7.95	29.08	85.71
Population (thousands)	197	1,557	761	2,496	14	21,285
Income inequality (80pct over 20pct)	197	4.60	4.55	0.40	3.60	5.89
Minority ratio	197	0.17	0.13	0.11	0.02	0.66
Non-college ratio	197	0.44	0.44	0.07	0.29	0.61
Rural score	197	3.25	3.13	1.44	1.00	7.64
Male ratio	197	0.49	0.49	0.01	0.46	0.52
Majority male (0/1)	197	0.24	0	0.43	0	1
Catholic/Protestant ratio	197	0.71	0.43	0.85	0.02	6.12
Broadband access rate	197	0.80	0.80	0.05	0.59	0.90
Median age	197	38.33	38.12	3.28	28.35	49.63
Fraction $<$ 25 years old	197	0.10	0.10	0.02	0.07	0.24
Married ratio	197	0.49	0.49	0.03	0.32	0.61
Unemployment rate	197	0.08	0.08	0.02	0.03	0.17
CFPB complaints (per 1000)	197	0.23	0.21	0.12	0.00	0.91
Libertarian Party vote share	197	0.01	0.002	0.02	0.00	0.07
Regional risk-taking preferences	197	-0.11	-0.08	0.20	-0.80	0.44
Advertisement spending ($ per 1000 population)	197	7.32	0.86	14.36	0	103.91
% Population in default on debt obligations	197	3.01	2.89	0.92	1.34	5.61

Panel B: ICO–Level Characteristics

	# Obs	Mean	Median	S.D.	Min	Max
ICO features						
Token retention (%)	937	47	48	16	0	87
KYC (0/1)	937	0.36	0	0.48	0	1
Accelerated pricing (0/1)	937	0.01	0	0.07	0	1
Platform (0/1)	937	0.54	1	0.5	0	1
Pre-sale (0/1)	937	0.45	0	0.5	0	1
White paper (0/1)	937	0.93	1	0.26	0	1
GitHub presence (0/1)	937	0.57	1	0.5	0	1
Team disclosure (0/1)	937	0.77	1	0.42	0	1
Primary market outcomes						
Funds raised ($ thousands)	937	26,304.72	12,600	150,740	2.57	4,197,956
Funds raised (log)	937	16.02	16.35	1.57	7.85	22.16
Funds raised (frac. of hardcap)	937	0.40	0.28	0.37	0	1
# Contributors	222	4,484.82	2,499	5,936.27	322	52,930
ICO retail attention						
ICO–DMA SVI	181,086	54.07	55	16.42	1	100
ICO Wallet–DMA SVI	181,086	48.11	47.67	12.80	0	99.33
ICO SVI	937	1.51	1.14	1.35	0.29	10.06

Panel C: NFT Collection–Level Characteristics

	# Obs	Mean	Median	S.D.	Min	Max
NFT collection features						
Total token supply	46	8,375	9,188	2,372	1,000	10,000
Advertises rare items (0/1)	46	0.85	1.00	0.36	0.00	1.00
Has Twitter presence (0/1)	46	0.93	1.00	0.25	0.00	1.00
Has Discord presence (0/1)	46	0.89	1.00	0.31	0.00	1.00
Creator's royalty fees (pp)	46	5.20	5.00	2.15	0.00	10.00
Primary market outcomes						
Log fund raised (ETH)	46	5.37	6.58	3.08	0.89	9.89
Days to mint 99%	46	79.31	3.54	208.90	0.08	821.21
# Minting wallets	46	3,434	2,955	2,461	239	9,255
NFT retail attention						
NFT–DMA SVI	2,053	46.04	44	20.22	2	100
NFT Wallet–DMA SVI	2,053	8.64	6.33	8.90	0	62.67
NFT SVI	46	1.34	1.28	0.99	0.20	3.85

https://doi.org/10.1017/S0022109024000681 Published online by Cambridge University Press

TABLE 2

Regional Gambling Propensities and Retail Crypto Attention

This table presents results documenting the relationship between the regional variation in gambling propensities and retail crypto attention. Panel A reports results for ICOs and the analysis is conducted at the ICO–DMA level. Panel B reports results for NFT collections and the analysis is conducted at the NFT collection–DMA level. Robust standard errors, double-clustered at the ICO and DMA (NFT collection and DMA) levels in Panel A (Panel B), are presented in parentheses. All variables are described in the appendix. *, **, and *** represent significance at the 10%, 5%, and 1% levels.

Panel A: Retail Investor Attention Toward ICOs

	1	2	3	4
Lottery sales per capita	6.878***	6.279***	6.280***	6.323***
	(0.982)	(1.031)	(1.031)	(1.036)
Demographic controls				
Population		1.035	1.036	1.055
		(0.807)	(0.807)	(0.812)
Broadband access		0.978	0.976	0.913
		(0.859)	(0.859)	(0.861)
ICO controls				
Token retention (%)			3.404***	
			(1.185)	
KYC (0/1)			-0.506	
			(0.370)	
Accelerated pricing (0/1)			-1.316	
			(2.798)	
Platform (0/1)			-0.772**	
			(0.357)	
Pre-sale (0/1)			-0.549	
			(0.374)	
White paper (0/1)			-0.0440	
			(0.690)	
GitHub presence (0/1)			-0.672*	
			(0.363)	
Team (0/1)			0.893*	
			(0.459)	
N	181,086	181,086	181,086	181,086
ICO fixed effects				✓
ICO controls			✓	
DMA controls		✓	✓	✓
Adj. R-squared	0.175	0.184	0.186	0.292

Panel B: Retail Investor Attention Toward NFT Collections

	1	2	3	4
Lottery sales per capita	10.270***	9.167***	9.261***	9.225***
	(1.175)	(1.133)	(1.142)	(1.222)
Demographic controls				
Population		1.138*	1.235**	0.657
		(0.565)	(0.555)	(0.523)
Broadband access		0.729	0.763	2.070**
		(1.070)	(1.078)	(0.918)
NFT collection controls				
Total token supply (thousands)			0.935**	
			(0.454)	
Creator's royalty fee			-0.986	
			(0.879)	
Advertises rare items (0/1)			-4.141	
			(4.016)	
Has Twitter (0/1)			8.200	
			(8.681)	
Has Discord (0/1)			-9.149	
			(8.488)	
N	2,053	2,053	2,053	2,053
NFT collection fixed effects				✓
NFT collection controls			✓	
DMA controls		✓	✓	✓
Adj. R-squared	0.285	0.295	0.305	0.543

TABLE 3

Robustness: Alternative Measures of Regional Gambling Propensities

This table presents results documenting the robustness of the results presented in Table 2 to alternative measures of regional gambling propensities. Column (1) and Column (2) report results for ICOs and NFT collections, respectively. Each row presents the point estimate obtained by regressing the regional crypto attention measure on the regional gambling preference measure reported in the row using equation (1). Robust standard errors are double-clustered at the ICO and DMA levels in Column (1), and at the NFT collection and DMA levels in Column (2). All variables are described in the appendix. *, **, and *** represent significance at the 10%, 5%, and 1% levels.

	ICOs	NFT Collections
	1	2
Catholic/Protestant ratio	2.910**	5.032***
	(1.378)	(0.828)
Median income	-2.589*	1.307
	(1.562)	(1.285)
Income inequality	5.640***	5.143***
	(1.158)	(1.249)
Non-college ratio	5.035***	2.299
	(1.552)	(1.424)
Rurality score	-5.050***	-2.069
	(1.284)	(1.478)
Fraction $<$ 25 years old	1.318	2.437*
	(0.840)	(1.252)
Married ratio	-3.926***	-3.294***
	(1.252)	(0.957)
Minority ratio	1.768*	1.049
	(1.005)	(1.050)
Majority male	2.516	1.796
	(2.051)	(2.033)
Unemployment rate	3.375***	2.407**
	(1.142)	(1.005)
N	181,086	2.053
Fixed effects	ICO	NFT collection
DMA controls	✓	✓

TABLE 4

External Validation: Attention and Investment

This table presents results documenting the external validation of the baseline results reported in Table 2. Panel A reports results exploring whether retail investor attention toward ICOs and NFTs translates into crypto investments by analyzing whether retail attention toward crypto-wallets increases around ICO and NFT collection introduction dates. In Panel A, robust standard errors are double clustered at the ICO and DMA levels (NFT collection and DMA levels) for the ICO (NFT collection) specifications, and are reported in parentheses. Panel B presents results documenting the association between retail attention and crypto token outcomes in the primary market. Columns (1)–(3) report results for ICOs, while Columns (4)–(6) report results for NFT collections. In Panel B, robust standard errors are clustered (double-clustered) at the year-quarter level (ICO origination region and year-quarter levels) for NFT collections (ICOs), and are reported in parentheses. All variables are described in the appendix. *, **, and *** identify significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Attention Toward Crypto Wallets

	ICOs	NFT Collections
Depvar: $WalletSVI_{[0,+14]}$	1	2
Lottery sales per capita	2.762***	0.893**
	(0.662)	(0.343)
N	181,086	2,053
Fixed effects	ICO	NFT collection
DMA controls	✓	✓
Adj. R-squared	0.330	0.454

Panel B: Retail Crypto Attention and Crypto Tokens' Primary Market Outcomes

	ICOs			NFT Collections		
	Funds raised (logged)	Relative raised	# Contributors	Funds raised (logged)	# Minting wallets	#Days to mint 99%
	1	2	3	4	5	6
SVI	0.681***	0.164***	3781.6***	1.853***	1514.5***	-71.46**
	(0.0642)	(0.0220)	(269.0)	(0.526)	(407.0)	(30.25)
N	937	937	222	46	46	46
ICO region × Year-Qtr fixed effects	✓	✓	✓			
Year-Qtr fixed effects				✓	✓	✓
ICO controls	✓	✓	✓			
NFT collection controls				✓	✓	✓
Adj. R-squared	0.303	0.222	0.659	0.380	0.352	0.299

TABLE 5

Ruling Out Alternate Channels

This table presents results documenting the robustness of the baseline results presented in Table 2 to alternative channels. Panel A reports results for ICOs, while Panel B reports results for NFT collections. Robust standard errors are double-clustered at the ICO and DMA levels in Panel A, and at the NFT collection and DMA levels in Panel B. These standard errors are presented in parentheses. The results documenting the robustness of the findings to controlling for per-capita crypto advertising expenditures are only reported for the NFT collection sample because the ICO sample period precedes the availability of advertising data. All variables are described in the appendix. *, **, and *** represent significance at the 10%, 5%, and 1% levels.

Panel A: ICOs

	1	2	3
Lottery sales per capita	6.046***	6.331***	6.021***
	(1.020)	(1.031)	(1.025)
Alternative channels			
CFPB complaints per 1000 population	2.190*		
	(1.242)		
2016 election Libertarian party vote share		0.321	
		(0.766)	
Regional risk-taking preferences			1.433
			(0.888)
N	181,086	181,086	181,086
ICO fixed effects	✓	✓	✓
DMA controls	✓	✓	✓
Adj. R-squared	0.305	0.293	0.299

https://doi.org/10.1017/S0022109024000681 Published online by Cambridge University Press

Panel B: NFT Collections

	1	2	3	4
Lottery sales per capita	9.074***	9.212***	9.495***	9.260***
	(1.184)	(1.223)	(1.211)	(1.230)
Alternative channels				
CFPB complaints per 1000 population	1.133			
	(0.812)			
2016 election Libertarian party vote share		-0.358		
		(0.523)		
Regional risk-taking preferences			-1.348**	
			(0.592)	
Advertisement spending by crypto firms ($ per 1000 population)				-0.496
				(0.945)
N	2,053	2,053	2,053	2,053
NFT collection fixed effects	✓	✓	✓	✓
DMA controls	✓	✓	✓	✓
Adj. R-squared	0.545	0.543	0.546	0.544

TABLE 6

Impact of Token Characteristics on Retail Crypto Attention

This table presents results exploring the different crypto token characteristics that moderate the gambling-driven attention generated by crypto tokens. Columns (1)–(3) report results for ICOs, while Column (4) reports results for NFT collections. Robust standard errors are double-clustered at the ICO and DMA levels in Columns (1)–(3) and at the NFT collection and DMA levels in Column (4), and are reported in parentheses. All variables are described in the appendix. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

	ICOs			NFT Collections
	1	2	3	4
Lottery sales per capita	6.145*** (1.013)	6.390*** (1.045)	6.293*** (1.032)	8.382*** (1.006)
Lottery sales per capita × Low-ICO open price	0.323*** (0.0513)			
Lottery sales per capita × KYC		-0.189*** (0.0547)		
Lottery sales per capita × Bubble period token			0.0747*** (0.0123)	1.942* (1.012)
N	111,696	181,086	181,086	2,053
ICO fixed effects	✓	✓	✓	
NFT collection fixed effects				✓
DMA controls	✓	✓	✓	✓
Adj. R-squared	0.293	0.292	0.292	0.545

TABLE 7

Impact of Sports Gambling Legalization on Retail Crypto Attention

This table presents results exploring the impact of sports gambling legalization on the gambling-driven attention generated by ICOs. The analysis is conducted at the ICO–DMA level. $PostSG$ is an indicator variable that equals 1 for DMAs in states where sports gambling is legalized, and where the ICO occurs after the legalization date, and 0 otherwise. Robust standard errors, double-clustered at the ICO and DMA levels, are reported in parentheses. All variables are described in the appendix. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

	1	2	3
PostSG	-0.497***	-0.159*	-0.160
	(0.038)	(0.081)	(0.114)
PostSG × Lottery sales per capita		-0.328***	-0.326***
		(0.050)	(0.075)
N	181,086	181,086	181,086
DMA fixed effects	✓	✓	✓
ICO-date fixed effects	✓	✓	
ICO controls	✓	✓	
ICO fixed effects			✓
Adj. R-squared	0.757	0.757	0.817

TABLE 8

Gambling-Driven Retail Crypto Attention and Consumer Credit Outcomes

This table presents results documenting the relationship between the regional variation in gambling propensities and ICO attention on subsequent regional consumer credit defaults for two broad credit score categories of consumers – subprime (credit scores < 620) and non-subprime (≥ 620). The analysis is conducted at the DMA–credit score category–year-month level. The dependent variable in all columns is the change in average default rates in a particular DMA–credit score category–year-month bin between a given month, t, and six months in the future, $t+6$. $HighSVI$ is an indicator variable identifying the top tercile of the ICO attention measure in a given month, while $Subprime$ is an indicator variable identifying the subprime consumer segment. Robust standard errors, double clustered at the DMA and year-month levels, are reported in parentheses. All variables are described in the appendix. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4
Lottery sales per capita	0.039	-0.001		
	(0.025)	(0.008)		
High SVI	-0.002	-0.002	-0.009	
	(0.043)	(0.012)	(0.048)	
High SVI × Lottery sales per capita	0.094***	-0.017	-0.069	
	(0.028)	(0.013)	(0.033)	
Subprime		8.629***		
		(0.842)		
Lottery sales per capita × Subprime		0.082	0.089	
		(0.051)	(0.056)	
High SVI × Subprime		0.018	0.011	0.099
		(0.082)	(0.090)	(0.182)
Lottery sales per capita × High SVI × Subprime		0.147**	0.193***	0.222***
		(0.053)	(0.063)	(0.064)
Observations	13,396	13,396	13,396	13,396
Adj. R-squared	0.258	0.313	0.550	0.462
DMA fixed effects			✓	
Year-month fixed effects			✓	
Credit category fixed effects			✓	
DMA × Year-month fixed effects				✓
DMA × Credit category fixed effects				✓
Controls	✓	✓	✓	✓