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December 9, 2022

Abstract

Previous studies document a relationship between gambling activity at the aggregate level and investments in securities with lottery-like features. We combine data on individual gambling consumption with portfolio holdings and trading records to examine whether gambling and trading act as substitutes or complements. We find that gamblers are more likely than the average investor to hold lottery stocks, but significantly less likely than active traders who do not gamble. Our results suggest that gambling behavior across domains is less relevant compared to other portfolio characteristics that predict investing in high-risk and high-skew securities, and that gambling on and off the stock market act as substitutes to satisfy the same need, e.g., sensation seeking.

Keywords: Gambling, Retail investors, Lottery stocks.

JEL classification: G50, G40, D14, G11, G15

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1 Introduction

Gambling is an attractive and widely popular instrument to satisfy an entertainment or "aspiration for riches" motive (Dorn and Sengmueller, 2009). In Germany alone, the online and offline betting markets have a turnover of about EUR 53bn annually excluding illicit gambling activity.[1] As of 2019, the percentage of people aged 16 to 70 in Germany who bet on lottery tickets (32.5%), slot machine and casino games (2.2%), or sports (4.1%) at least once over the past year is more than double that of stock market investors.[2,3]

Next to understanding the drivers of this ubiquitous gambling preference, a growing literature in finance has identified gambling motives as a strong predictor of retail investor decision-making. More precisely, traders have been shown to be attracted to stocks with positively skewed returns. Such assets bear a certain likeness to gambles, specifically lotteries. Recent attention to the organized behavior of retail investors in GameStop and other 'meme' stocks has once more sparked an academic and public debate on the interplay of retail investing, gambling, social media, and low-cost brokerages.[4] Finally, a combination of sensation-seeking and gambling motives may have drawn investors especially prone to gambling-like investing to neo-brokerage platforms such as Robinhood during the recent Covid-19 pandemic.[5]

The work of Kumar (2009) reveals that investors who live in areas with higher lottery demand are more likely to invest in lottery stocks by showing that real lottery demand spills over to demand for lottery-type stocks at the aggregate level. This seminal analysis has sparked a plethora of research on investors' preferences for such instruments, behavioral determinants of this preference, and what drives their demand. For instance, gambling motives have been shown to be associated with excessive trading that adversely impacts portfolio performance (Dorn and Sengmueller, 2009; Grall-Bronnec et al., 2017; Markiewicz and Weber, 2013; Liao, 2021).

[1] For the legal offline gambling market, DHS (2021) quote a turnover of EUR 44.2 billion in Germany for 2019. Franke (2021) find a German sports betting market size of EUR 9 billion in 2019.

[2] Among gamblers, the prevalence of online gambling was about 7% in 2019 (BZgA, 2020).

Given their lottery-like characteristics, prior studies assume that lottery stocks and lotteries attract similar clienteles, and that gambling preferences therefore spill over between traditional gambling and investing. Notwithstanding, this link has not been tested directly. A methodologically simple test of the hypothesis that traditional gamblers are more attracted to lottery stocks than investors who do not gamble would be to relate elicited or revealed gambling preferences to lottery stock investment at the individual level. Impeding this approach, however, is the fact that eliciting information on gambling preferences has proven challenging. In the prior literature, most studies are based on self-reported information from either voluntary surveys or surveys conducted in psychiatric treatment facilities, which are arguably not generalizable to the wider population. In addition, problem gambling is associated with a considerable social stigma which leads to under-reporting biases in the elicitation of gambling harms (e.g. Grinblatt and Keloharju, 2009; Cookson, 2018; Price, 2020). These complications lead to most prior studies resorting to relatively low sample sizes. Perhaps due to these obstacles, the question whether casino gambling and investment in lottery stocks, commonly referred to as gambling on the stock market (Kumar, 2009), act as complements or substitutes has not yet been established directly and on sufficiently large samples.

In this paper, we connect individuals' revealed gambling preferences with their actual investment behavior by leveraging administrative data on observed online betting transactions. This allows us test (i) whether gamblers are indeed attracted to specific investments which carry lottery-like features and (ii) whether these investment choices are a complement or a substitute to gambling behavior. To this end, we identify 12,783 clients of a large German retail bank directly as gamblers by matching

[3]All gambling figures are based on a representative survey of the German population conducted by the BZgA (2020). Across gambling activities, the prevalence of at least one gamble per year in this representative study is therefore 38.8%. Fey (2020) quotes 9.7 million retail equity and equity fund investors in Germany in 2019, which corresponds to a 16.7% prevalence of stock investing of citizens aged 15 to 69 in 2019, based on the 58.2 million people in that age group in 2020 (DESTATIS, 2021).

[4]Recent attention has spanned a congressional report by the U.S. House Committee on Financial Services ("Game Stopped? Who Wins and Loses When Short Sellers, Social Media, and Retail Investors Collide", Waters and Green, 2022), popular business nonfiction such as "The Revolution That Wasn't: GameStop, Reddit, and the Fleecing of Small Investors", (Jakab, 2022a), the popular press "Who Really Got Rich From the GameStop Revolution?" (Jakab, 2022b), and academic studies, e.g., Pedersen (2022); Hasso et al. (2022).

checking account transactions with online betting providers. The online betting services we observe encompass lotteries, casino-style games, and the largest sports betting agencies in Europe. Across all individuals, we observe precise administrative data on socio-demographics, trade-level investments, portfolio holdings, financial assets and debt, as well as transaction-level data on consumption and income.

While several important studies posit that gambling and investing are complementary and driven by gambling preferences (Kumar, 2009; Grinblatt and Keloharju, 2009; Dorn and Sengmueller, 2009), just as many others propose that gambling is a substitute to risk taking in the stock market (Dorn, Dorn, and Sengmueller, 2015; Cox, Schwartz, and Van Ness, 2020; Cookson, 2018). If investing in lottery-type instruments is indeed driven by gambling preferences – and the two activities are complementary – we should expect to find higher lottery-stock portfolio shares and participation rates for gamblers than for non-gamblers. Further taking into account the findings of Bali et al. (2021), we would expect gamblers to invest more actively in attention-grabbing stocks as well.

We provide novel evidence that investors perceive the two activities as substitutes. Specifically, we relate the *revealed* gambling preference and a set of behavioral characteristics to (i) the *perceived* gambling preference based on Kumar (2009) and Bali et al. (2011), and (ii) a preference for attention-grabbing stocks, i.e., stocks with high media sentiment.[6] We find that gamblers exhibit higher rates of lottery stock investing than the average investor conditional on financial market participation (12.12% and 31.34% for the Kumar, 2009, and Bali et al., 2011, definitions, respectively, compared to 9.73% and 23.92%), but lower propensities to invest in Bali et al. (2021) attention stocks (23.01% compared to 25.70%). Moreover, formal analyses reveal that behavioral characteristics other than gambling are better predictors of lottery stock investing than gambling preferences. More precisely, gambling is associated with a 1.9% higher likelihood

[5]Estimates suggest that Robinhood had close to 13 million customers at the time of the GameStop short squeeze and 18 million some months later, i.e., a roughly 40% increase in its investor base coinciding with the first wave of international Covid-19 lockdowns (Jakab, 2022a).

[6]High media sentiment has been shown to amplify investor demand for lottery-type instruments (Kumar, 2009; Bali, Cakici, and Whitelaw, 2011; Bali, Hirshleifer, Peng, and Tang, 2021)

to invest in lottery stocks, whereas an increase in monthly trading volumes (trades) by one standard deviation leads to a 4.3% (3.7%) higher likelihood to invest in and 19.8% (12.1%) higher portfolio weights held in lottery stocks.

Based on these initial results, we identify a group of investors who trade actively and do not gamble traditionally, finding that an above-average trading activity is associated with higher lottery and attention stock investments than gambling: Conditional on investing, this active trader group exhibits the highest propensity to invest in lottery (17.55% for Kumar, 2009, and 38.76% for Bali et al., 2011, lottery stocks, respectively) and attention stocks (39.91%). The participation rates of active traders surpass even those of gamblers who trade actively, i.e., a group with a preference for both gambling and active trading (15.70%, 32.09%, and 27.87%, respectively). Even after controlling for demographics, income, and wealth, we find that active traders hold significantly higher conditional portfolio values in high-skewness, lottery, and attention stocks than other investors despite the empirically low prices of such instruments. Our findings therefore contrast previous accounts of spillover effects between gambling and investing in lottery stocks.

Finally, we propose that – contrary to the belief that lottery stock investors are essentially gamblers on the stock market and therefore in similar need for financial education or protection – gamblers and lottery stock investors generally have starkly different socio-economic and behavioral traits: Active traders as the most active lottery stock investor group are wealthier, earn higher income, and hold riskier assets than the average investor (irrespective of their gambling preferences). Gamblers, on the other hand, have much lower net wealth and portfolio holdings than non-gambling investors despite earning above-average income in our sample, and while their trading and portfolio risk profiles point to more risk-taking than exhibited by average investors, these risk preferences are less strongly pronounced than those of active traders.

Overall, our results suggest that investing in lottery stocks may not be as associated with gambling preferences as suggested by the prior literature. Instead, we argue that active trading as a behavioral trait is tied to investing in lottery stocks to a much larger extent. If they are not driven by gambling preferences, lottery stock investments might instead follow from by two competing mechanisms: First, lottery stock investing could be rational if it were based on perceived information or skill. Second, lottery stock investing might follow from a behavioral explanation, e.g., sensation-seeking, entertainment, or overconfidence. We therefore try to distinguish between these potential mechanisms by examining the investment performance of gamblers, active traders, and lottery stock investors.

These analyses reveal that gambling preferences alone result in lower portfolio performance, whereas lottery stock investing is not associated with significant differences in performance. We draw this conclusion from the finding that active traders fail to exhibit behavioral mistakes that have previously been attributed to lottery stock investors, such as excessive trading or under-diversification, and that they do not experience the associated losses on portfolio returns. Among casino gamblers, however, we find a significantly higher prevalence of such mistakes and the resulting lower returns: Gamblers have 7.74% higher monthly portfolio turnovers than the overall sample (16.41% higher than for active traders). Even after controlling for socio-demographic characteristics, Gambler portfolios achieve significantly lower returns (-1.035%) and Sharpe ratios (-0.00122) than other investors. Similarly, actively trading gamblers earn lower returns (-0.930%) and Sharpe ratios (-0.00139) compared to non-gambling active traders and the remainder of the sample. Active trader portfolios, on the other hand, significantly outperform those of other non-gambling investors (0.521% higher returns, 0.00072 higher Sharpe ratios).

With the advent and widespread use of ('free') online and app-based investment platforms ('neo-brokers')[7], the lines between trading and gambling are becoming more and more blurred. In light of the similarity of gambling and certain types of investing, the recent

[7]Techcrunch defines neo-brokers as "startups that are disrupting the investment industry by providing a platform for a wider range of consumers to partake in the stock market by offering them more incremental investment options and modern and easy mobile-based interfaces to manage their money" (Lunden, 2021). Germany's Federal Financial Supervisory Authority, BaFin, warns consumers on the promises and pitfalls associated with neo-brokers, particularly that free trading may result in indirect costs (Frölich and Lembach, 2021).

and arguably Covid-fueled influx of day traders on highly gamified trading apps such as Robinhood (U.S.) or TradeRepublic (Germany) has given rise to a debate in the press and academic literature about the potential of such apps to induce gambling-like, and thereby potentially pathological, levels of day trading (see, for instance, Håkansson, 2020; Håkansson et al., 2021). In a similar vein, popular media offer anecdotal evidence linking gambling and day trading: A considerable number of retail investors in the U.S. invested their Covid-19 relief checks entirely into 'quick stock market gambles' (Phillips, 2021), and Germany has seen a similar influx of gambling-like day trading during lockdowns (Mühl, 2021). In support of these accounts from the media, recent work by Greenwood et al. (2022) finds that stimulus payments increased retail buying activity, share prices of primarily retail-dominated stock portfolios, and overall market turnover.[8]

One associated concern with our study is that gamblers may turn to such neo-brokerages to invest or gamble in the stock market and that risky investing complementary to gambling would therefore fall outside of our administrative bank data and go unobserved. If gamblers chose to trade on such platforms rather than their main bank account, our inferences would be biased towards gambling and trading as substitutes, rather than complementary activities. Our setting and data allow us to rule out this concern and test whether different investor groups exhibit heterogeneous demand for trading on such neo-brokerage platforms. Based on sample averages, we find that gamblers indeed have higher participation rates in neo-brokerage trading among all compared investor groups: 2.71% of the gamblers in our sample own a neo-brokerage account (4.54% of gamblers with above-median trading activity), and 1.75% (2.06%) own a TradeRepublic account, compared to less than 1.15% (0.54% for TradeRepublic) for the overall sample. However, these differences are unlikely to be economically meaningful: Neo-broker participation of non-gambling active traders is statistically insignificantly lower than that of gamblers, and actively trading gamblers exhibit even higher rates than other gamblers. In cross-sectional and time-series analyses we confirm that gambling

[8]Contrary to these accounts, Welch (2022) finds that Robinhood investors have a preference for extreme recent winners and losers, invest predominantly in large rather than obscure stocks, and acted as a stabilizing force during the Covid-19 stock market crisis.

preferences do not meaningfully explain owning a neo-broker account. Rather, younger men and those with above-median trading activity (and without a gambling preference) are most likely to use such brokerage services.

Another issue raised by our study and the understanding of gambling activity is that gamblers may not necessarily be a group of unsophisticated individuals as implied, but rather those who trade on sports events or poker games based on perceived experience, skill, or information. We make use of the period of widespread cancellations of sports events due to Covid-19, and find that gambling activity in our setting does not seem to be event-driven, supporting existing hypotheses that gamblers act somewhat impulsively. This also highlights that gamblers are not participating solely in events where they may possess skill and an information advantage. Rather, they gamble for entertainment or consumption purposes with negative expected returns.

Our study contributes to a large and interdisciplinary literature on gambling and trading, as well as a large literature on retail investing. Several examples from the prior literature following Kumar (2009) analyze the similarities and differences between gambling and (day) trading, as well as the individuals undertaking both activities. This seminal work generally finds that gambling and gambling-like investing act as complements. According to Grinblatt and Keloharju (2009), both gambling and day trading can be aligned with sensation seeking behavior in that they are financially risky and driven by a desire for novelty and variety, i.e., placing repeated bets or frequently reshuffling one's portfolio. Similarly, Dorn and Sengmueller (2009) finds that investors who self-reportedly enjoy both gambling and investing exhibit significantly higher portfolio turnover rates than those who do not, and that the enjoyment sourced from both activities helps explain excessive trading behavior. Mosenhauer et al. (2021) and Liu et al. (2022) provide additional evidence to the link of gambling motives and excessive trading. The latter find that gambling preferences and the perceived information advantage of investors dominate all other surveyed motives in explaining excessive trading. Jadlow and Mowen (2010) find that the personality traits of a representative panel of the U.S. population for less and heavily involved gamblers on the one hand and investors on the other exhibit some similarities. In that vein, Arthur and Delfabbro (2017) find that day-traders tend to be heavily involved gamblers. Kumar et al. (2016) present evidence on stock return co-movement in areas with a particularly high concentration of gamblers and Liao (2021) finds that visiting newly opened casinos to gamble causes individual investors to increase idiosyncratic portfolio risk compared to non-gamblers.

In contrast, the substitution hypothesis predicts that both activities as substitute goods satisfy one and the same need, which could be entertainment, sensation seeking, or something else entirely. Cookson (2018) utilizes the introduction of prize-linked savings accounts which cater to retail investors' gambling preferences and finds that residents of the treated regions reduce gambling compared to unaffected populations. Cox, Schwartz, and Van Ness (2020) find that lottery stocks are used by football bettors to offset previous gambling losses, supporting the notion of a substitution effect between the two activities in that both are viewed as interchangeable ways to break even. Dorn et al. (2015) provide additional evidence in support of the substitution hypothesis and finds that investors are less likely to trade highly speculative assets during peaks of lottery jackpots. Similarly, Gao and Lin (2015) and Huang et al. (2019) provide additional evidence supporting a substitution effect between the two activities. Chava et al. (2022) also find that at the aggregate level, attention to cryptocurrencies, initial coin offerings (ICOs), and non-fungible tokens (NFTs) is positively related to lottery stock demand and socio-demographic characteristics.

To establish whether gambling and investment in lottery stocks are perceived as complements or substitutes while addressing concerns with aggregate-level and survey-based measures of gambling preferences, objective data on gambling preferences at the individual and transaction level is required. Our study contributes to this literature and provides novel evidence to the competing hypotheses by testing directly how gamblers participate in risky investments and lottery stocks at the extensive and intensive margins.

Related to our study is Muggleton et al. (2021), who also use transaction-based data on gambling that is comparable to ours in granularity, size, and objectivity. Muggleton et al. (2021) employ classified gambling transactions based on bank account transaction data of UK clients to analyze a broader picture of outcomes for gamblers, some of them financial, but also related to health and well-being. Our study differs by focusing on the link between gambling on and off the stock market.

Finally, we contribute to a large and growing literature in household finance and the trading behavior of (retail) investors. Generally, this literature points to the fact that retail investors overtrade (Barber and Odean, 2000, 2013) chase trends and high-attention stocks (Barber and Odean, 2008), and are influenced by brokerage features (Arnold et al., 2022; Shaton, 2017). Retail investors have been documented to tilt their portfolios towards specific assets or asset classes, e.g., local stocks (Seasholes and Zhu, 2010), dividend-yielding assets (Bräuer et al., 2022; Hartzmark and Solomon, 2019), and cryptocurrencies or meme-stocks (Hackethal et al., 2021; Hasso et al., 2022). A number of related studies suggest that retail investor behavior is largely driven by the investment behavior of their peers, both through personal connections (Balakina et al., 2022; Balakina, 2022; Knüpfer et al., 2021) and anonymously networked peers (Han et al., 2022; Heimer, 2014, 2016; Pelster and Gonzalez, 2017). We contribute to this stream of the literature by documenting the link between online gambling behavior and trading in related securities.

2 Data and setting

2.1 Account transactions and securities holdings

We study proprietary, fully anonymized customer data from a large German bank that offers the full range of retail banking services, i.e., checking, savings, securities, and online brokerage accounts to more than a million customers. Customers can further choose among additional services such as (securities) savings plans, retirement products, home financing, and personal (installment) loans offered in-house by this bank or through third-party providers. The transaction data is augmented by administrative customer data (socio-demographic information) collected or computed by the bank, such as age, profession, marital status, micro status, probability of default (PD), or the trading risk class, which is assigned by the bank at customer onboarding based on the customer's prior trading experience and stated risk appetite. The full data includes not only daily transactions in checking and securities accounts, but also end-of-month data on securities account balances, deposits, loan balances, and securities holdings.[9]

Checking account transactions are initially recorded at transaction level with timestamps at the second level, where timestamps correspond to the time when bookings are completed at the bank, which is not necessarily the exact time the transaction was made. For securities account transactions, it likely is. Nevertheless, we aggregate both checking and securities account transactions at the daily level. The bank uses a proprietary algorithm to sort inflows to and outflows from checking accounts into over 100 categories, among them permanent and transitory income and common expense categories that can be aggregated to total consumption levels. All transactions that the algorithm cannot categorize are labelled as 'uncategorized', but still taken into account in computing our main definition of total consumption. Account and loan balances, total savings, deposit balances, and securities holdings are observed not at daily level but at the end of every month.

2.2 Construction of investor samples

We compare two main distinct and non-overlapping groups in our analysis. The first group consist of a representative sample of the bank's customer base who do not gamble, subject to the restriction that customers use their accounts actively so as not to capture

[9]See Bräuer et al. (2022), specifically, pp. 7 ff. for a detailed description of the unique administrative bank-client data we use. The study uses a similar, albeit smaller, data set of the same bank.

any effects potentially driven by occasional or specific account usage. The final sample for this group consists of a total of 166,376 non-gamblers (referred to as (S) from here on out and in all tables).

The second group are online gamblers. Within the transactions of all checking account customers at our partnering bank, we select those that have transactions with one or more of eleven online betting services legal and licensed in Germany between July 1, 2020 and June 30, 2021. These betting providers are *bet365*, *interwetten*, *bwin*, *tipico*, *William Hill*, a German online lottery provider,[10] as well as the Austrian, Swiss, German, U.S.-American, and international subsidiaries of *bet-at-home*. Every account transaction that matches one of the IBANs of the aforementioned online betting providers between July 1, 2020 and June 30, 2021 is flagged as a gambling expense or inflow, and we add the corresponding customer to our sample of gamblers. The final gambler sample consists of 12,783 customers.

Contrary to sports gambles, betting on casino games, slot machines, and poker online was illegal in all but one German federal state (Schleswig-Holstein) prior to July 1, 2021. Between mid-June 2021 and July 1, 2021, however, there was a grace period during which prior illicit online gambling activity on such games was tolerated, i.e., gamblers and online betting providers were not legally prosecuted if they bet on casino games online or offered such services. Since the practice has been legalized on July 1, 2021, some of the selected betting providers also offer online gambling on slot machines (*bwin*, *bet-at-home*, *interwetten*, and *William Hill*), poker (*bwin* and *William Hill*), bingo (*William Hill*), and (casino) games (*bwin*, *tipico* and *William Hill*). The gambler group analyzed in this sample can therefore be understood as both sports bettors and gamblers on casino games, slot machines, or comparable games.

Muggleton et al. (2021) base their analyses on similarly objective measurements of gambling preferences. While the authors rely on the bank's correct classification of

[10] We analyze transfers to one local lottery provider run by the federal state in which the bank is headquartered. For data privacy reasons, we cannot disclose the name of the federal state here.

account transactions as gambles, we match the whole universe of individual bank clients' account transactions directly to counterparty identifiers of the largest online betting providers licensed in Germany. This model-agnostic and direct matching reduces potential measurement error which may arise from false predictions inherent to many automated categorization systems. Bräuer et al. (2022), who use a similar (albeit smaller) bank-client dataset to ours, find that roughly 35% of consumption transactions are uncategorized. Importantly, it tends to be specific transactions, i.e., transactions with smaller, less well-known counterparties, that cannot be categorized well by classification algorithms commonly used by retail banks. It is conceivable that gambling transactions are more frequently conducted with smaller, less 'generalizable' counterparties, and therefore fall into uncategorized consumption systematically more often than other transactions. This would introduce a second source of measurement error. Our measurement of gambling based on screening the full set of bank clients reduces such potential issues with selection biases or pseudo-random selection.

For all investors, we analyze transaction, trading, and asset holdings between September 1, 2018 and June 30, 2021. Due to internal data wareghousing rules of our partnering bank, checking account data is only monitored for a period of 13 consecutive months in a sufficiently granular way to allow matching transactions to the eleven betting providers. We therefore observe online betting transactions for the 13-month period from July 1, 2020 to June 30, 2021 at the transaction level. For the purpose of this paper, we define gamblers as customers who have matching transactions with one or more of the betting provider IBANs at any time during this period, although we do not observe gambling transactions directly before July 1, 2020. Based on findings from the extant psychological literature on the strong intertemporal persistence of gambling preferences, we assume that gamblers also gambled before July 1, 2020 (see, e.g. Rachlin, 1990, for seminal work on the subject).

2.3 Definition of lottery and attention stocks

We define lottery stocks following Kumar (2009) as stocks with low prices, high idiosyncratic skewness, and high idiosyncratic volatility. Kumar (2009) stipulates that predominantly positive skewness drives retail investor demand for lottery stocks. Therefore, we analyze participation rates and portfolio shares/volumes held in high-skewness stocks in addition to lottery stocks following this definition. Stocks are assigned high (low) labels of each individual property if their cross-sectional average between September 2010 and September 2019 exceeds the median of each characteristic's distribution.

We extend the scope of our analysis to two further stock types of interest, namely, that of Bali et al. (2011) for lottery stocks and a definition of high-attention stocks following Bali et al. (2021). The definition of lottery stocks following Bali et al. (2011) emphasizes investor demand for the high-skewness properties of lottery stocks: The authors define a measure which ranks the maximum daily returns over the past month from highest to lowest (MAX). In support of the notion that skewness underlies the demand for lottery stocks, the authors find that the stocks ranking in the top decile of MAX are particularly attractive to investors. They subsequently label these stocks as lottery stocks. In later work, Bali et al. (2021) find that stocks with high investor sentiment, i.e., those receiving high media attention, amplify this demand. Hence, we also analyze investment in high-attention stocks.

We adjust the Bali et al. (2011) and Bali et al. (2021) measures slightly and in a similar vein as Balakina et al. (2022): To this end, we obtain daily closing prices and compute daily returns from July 1, 2020 to June 30, 2021, which is the same time period during which we observe gambling transactions, and for the complete set of stocks traded or held by investors in our sample. Within months, we compute the maximum daily return for each stock, and rank stocks according to this maximum return cross-sectionally. Stocks ranking in the top decile of the resulting cross-sectional return distribution are subsequently assigned a Bali et al. (2011) lottery stock label. Analogously and for the same period of time and universe of stocks, we compute, rank, and select attention stocks based on the top decile of the mean composite sentiment score variable available from RavenPack.

For some analyses, we also group all four stock types of interest together in one category (labeled *Any* in the tables). Studying the relation of traditional gambling and investing in any of the lottery, high-skewness, or attention stocks serves two purposes: First, it abstracts from any one stock definition, and therefore highlights directional effects more generally. This might be helpful in cases where different stock definitions yield different results, thereby providing an assessment of potential joint effects. Second, the *Any* label is assigned to more stocks than any of the four constituent security types individually; therefore, it captures a broader range of investors, which can help assess the robustness of our results to alternative definitions. In cases of marginally significant relations, the *Any* stock type category should help evaluating the significance of the results obtained for lottery, skewness, and attention stocks individually.

3 Determinants of lottery stock investing

We first study the determinants of lottery stock investing generally. The prior literature suggests that lottery stock investors are essentially gamblers on the stock market. Using our measure of revealed gambling preferences, we can evaluate this notion objectively. To assess whether gamblers indeed exhibit a higher preference for lottery stocks than other investors, we regress participation rates and portfolio weights held in Kumar (2009) lottery stocks on an indicator variable equal to one for gamblers. We subsequently include a set of additional portfolio- and investor-level variables to assess the robustness of this perceived relation to other potential drivers of the demand for lottery stocks.

The results are presented in Table 1. We estimate marginal effects of each variable on participation in Kumar (2009) lottery stocks using logistic regressions presented in columns 1 through 5. Columns 6 through 10 show analogous results for OLS regressions with individual-investor portfolio shares held in lottery stocks as the dependent variable, more closely following the analyses presented in Kumar (2009). More specifically, columns 1 and 6 present estimates from univariate regression models with only one independent indicator variable equal to one for gamblers and zero otherwise. In columns 2 and 7, we add control variables similar to those presented in Kumar (2009). Specifically, we include age, marital status, gender, professions, and average monthly income as well as median net wealth (the sum of deposits and securities holdings less outstanding debt). Net income and wealth are winsorized at the 0.1% level to limit the influence of outliers. In columns 3 through 5 and 8 through 10, we additionally include investor-level portfolio turnovers computed following Dorn and Sengmueller (2009), standardized portfolio values, dichotomous variables for participation in certificates, active funds, and passive funds (including ETFs), as well as standardized trading volumes (3 and 8), the annual sum of trading transactions (4 and 9), and an indicator variable equal to one for investors with an above-average number of monthly trades (columns 5 and 10) based on previous accounts of excessive trading among lottery stock investors.

The additional participation, portfolio-level, and trading behavior variables proxy for characteristics associated with gamblers and lottery stock investors in the prior literature. Such well-documented characteristics are increased risk-taking, excessive trading, and chasing cheap bets (Dorn and Sengmueller, 2009; Kumar, 2009; Grall-Bronnec et al., 2017; Markiewicz and Weber, 2013; Liao, 2021). Participating in certificates and active funds proxies for active investing and an increased risk appetite, which suggests a positive relation to lottery stock investing. Passive fund participation, including investing in ETFs, counterfactually proxies for less active, and less risky, investment behavior. We therefore expect a negative relation with lottery stock investing. Portfolio turnovers and trading transactions/volumes are likely to be positively associated with lottery stock participation and portfolio weights (Dorn and Sengmueller, 2009). If lottery stock investors are gamblers, portfolio values should be negatively associated with lottery stock investments. This follows from the notion that lottery stock investors as gamblers are less affluent than other investors and experience (return) losses by investing in lottery stocks (e.g. Dorn and Sengmueller, 2009; Kumar, 2009; Markiewicz and Weber, 2013).

[Table 1 about here]

In the univariate model (columns 1 and 6), gambling is significantly and positively related to the propensity and intensity of lottery stock investing: Before controlling for socio-demographics, gamblers are 2.2% more likely to invest in Kumar (2009) lottery stocks and hold 0.437% higher portfolio shares compared to other investors (significant at the 1% and 10% level, respectively). After including Kumar (2009) control variables, the effect on portfolio weights loses statistical significance altogether, and the gambler propensity to invest in lottery stocks decreases to 1.9% (significant at the 5% level). Nonetheless, the coefficient seems to be robust to the inclusion of control variables, suggesting that revealed gambling preferences explain lottery stock investing even after controlling for income, profession, age, gender, and wealth. However, after the inclusion of portfolio and trading behavior variables, the marginal effect decreases even further to 1.4%, 0.8%, and 0.5% for columns 3, 4, and 5, respectively. Only in column 3, after including portfolio turnovers, portfolio sizes, participation in active funds, passive funds, and certificates, as well as trading volumes, gambling preferences offer additional explanatory power for lottery stock investing. The pseudo-R^2 additionally increases to a large extent from 2.81% (column 3) to 11.06% (4) after including these determinants (0.28% to 1.82% for the $R^2_{adj.}$ in columns 7 and 8). In specifications 4, 5, and 7 through 10, gambling preferences are not significantly related to lottery stock investing and portfolio weights held in lottery stocks. This means that the new included variables (participation rates and trading behavior variables) explain lottery stock investment better than gambling – contrary to the notion of lottery stock investors as gamblers on the stock market. As expected, portfolio turnovers, certificate participation, and active fund participation are significantly and positively related to trading lottery stocks. All coefficients are statistically significant at the 1% level, except for turnovers in column 3

(5% level) and active fund participation in columns 3 (5% level), 4 (insignificant), and 5 (10% level). For lottery stock weights, the results are less strongly pronounced but generally follow the same patterns. Across specifications, the coefficient on passive fund participation is highly significant and negative (1% level).

Some of the presented results point towards a substitution mechanism as described in, e.g., Dorn et al. (2015): Contrary to the notion following from Kumar (2009), lottery stock weights are not unambiguously and negatively related to measures of high risk-taking (as evidenced by the lack of significant coefficients in columns 8 through 9 of Table 1), and gambling is not significantly and positively related to lottery stock participation or weights after including well-documented predictors of lottery stock investing. These measures have been shown to be related to preferences shared by gamblers (Dorn and Sengmueller, 2009; Grinblatt and Keloharju, 2009), but are not exhibited by gamblers only. Especially the positive coefficient on portfolio sizes contradicts previous accounts of gamblers as less wealthy gamblers on the stock market (Dorn and Sengmueller, 2009; Kumar, 2009; Markiewicz and Weber, 2013). Since trading volumes (columns 3 and 8), the number of trading transactions (4 and 9), and having an above-median number of trades (5 and 10) are unambiguously, positively, and significantly related to lottery stock investing, active trading seems to be an important driver of the demand for lottery stocks in addition to gambling motives, or even to a larger extent. All three measures essentially capture the same propensity: to trade actively. We therefore resort to using one of the variables in the following. Since both the marginal effects (estimated coefficients) and pseudo-R^2 ($R^2_{adj.}$) are higher for specifications 5 and 10 than the alternative using the standardized number of trades (4 and 9), and much larger for specification 5 than 1 through 4, we include the dichotomous indicator for investors with an above-median number of average monthly trades in the following analyses.

We present analogous results to Table 1, which is based on the Kumar (2009) definition of lottery stocks, for Bali et al. (2011) lottery stocks in Table A.2 in Appendix A. The results are qualitatively and quantitatively similar. There are only minor differences for portfolio values (the coefficient in column 8 becomes insignificant) and participation rates. These differences in participation rate coefficients do not refute our takeaways from the main analysis. Rather, they support that gambling and lottery stock investing are substitutes instead of complements, as participation in more risky assets is not generally related to lottery stock investment outcomes.

4 Gambler characteristics

4.1 Gambling transactions

Table 2 shows summary statistics for gambling transactions of gamblers. For the total of 12,783 gamblers for whom we observe betting transactions in our sample, we obtain daily inflows and outflows to and from any of the eleven online betting providers between July 1, 2020 and June 30, 2020. The sum of inflows and outflows across all betting providers analyzed constitute total amounts bet and won, respectively.

[Table 2 about here]

Consistent with well-documented properties of gambles and lottery stocks, both monthly and transaction-level wins and betting amounts have positive skewness, i.e., offer potentially high wins, albeit rarely: Gamblers spend an average (median) EUR 65.85 (EUR 25.00) on each bet, and in the case of a win earn EUR 225.90 (EUR 45.80). At the monthly level, gamblers bet an average (median) EUR 151.04 (EUR 50.00), or win EUR 334.87 (EUR 55.00). Despite the higher average amounts won than lost gambling, the observed frequency of wins pales in comparison to the amount spent at 6,856 total individual wins, and 4,625 monthly observations conditional on winning, compared to a total of 91,339 individual-bet observations and 39,820 monthly observations conditional on betting.

[Figure 1 about here]

The Covid-19 pandemic offers the potential to address one potential concern with our selection of gamblers in a natural experiment, namely, that the analyzed gamblers are a group of informed traders on sports events with a certain degree of (perceived) experience or skill instead of financially or rationally unsophisticated individuals as implied by the bulk of the prior literature. To investigate this concern, we use the period of Covid-19 lockdowns in Germany between March 13 and late April, 2020. During the pandemic, sports events were widely cancelled. Especially the more famous national and international leagues with highest betting volumes cancelled their games at least during the period between March and Summer 2020, some national league games were cancelled for a longer period.

We observe betting volumes during this period of cancellations, which can help address two questions simultaneously: First, whether gamblers in our setting are primarily driven to sports bets or casino games and second, whether their betting activity is event-driven, i.e., depends on the availability of events. Figure 1 shows marginal daily spending on gambling for each day for an extended gambling transaction sample between January 1, 2020 and June 30, 2021. In January 2020, we obtained a preliminary sample containing only gambling amounts for a total of 1,399 gamblers. We extend this sample by our main-sample gambler group of 12,783 gamblers in June, 2020. Only for this indicative, visual inspection of daily marginal spending on gambling, we append both samples and regress betting amounts on each day of the appended sample.

The marginal coefficients displayed in Figure 1 are obtained from regressing gambling outflows on each day of the sample, where January 1, 2020 is the reference day. Each coefficient is annotated by standard errors (vertical lines of the same color). The colors of the error bars and coefficients indicate statistical significance: Gray stands for statistically insignificant marginal daily gambling activity, blue for coefficients that are statistically significant at the 5% level, and red dots with orange bars indicate significant coefficients during Covid-19 lockdowns in Germany. Coefficients are plotted on top of a shaded blue area showing cumulative search volumes on Google for six major and four minor national and international sports leagues. This measure proxies the availability of sports events und the assumption that sports events are searched for more frequently on Google when they are occurring. Each of the selected sports has a major global following, and bets can be placed on the associated outcomes on one or more of the online betting platforms analyzed in this study and at any given point in time. We inspect major league search volumes for soccer, American football, basketball, baseball, hockey, and rugby, as well as minor league volumes for soccer, basketball, baseball, and rugby. For all sports, volumes are aggregated across searches for European, Canadian, and U.S.-American leagues and teams. The search volumes, plotted on the right-hand y-axis of Figure 1, can therefore serve as an indication of global aggregate interest in and availability of sports events.

Figure 1 suggests that gambling activity in our sample is neither event-driven nor related to the availability major sports betting events. Overall, daily marginal spending on gambling seems to increase more or less randomly. In fact, marginal gambling consumption increases during Covid-19 lockdowns: The dark red line shows a moving average over 23 business days (one month). This trend shows the only notable increase in gambling activity around the same period when coefficients are largest in our sample (between March and April 2020). This period coincides with the first wave of strict Covid-19 lockdowns in Germany.

One explanation for this finding may be the lower availability of physical sports betting outlets during widespread closures due to lockdowns. This notion is supported by Håkansson (2020), Håkansson et al. (2021), and Xuereb et al. (2021), who document a migration from land-based to online gambling during Covid, especially for gamblers who were heavily involved pre-pandemic (Sharman et al., 2021; Xuereb et al., 2021). Interestingly, however, most major league events were also cancelled during this period, leaving less outcomes to bet on during lockdowns. As Håkansson (2020) finds not only a move to online gambling, but also to casino games and slot machines during the pandemic, the increase in gambling activity during this period may be driven by rather involved (casino) gamblers. This, in turn, also means that our gambler sample does not consist primarily of pure sports gamblers who gamble based on perceived skill, but more likely captures a significant share of casino gamblers.

4.2 Descriptive statistics

Socio-demographics and financial assets Tables A.1.A, A.1.B, and A.1.C in Appendix A show descriptive statistics for the overall sample (S, column 1 in all tables) and gamblers (G, column 2). Since active trading is influential in predicting investment in lottery stocks (see Table 1), we also present summary statistics for active traders (AT, column 3) and the intersection of both groups (gambler-active traders, GAT, column 4). We compare socio-demographic and income information among these groups in Table A.1.A, financial asset holdings in Table A.1.B, and trading and investment characteristics in Table A.1.C. In each table, Columns (5) through (8) show pair-wise differences in sample averages between gamblers and each comparison group, annotated by asterisks that indicate the level of statistical significance of the difference between groups. All differences in sample averages are tested for statistical significance using Welch's paired t-test with unequal variances. Gamblers are tested against the overall non-gambling sample in column 5 of each table (G – S), against active traders in column 6 (G – AT), and against gambler-active traders in column 7 (G – GAT). Column 8 of Tables A.1.A through A.1.C tests gambler-active traders against non-gambling active traders (GAT – AT).

In line with the prior literature, gamblers tend to be more often male male, younger, and less often married compared to the other groups. They exhibit the highest percentage of blue-collar workers and have the highest probability of default (PD) among all four groups. Gamblers generally differ significantly from the three comparison groups regarding socio-demographics, with significance levels concentrating on 1%. Differently to prior accounts of gambler characteristics, however, gamblers in our sample earn above-average income (Table A.1.A), which does not translate to higher wealth levels (Table A.1.B). In addition, gamblers under-invest in securities and real estate compared to other groups and have significantly higher levels of loan ownership driven primarily by costly short-term debt such as consumer and installment loans (Table A.1.B).

Table 1 presented in Section 3 above highlights that active trading explains lottery stock investing to a larger extent than gambling preferences. Contrary to the notion of lottery stock investors as gamblers on the stock market (see, e.g., Kumar, 2009), active traders as the more active investors in lottery stocks are significantly more wealthy, earn higher income, more likely to work as managers, and have the lowest PD among all groups. Descriptives for gambler-active traders tend to fall somewhere between both groups.

Investment behavior Investment characteristics are of particular interest to this study. Table A.1.C presents, among others, statistics for trading risk classes elicited by the bank.[11] Trading risk is higher among gamblers only compared to the overall sample. Differences to active traders are statistically insignificant, pointing towards a substitution of risky investment activities.

Figure 2 displays the distribution of monthly trades for the gambler compared to the overall, active trader, and gambler-active trader samples, highlighting this concentration of (gambler-)active traders at higher ends of the distribution. This descriptive finding should be interpreted with caution since we condition the sampling of active traders on a high number of monthly trades, thereby introducing these differences mechanically. Nevertheless, the prior literature suggest that excessive trading is present primarily among self-reported gamblers (Dorn and Sengmueller, 2009; Grall-Bronnec et al., 2017; Markiewicz and Weber, 2013; Liao, 2021). Figure 2 highlights that active traders as a non-gambling group might be more prone to excessive trading, which would point towards

[11]Risk classes are assigned by the bank to each investor upon opening a securities account and capture prior trading experience in general and with complex securities in particular. The bank defines a risk profile for each investor based on this information and the investor's self-identified risk appetite. Values range from 1 to 5, where 5 indicates high prior experience and the willingness to invest in riskier assets.

substitution of gambling with investing for active traders. We inspect this notion in more detail in our regression analyses.

[Figure 2 about here]

We compute portfolio turnovers similarly to Dorn and Sengmueller (2009) as one half of the sum of monthly buys and sells divided by end-of-month portfolio values. Figure 3 presents the distribution of the obtained portfolio turnovers for gamblers compared to the overall, active trader, and gambler-active trader samples. Gamblers exhibit the highest portfolio turnovers among all groups at an average monthly turnover of 27.49% (Table A.1.C). Figure 3 also demonstrates visually that gamblers' portfolio turnovers are more concentrated on high ends of the distribution than those of (gambler-)active traders, in line with spillovers between gambling and investing. However, those of the full investor sample are more concentrated on *both* extremely high and extremely low ends compared to gamblers. Higher portfolio turnovers among gamblers would be in line with the prior literature, but the lack of a unambiguous result based on Figure 3 emphasizes the need for a more formal analysis which we present in Section 5.

[Figure 3 about here]

Inching closer to our key question whether gambling and investing in lottery-type stocks are complementary or substitute goods, we next inspect asset participation rates. Next to gamblers generally under-investing (compare Table A.1.B), gamblers have lower participation rates in ordinary stocks, ETFs, and bonds conditional on investing. Active traders, on the other hand, have higher participation rates in certificates as a comparably high-risk investment category, followed by the overall and gambler-active trader groups, with gamblers taking last place. These indicative findings suggest that risk-taking is not unambiguously higher among gamblers.

Next to standard asset classes, lottery and attention stock participation are of particular interest in our analyses. Figure 4 presents distributions of participation in Kumar (2009) skewness and lottery, Bali et al. (2011) lottery, and Bali et al. (2021) attention stocks visually. The graphs show extensive margins of participation in each stock type for gamblers, active traders, and gambler-active traders from on left to right. Orange error bars are based on 95% confidence intervals.

[Figure 4 about here]

The graphs presented in Figure 4 provide further evidence of a substitution mechanism between gambling and investing: Overall, active traders participate most actively in high-skewness, lottery, and attention stocks at the extensive margin and even after conditioning on active trading within gamblers. While a higher percentage of gambler-investors hold Kumar (2009) lottery and high-skewness stocks than in the overall sample, their participation rates are surpassed by far by those of active traders: 17.55% (12.12% and 15.70%) of active traders (gamblers and gambler-active traders) invest in Kumar (2009) lottery, and 42.56% (27.91% and 32.09%) in skewness stocks, with statistically significant differences (Table A.1.C in Appendix A). We find similar results for Bali et al. (2011) lottery and Bali et al. (2021) attention stocks. These investors do not have a need to make money fast, as they are by far the wealthiest and highest-earning group in our sample (compare Tables A.1.A and A.1.B). Therefore, their demand for positively skewed lottery stocks is unlikely to follow from an aspiration for riches. Rather, it is more likely to be driven by the same need that motivates casino gambling, which in turn suggests that lottery or attention stock investing and gambling are perceived as substitutes rather than complements. Nevertheless, we offer a more formal analysis of these findings at the extensive and intensive margins based on regression analyses in the following (Section 5).

5 Results

5.1 Gambling and active investing

Tables 1 and A.1.C, as well as Figure 4 suggest that gamblers are not necessarily the investor group with the highest preference for lottery stocks. Instead, active trading as a behavioral characteristic seems to be more associated with lottery stock participation than gambling preferences. We test this notion in a more formal setting in Tables 3 and 4.

Investor groups In the first set of analyses, we test how lottery and attention stock participation of gamblers, active traders, and investors who belong to both groups differ at the extensive margin. Table 3 presents results from cross-sectional logistic regressions. For each of the outcome variables of interest, we assign the value 1 to all investors who have end-of-month holdings in one or more of these stock types at any time during our sample period between September 1, 2018 and June 30, 2021. These outcome variables are indicator variables for investing participation in Kumar (2009) lottery (columns 1 through 3, Panel A), skewness (4–6, Panel A), Bali et al. (2011) lottery (1–3, Panel B), Bali et al. (2021) attention (4–6, Panel B), and any of the lottery, skewness, or attention stock types (*any*, columns 7–9, Panel B) as defined in Section 2.3. In addition, all regressions are conditional on stock market participation.

Since the dependent variables are time-invariant, we aggregate the data cross-sectionally for each investor. The two main predictor variables of interest are equal to one for gamblers and active traders, respectively, and zero otherwise. All investors, gambler or other, who have an above-median average number of monthly trades over the whole sample period are considered active traders. Columns 3 and 6 in Panel A (3, 6, and 9 of Panel B) additionally include an interaction term for the gambler and active trader indicator variables (gambler-active traders). In these regression specifications, the gambler, active trader, and gambler-active trader groups are non-overlapping to enable robust inferences. All regressions control for demographic information on age, professions, gender, and marital status, average monthly net income levels, as well as median net wealth at the individual-investor level (the sum of wealth held in deposits, savings, and securities less outstanding debt).

[Table 3 about here]

Table 3 highlights that, compared to investors who do not gamble, gamblers have a significantly higher propensity to invest in all of the tested stock types of interest except for Bali et al. (2021) attention stocks (columns 1, 4, and 7). Values range from 1.9% (column 1, Panel A) to 6.4% (column 1, Panel B) higher participation for gamblers compared to non-gamblers (all significant at the 1% level). However, these coefficients are biased downward when estimated only for gamblers compared to other investors: When we distinguish between gamblers, active traders, and other investors, we find statistically significant and much higher coefficients for gamblers (now also for attention stocks, all significant at the 1% level, columns 2, 5, and 8 of Panels A and B). All gambler estimates are surpassed in magnitude by those of active traders, occasionally even by a factor of more than two (compare, e.g., 9.1% [G] and 18.7% [AT] in column 5 of Panel B).

In light of the generally higher propensity of active traders to invest in lottery stocks compared to gamblers, it might be possible that gamblers who invest actively have even higher participation rates. Such a finding would be in line with the spillover hypothesis which suggests that gambling and (day) trading are perceived as complementary activities by investors (Kumar, 2009; Grinblatt and Keloharju, 2009; Dorn and Sengmueller, 2009). However, the estimated participation rates for gamblers, active traders, and gamblers who trade actively (columns 3, 6, and 9 of Table 3) provide evidence to the contrary (i.e., the substitution hypothesis) in that active investing remains the strongest predictor of lottery and attention stock investing compared to both gambling and the interaction of both characteristics. None of the coefficients on the active trader dummy change in magnitude or significance, while those on the gambler dummy remain largely unchanged, with some increasing and some decreasing slightly in size.

Estimates for gambler-active traders, however, are much lower than those for active traders, and roughly the same size as gambler estimates at 15.7% and 9.8% for Bali et al. (2011) lottery and *any* stocks (columns 3 and 9, Panel B), or more than twice as large at 10.7% (Kumar, 2009 lottery stocks, column 3 of Panel A), 14.0% (Kumar, 2009 high-skewness stocks, column 6 of Panel A), or 13.8% (Bali et al., 2021 attention stocks, column 6 of Panel B, all significant at the 1% level). For attention stocks, the gambler coefficient decreases in statistical significance after including the interaction term (from 1% to 10% level, column 6, Panel B).

Transactions In this next set of analyses, we delve further into the inspection of gambling vs. active trading as predictors of lottery stock investing. Compared to Table 3, we use roughly the same methodological setup. Table 4 presents analogous results using roughly the same methodological setup as presented above and in Table 3. This time, however, we replace the indicator variables for gamblers and active traders with standardized Euro amounts of gambling consumption and trading volumes (Panel A), as well as the standardized number of gambling vs. trading transactions (Panel B). Euro amounts and transaction counts are defined as investor averages of annual sums, standardized, and winsorized at the 0.1% level. The presented results again display marginal effects from logistic regressions of participating in Kumar (2009) lottery or skewness, Bali et al. (2011), Bali et al. (2021), or *any* of these stock types.

[Table 4 about here]

Gambling consumption is occasionally and weakly significantly associated with lottery or attention stock investing: For Kumar (2009) lottery and Bali et al. (2021) attention stocks, a one standard deviation increase in the amount spent on gambling leads to an increase in participation by 0.3% and 0.7%, respectively (Panel A of Table 4, significant at the 10% level). For Kumar (2009) lottery stocks, this effect is robust to the inclusion of trading volumes (Panel A, column 2). For Bali et al. (2021) attention stocks, however, it is not. Across all analyzed stock types, the influence of trading volumes by far surpasses that of gambling consumption in terms of magnitude and statistical significance, with coefficients ranging from 4.9% to 22.8% higher participation for an increase in trading volumes by one standard deviation (columns 2, 4, 6, 8, and 10 of Panel A, Table 4, all significant at the 1% level).

We repeat the analysis presented in Panel A of Table 4 for the standardized number of gambling and trading transactions (Panel B). The results are largely similar, however, a one standard deviation increase in gambling transactions is associated with higher likelihoods of investing in Bali et al. (2011) lottery stocks, Bali et al. (2021) attention stocks, or any of the analyzed stock types (0.7%, 1.2%, and 1.1%, significant at the 5%, 1%, and 1% levels, respectively, Table 4, Panel B). Contrary to the analysis of Euro amounts spent on gambling or trading (Panel A), the gambling-transaction coefficients for Bali et al. (2021) and *any* stocks are robust to the inclusion of trading transactions, decreasing only slightly to 1.0% and 0.9%, respectively. The effect for participation in Bali et al. (2011) lottery stocks, however, is not robust to this inclusion. As in Panel A, the number of trading transactions is highly significant across all analyzed stock types, surpassing the effects for gambling transactions by orders of more than seven even in cases where those remain statistically significant after including trading transactions (columns 2, 4, 6, 8, and 10, all significant at the 1% level). Increasing the number of trading transactions by one standard deviation is associated with 3.6% to 7.8% higher likelihoods of investing in lottery or attention stocks.

The results presented in Tables 3 and 4 emphasize that, even after controlling for investor characteristics other than gambling, active trading as a behavioral factor is more influential in predicting lottery stock investing than gambling at the extensive margin, thereby challenging the prevalent notion that gambling preferences drive the demand for lottery stocks (e.g. Kumar, 2009; Bali et al., 2011; Dorn and Sengmueller, 2009) and suggesting a substitution mechanism between trading and gambling. Even when we condition on especially active traders within gamblers, we find that active traders who do not gamble at all still exhibit the highest participation rates across all analyzed lottery, skewness, and attention stock types. Additionally, active trading *within gamblers* is at least as influential as gambling itself in predicting lottery stock investing. These results together suggest that gambling and investing act as substitutes, not as compliments, to satisfy a specific financial desire.

5.2 Lottery stock investing at the intensive margin

We have identified active traders as a group of investors that is more drawn to lottery and attention stocks than gamblers, speaking to a substitution of gambling and investing. Some level of spillover seems to be present, however, it is not unambiguously robust to the inclusion of (active) trading dummies, emphasizing that lottery stock investing is more prevalent among those who do not gamble traditionally *at all*, and not gamblers as the spillover hypothesis would suggest.

We next inspect whether active traders also invest more in such stocks than gamblers at the intensive margin. As a firs graphical exploration of this question, Figures 5, 6, and 7 depict the distribution of Euro portfolio values held in Kumar (2009) lottery and high-skewness, Bali et al. (2011) lottery, and Bali et al. (2021) attention stocks for gamblers (green) overlaid with the respective distribution for the overall sample (light blue, Figure 5), active traders (Figure 6), and gambler-active traders (Figure 7), respectively. To aid readability of the graphs, we truncate values above EUR 10,000 and set them to EUR 10,000. Each distribution displayed is conditional on investing in the respective stock class.

[Figures 5, 6, and 7 about here]

Figures 5, 6, and 6 demonstrate that – again in favor of the substitution hypothesis – the share of gambler-investors is higher (lower) for the low (high) ends of portfolio value distributions compared to both the overall and active trader samples across all stock classes.

To put these indicative findings into perspective, it is important to note that gamblers have significantly lower wealth and income levels compared to active traders (see Tables A.1.A and A.1.B). It is possible that an inspection of portfolio values therefore measures an income effect rather than a preference for lottery and attention-stocks at the intensive margin. However, gambler income levels across categories of permanent income are significantly higher than those of the overall sample (differences statistically significant at the 1% level, Table A.1.A). Therefore, it is unlikely that the results are driven solely by income effects. Nevertheless, we present more formal evidence of the relation of traditional gambling, active investing, and investing in lottery stocks at the intensive margin and controlling for income in Table 5.

[Table 5 about here]

Table 5 presents results for regressions of conditional portfolio values (columns 1 through 3) and portfolio shares (columns 4 through 6) held in Kumar (2009) lottery stocks on the same set of variables and controls we use in the regressions presented in Tables 1, 3 and 4. Since we control for income and wealth levels, the presented results should rule out pure income effects which might be driving the visual results presented in Figures 5, 6, and 7. Table 5 presents results for portfolio values and shares held in Kumar (2009) lottery stocks only. In addition, analogous results for Kumar (2009) skewness, Bali et al. (2011) lottery, and Bali et al. (2021) attention stocks are presented in Table A.3 of the Appendix. We do not present the full set of results in the main text for the sake of brevity and since results across stock types are quantitatively and qualitatively similar.

Conditional on investing in lottery stocks, the difference in lottery stock portfolio holdings between gamblers and non-gamblers is negative but rarely significant. Only after disentangling active traders from gamblers and gambler-active traders (column 3, Table 5) do we find a significant difference of EUR −2,188 for gamblers relative to non-gamblers, active traders, and gambler-active traders (significant at the 10% level). Even after controlling for income, active traders have significantly higher portfolio holdings in Kumar (2009) lottery stocks than gamblers or gambler-active traders (EUR 6,676 and EUR 6,699, column 2 and 3, significant at the 1% level).

Panel B of Table 5 shows analogous results for portfolio weights held in Kumar (2009) lottery stocks. Generally, results are similar as those for portfolio values but with flipped signs, and the gambler dummy coefficient is statistically significant at the 1% level throughout (8.874%, 2.255%, and 15.120% for columns 4, 5, and 6, respectively). The active trader and gambler-active trader coefficients are statistically significant and negative across specifications (1% level, columns 4, 5, and 6). Gambler-active traders, on the other hand, have significantly *lower* portfolio shares devoted to lottery stocks by 7.125% compared to gamblers, active traders, and other investors (significant at the 1% level, column 6).

It is important to note that lottery stocks have empirically lower prices than other stocks. This might affect results for the different trader groups differently, for instance if some groups have generally higher portfolio values than others, as is the case for active traders (see Table A.1.B). Therefore, it is conceivable that the relationship of lottery stock holdings and portfolio sizes is not linear, i.e., portfolio shares are bound to be lower for groups with higher overall portfolio values. This in turn implies that the analysis of portfolio shares devoted to lottery stocks on its own cannot speak to the relevance of gambling preferences in explaining the demand for lottery stocks against the backdrop of these mechanical issues; rather, the results need to be interpreted against the backdrop of the differences in overall portfolio values between the analyzed groups.

The results presented in Table 5 once more emphasize the difference between gamblers and active traders, and thereby provide additional evidence that gambling and trading act as substitutes rather than as complements. Gamblers as a vulnerable group in terms of indebtedness, wealth accumulation, and financial sophistication behave very differently to active traders as primary lottery stock investors. The fact that they overweigh lottery stocks in their portfolios with already-low overall values highlights their differential needs in terms of financial literacy and education.

The results presented in this Section emphasize the importance of using objective measurements for gambling (and arguably other) preferences and inspecting the resulting differences in behavior using equally objective measures, i.e., transaction data. We present evidence from several angles that traditional gambling and investment preferences commonly referred to as gambling on the stock market are less strongly related than previously assumed. In addition, gambling and trading are unambiguously perceived as substitutes rather than complements based on our findings. Therefore, gambling preferences are less relevant in explaining demand for lottery-type instruments than suggested by the prior literature which relies overwhelmingly on self-reported or aggregate measures.

5.3 Neo-brokerage investing

The results so far generally suggest a substitution of gambling and lottery stock investing. As mentioned initially, neo-broker services and their design bear a considerable likeness to gambling, and anecdotal as well as academic evidence points towards a link between gambling and investing with neo-brokerages (Håkansson, 2020; Håkansson et al., 2021; Phillips, 2021; Mühl, 2021; Greenwood et al., 2022).[12] In that sense, inspecting the propensities of gamblers compared to active traders to invest with neo-brokerages provides an additional piece of evidence to answer the question whether gambling and investing are complements or substitutes. If they are complements, we expect gamblers to have significantly higher propensities to invest with neo-brokerages. If they are substitutes, we expect the opposite.

Since we observe trading activity within the scope of our partnering bank, in case gamblers

[12] We additionally analyze participation in 'meme' stocks specifically. Untabulated findings reveal that gamblers in our sample did not hold any of the meme stocks popularized during and after the GameStop trading frenzy during our sample period, whereas 34 of the 33 investors in our sample who invested in such stocks are active traders.

turn to neo-brokerages to invest or gamble in the stock market, our results would be biased towards gambling and trading as substitutes instead of complements. We can rule out this concern by testing whether the analyzed investor groups exhibit heterogeneous demand for neo-brokerage platforms. Table A.1.B highlights that, compared to the average investor, gamblers and active traders tend to invest more with neo-brokerages such as TradeRepublic, the German counterpart to Robinhood, or competitors.

We repeat the analyses presented in Table 3 and estimate marginal propensities to trade with one or more of 14 German and European neo-brokerages for gamblers (column 1), active traders (column 2), and gambler-active traders (column 3). Similarly to the matching of online gambling transactions, we select from the pool of overall investors those who invest with TradeRepublic (the largest German neo-broker), BUX (offered by ABN Amro), flatex, Onvista (offered by Comdirect), CapTrader (offered by JP Morgan), Smartbroker of BNP Paribas S.A., S-Broker of a German regional bank (Sparkasse), xtb, AvaTrade, Plus500, Admiral Markets, Webull, InteractiveBrokers, and eToro. These neo-brokerages comprise traditional banks' application-based offerings but also pure option or crypto currency brokerages such as eToro or Webull. We group investment across neo-brokerages with different customer groups and core business models in the overall neo-broker variable (results presented in columns 1 through 3 of Table 6). Since the demarcation and categorization of neo-brokers, digital currency exchanges, and more traditional online brokerages can be fuzzy, we present a robustness test of the participation with any of the analyzed neo-brokerage platforms for investment with TradeRepublic only (columns 4 through 6). Measuring the use of TradeRepublic with its core and universal investment offerings, comparable in target audience and product portfolio to Robinhood, is the more conservative estimate of neo-brokerage investment. This approach avoids capturing investors who want to trade crypto assets or specialized contracts only.

[Table 6 about here]

Conditional on owning a securities account, Table 6 presents the results from logistic regressions of the propensities to invest in any neo-brokerage (columns 1, 2, and 3) and with TradeRepublic specifically (columns 4, 5, and 6). A considerable portion of the total variance in neo-brokerage (TradeRepulic) participation can be explained with gambling, active trading, the presented demographics, and the included controls of net wealth and annual net income, with pseudo-R^2 of 7.52% (14.15%). Conditional on owning a securities account, 1.91% of all investors use any of the 14 analyzed trading apps, and 0.80% use TradeRepublic. The descriptives presented in Table A.1.B display unconditional sample averages and do not control for demographics, wealth, or income. In contrast to those descriptives, gamblers do not have significantly different propensities to invest in neo-brokerages in this more formal regression setting, although coefficients are positive across specifications 1, 2, and 3 (any neo-broker). For the TradeRepublic analysis, they are zero or negative. Similarly, active traders exhibit positive but largely insignificant marginal effects (significance at the 10% level for any neo-brokerage account in columns 2 and 3). For gambler-active traders, there is no significantly different likelihood to invest using neo-brokerage platforms.

Table 6 presents not only results for gamblers, active traders, and the intersection, but also for the full set of demographic covariates used in our analyses. Intuitively, the propensity to use neo-brokerage platforms decreases with age by 0.8% (0.6% for TradeRepublic) for each 10-year increment (significant at the 1% level). Males are also 1.8% more likely to invest in any neo-brokerage (0.7% for TradeRepublic, all statistically significant at the 1% level). For professions, the base category are regular employees, and the reported coefficients therefore capture differences between the indicated profession and regular employees. Compared to regular employees, civil servants are 1.1% less likely to invest in any neo-brokerage (significant at the 5% level), and investors who are unemployed or for whom employment information is not available are 0.5% (0.4%) less likely to invest in any neo-brokerage (TradeRepublic, all coefficients significant at the 10% level). The difference between married and unmarried investors is consistently negative but statistically insignificant. The difference between regular employees and managers (retirees) is consistently negative, albeit statistically insignificant. Students are 0.3% less likely to invest with TradeRepublic than regular employees (significant at the 10% level). For any neo-brokerage platform, the difference between students and employees is more strongly pronounced but rarely statistically significant (only in column 1, significant at the 10% level). Surprisingly, the difference between blue-collar workers (homemakers) and regular employees is also negative (positive) but not statistically significant.

Based on results presented in Table 6, it seems as though neo-brokerage investment does not follow from a gambling motive or an aspiration-for-riches motive (see the negative and insignificant estimates for blue-collar workers). If anything, the particularly wealth active trader group and regular employees as the typical middle-class investor seem to be more drawn to neo-brokerage platforms. Especially the significant difference found for active traders and any of the analyzed neo-brokerage platforms, as well as the lack of significant differences for gamblers, point once again towards a substitution of risk between gambling-like trading and traditional gambling.

6 Portfolio performance

6.1 Portfolio performance measures

The results presented above suggest that investing in lottery stocks is not tied to gambling preferences at the extent proposed by the prior literature. The behavioral trait of trading actively seems to be much more influential in explaining the demand for lottery-type instruments. Importantly, however, if lottery stock investments are not driven by gambling preferences, they should follow from a different motivation. Two competing drivers are conceivable: First, if investors believe themselves to have an information advantage concerning lottery stocks, they might rationally trade them based on perceived skill. However, this mechanism seems unlikely as it counters the majority of findings from the prior literature. The amplification of demand for lottery stocks which receive high attention might speak to a perceived information advantage of investors in such stocks

(Bali et al., 2021). It is not unambiguously in line with the rational explanation of perceived information advantages, however, since the authors provide evidence that their findings are driven by recency or social biases. Lottery stock investing is not rational, however, if it has a behavioral explanation in that it is driven by well-documented biases such as, e.g., overconfidence, sensation- or entertainment-seeking.

To aid the distinction between these potential mechanisms, we therefore compute and examine annualized portfolio returns and Sharpe ratios to distinguish between the investment performance of gamblers, active traders, and the intersection. We additionally relate investor performance directly to lottery stock investing irrespective of their gambling preference or trading activity.

We estimate annualized and risk-adjusted portfolio returns based on a monthly CAPM and following Balakina et al. (2022), who in turn follow Calvet et al. (2007) to compute returns, return losses, relative Sharpe ratio losses (RSRL), and diversification losses. Balakina et al. (2022) include a comprehensive description of the computation of each metric in their Appendix. Broadly speaking, return losses, RSRL, and diversification losses measure the loss of under-diversification compared to investing in the benchmark index as a more well-diversified portfolio. Since we analyze German investors, we use the DAX performance index as benchmark and the monthly EURIBOR as the risk-free rate. DAX total return series and EURIBOR rates are obtained from Refinitiv Eikon. We compute the portfolio Herfindahl-Hirschman-Index (HHI) and the HHI specifically for equities as two additional measures for under-diversification. Each measure is computed for each investor and month between September 2018 and June 2021, inclusive. We then aggregate by investor and use cross-sectional averages as outcome variables to estimate differences in portfolio performance for gamblers, active traders, attention, and lottery investors.

6.2 Portfolio statistics

Table 7 displays descriptive statistics for CAPM betas, expected portfolio returns and standard deviations based on the CAPM (annualized), Sharpe ratios, RSRL, diversification loss, and portfolio as well as equity HHI for the full sample, gamblers, active traders, and gambler-active traders in columns 1 through 4. Columns 5 through 7 additionally test sample averages for gamblers against those of the full sample (5), active traders (6), and gambler-active traders (7). Column 8 presents the difference and its level of statistical significance for gambler-active traders compared to non-gambling active traders. Market betas, expected portfolio returns, and Sharpe ratios are significantly lower for gamblers than for overall investors and active traders, and for gambler-active traders compared to active traders (all differences statistically significant at the 1% level). The portfolio diversification and loss metrics (RSRL, diversification loss, and both HHI measures) indicate that gamblers (actively trading gamblers) hold significantly less well-diversified portfolios and incur the corresponding diversification losses compared to the overall and active trader samples (compared to active traders, all differences significant at the 1% level).

[Table 7 about here]

It is possible that portfolio performance is driven by demographics, wealth, or income. To disentangle such effects from gambling preferences and demand for lottery stocks, we next present regressions of expected portfolio returns and Sharpe ratios (both in percentage points to enable better readability of coefficients). We regress cross-sectional investor-level averages of both measures on three dummy indicators equal to one for the respective investor sample, controlling for demographics, income, and wealth: gamblers only (columns 1 and 6), gamblers and active traders (columns 2 and 7), gamblers, active traders, and gambler-active traders (columns 3 and 8), gamblers and Kumar (2009) lottery stock investors (columns 4 and 9), and gamblers and lottery stock investors (columns 5 and 10).

Results from these regression are presented in Table 8. Across specifications, gamblers have significantly lower portfolio returns by 0.831% to 1.035% compared to the other investor groups. Analogously, they have significantly lower portfolio Sharpe ratios by 0.00106 to 0.00150 (all coefficients statistically significant at the 1% level). Similarly, gambler-active traders underperform other investors by 0.930% (0.973%) and have 0.00139 (0.00143) lower Sharpe ratios (columns 3, 5, 8, and 9, respectively, all significant at the 1% level). Consistent with our previous findings, active traders, despite the fact that they are primary investors in lottery stocks, achieve significantly higher returns and Sharpe ratios than other investors (0.521% and 0.00072%, respectively, significant at the 1% level). Finally, contrary to the notion that lottery stock investors as gamblers on the stock market underperform other investors, the differences in returns and Sharpe ratios for lottery stock investors are not statistically significant. To test the robustness of our findings to the definition of lottery stocks, we present analogous results to Table 8 using the Bali et al. (2011) definition in Table A.4 in the Appendix. The results are quantitatively and qualitatively equivalent.

[Table 8 about here]

The results presented in Table 8 point once more to the starkly different investment behavior of gamblers compared to lottery stock investors or active traders. Trading mistakes such as excessive portfolio turnovers or under-diversification that entail return losses and lower Sharpe ratios are prevalent only for gamblers, in line with the prior literature on traditional gambling, but not for lottery stock investors or active traders who invest most actively in such assets. This is contrary to the notion that lottery stock investors are gamblers on the stock market and therefore make similar financial mistakes. We argue that this difference in findings is likely caused by the subjective elicitation of gambling preferences using surveys or by relating gambling proxies to lottery stock investing at the aggregate level, both of which are methods prevalent in the prior literature (e.g. Dorn and Sengmueller, 2009; Kumar, 2009; Kumar et al., 2016).

7 Conclusion

In this paper, we leverage large-sample and high-frequency transaction data at the individual investor level to measure gambling preferences directly through betting consumption, and connect this revealed preference to a commonly studied behavioral preference of retail investors for high-skewness or lottery stocks. The gambling preference has been identified as the driver of individual investors for lottery stocks at the aggregate level. Importantly, however, most prior studies rely on survey measures prone to self-reporting bias or on aggregate measures to elicit gambling preferences.

Our analysis can provide a more direct and objective approach to the analysis of the link between gambling preferences and lottery stock investment. We find that gamblers are neither the most active investor group, nor the one most attracted to lottery stocks, high-skewness stocks, or stocks with high media attention. Instead, we find that trading volumes and trading activity are stronger predictors of lottery stock participation and portfolio shares than gambling or the number (volume) of gambling transactions. Based on these findings, we identify a group of especially active traders who do not participate in traditional gambling as more active investors in lottery stock than casino gamblers: In descriptive and formal analyses, we confirm that these investors exhibit higher participation rates in lottery and attention stocks and hold higher conditional portfolio values in lottery stocks. These results provide objective evidence of a substitution effect between traditional gambling and lottery stock investing as gambling on the stock market. Finally, we address one potential concern associated with our study that gambler risk-taking might spill over to neo-brokerage investment instead of investing with the in-house brokerage, which, if left out of our analysis, would bias our inference towards substitution. We formally analyze participation in neo-brokerages for gamblers compared to other investors. Failing to find a significant difference between gamblers and other investors, we are able to rule out this concern. Instead and line with a substitution effect, we find that active traders are significantly more likely to invest with any of the analyzed neo-brokerage platforms. We therefore propose that both the gambler and active trader groups choose different outlets in pursuit of the same need, e.g., a desire for novelty or excitement.

Active traders are not only significantly more likely to invest in lottery stocks than gamblers, but are also wealthier, earn higher income, and their portfolios achieve higher returns and Sharpe ratios. These findings contrast prior accounts of the positive relationship between lower socio-economic status or financial sophistication and gambling on the stock market. Active traders fail to exhibit excessive trading and under-diversification as financial mistakes that have been associated with investing in lottery stocks. Instead, our analyses reveal that lower returns and less favorable portfolio characteristics are only prevalent among gamblers. Adding this to the generally higher (lower) levels of indebtedness (overall wealth) among gamblers, the substitution of gambling on the stock market with traditional gambling seems to be associated with much more detrimental long-term financial outcomes.

The aim of this work is twofold: First, we provide evidence that emphasizes the importance of inspecting objective and granular individual-level data to unambiguously disentangle the drivers of retail investor demand for certain financial instruments. Previous studies on the subject have been invaluable in identifying this demand and its repercussions on investors' financial well-being, but have stopped short of tackling the direct link between the perceived and actual gambling preference in order to establish whether gambling and investing serve as complements or substitutes. Second, we hope to spur a discussion of whether gambling on the stock market can really be characterized as such, or whether it might be more adequate to recognize gambling and investment in lottery-type stocks as two separate methods of satisfying the same need for excitement and novelty – with the important implication that the financial actors undertaking both activities differ starkly in their characteristics and degree of financial sophistication with respect to wealth, behavioral biases, and trading experience. This is especially important when we consider that traditional gambling is predominantly prevalent among those most financially vulnerable, and that any attempts at educating or aiding this and other vulnerable groups should be developed and targeted based on accurate measures of gambling preferences. Imperative to this adequate measurement is a sufficient level of granularity and objectivity of the analyzed data.

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Figures

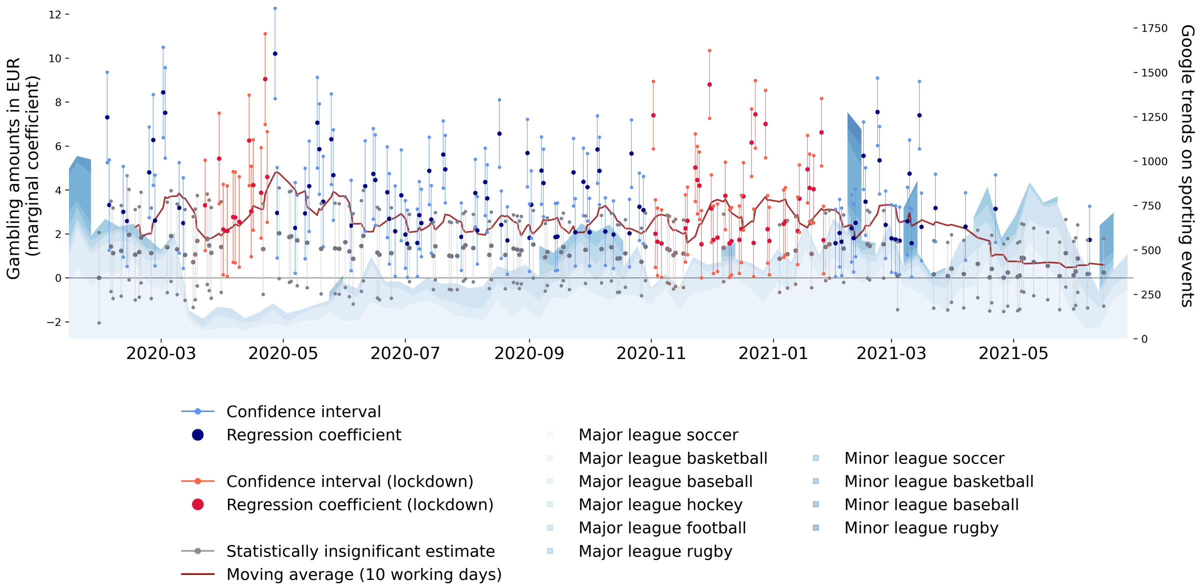

Figure 1 Daily marginal spending on online gambling and interest for sports events

Note. The above figure shows daily marginal gambling activity based on observed gambling transactions of an initial sample of 1,399 starting January 1, 2020, appended with the full sample of 12,783 gamblers for whom we observe gambling transactions between July 1, 2020 and June 30, 2020. Each dot shows the marginal coefficient relative to the base date, January 1, 2020, and vertical lines show the error bars. Grey dots and bars denote coefficients which are not statistically significantly different from zero. Blue coefficients and error bars indicate statistically significant estimates, and red dots with orange error bars indicate significant estimates during periods of national Covid-19 containment measures, i.e., lockdowns. The secondary right-hand axis refers to the area chart in the background of the figure, which presents weekly Google search volumes for national and international major sports leagues. The sports leagues chart indicates whether there is public interest in sports events, and suggests lower awareness of sporting events to bet on during the first wave of Covid-19 infections and subsequent event cancellations.

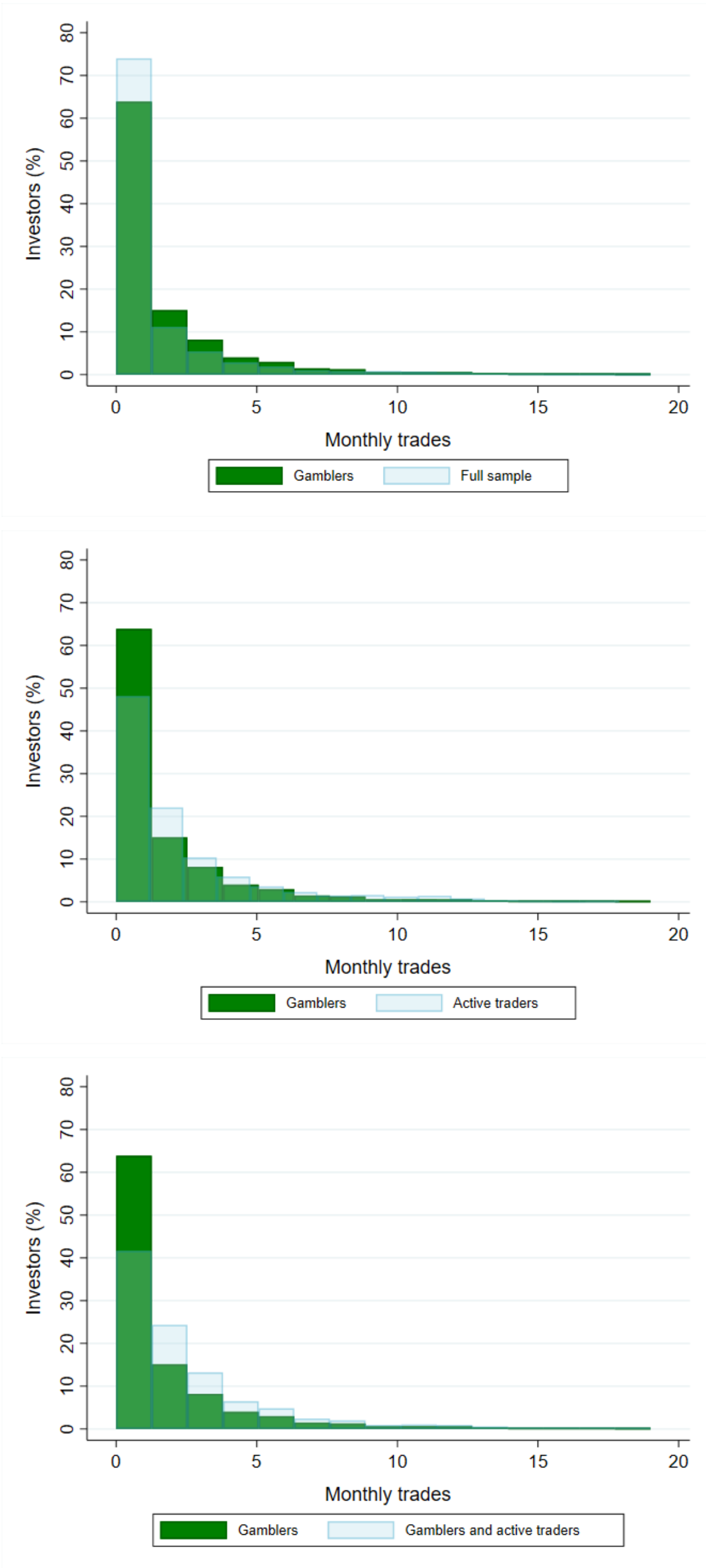

Figure 2 Distribution of monthly trades

Note. The two figures above show the distribution of the number monthly trades for gamblers compared to the overall sample (top), active traders (middle), and to gamblers who are also active traders (bottom). Green bars present the distribution for gamblers, which is overlaid by transparent blue bars for the distribution of the respective comparison group (overall sample, active traders, or gambler-active traders).

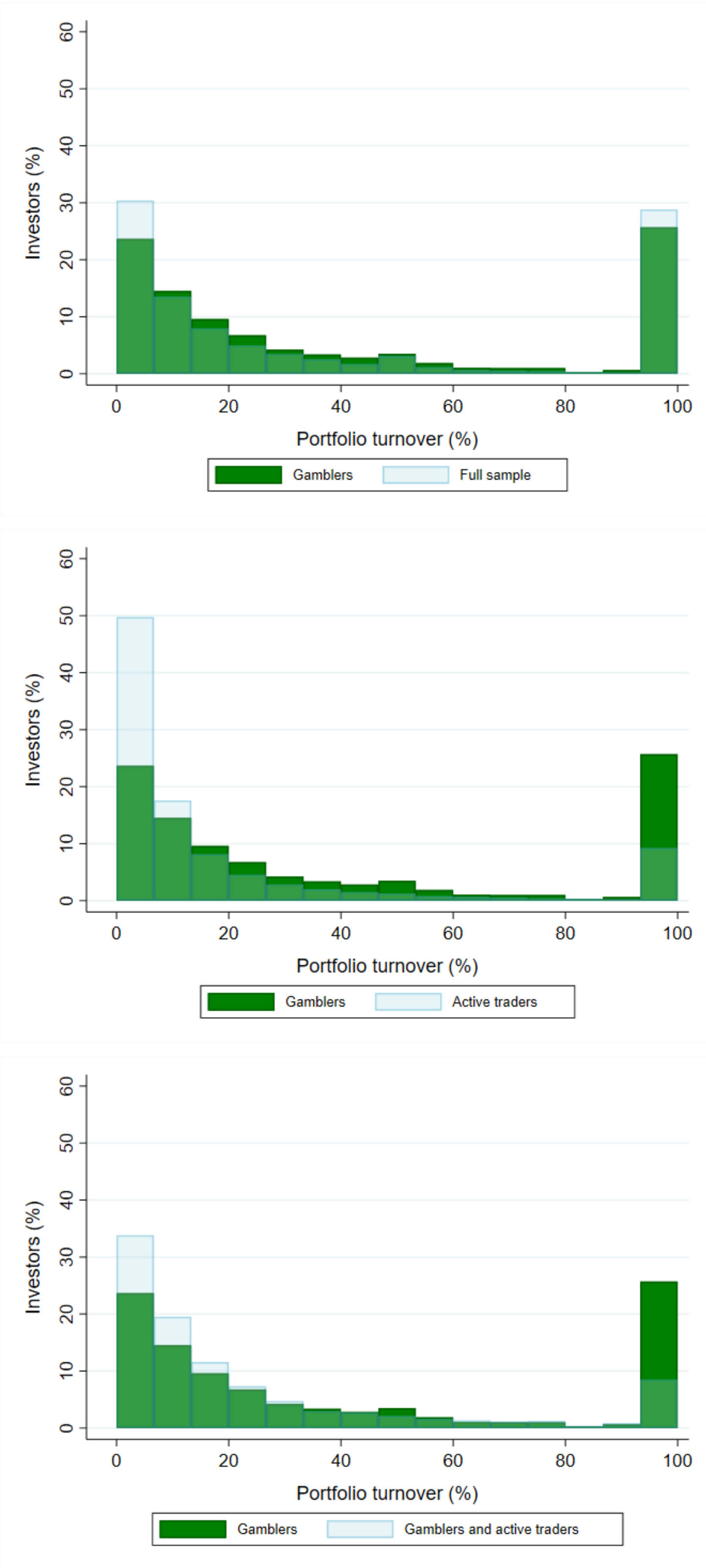

Figure 3 Distribution of portfolio turnover

Note. The two figures above show the distribution of portfolio turnovers for gamblers compared to the overall sample (top), active traders (middle), and to gamblers who are also active traders (bottom). Green bars present the distribution for gamblers, which is overlaid by transparent blue bars for the distribution of the respective comparison group (overall sample, active traders, or gambler-active traders). Turnovers are computed following Dorn and Sengmueller (2009), and values larger than 100% are truncated.

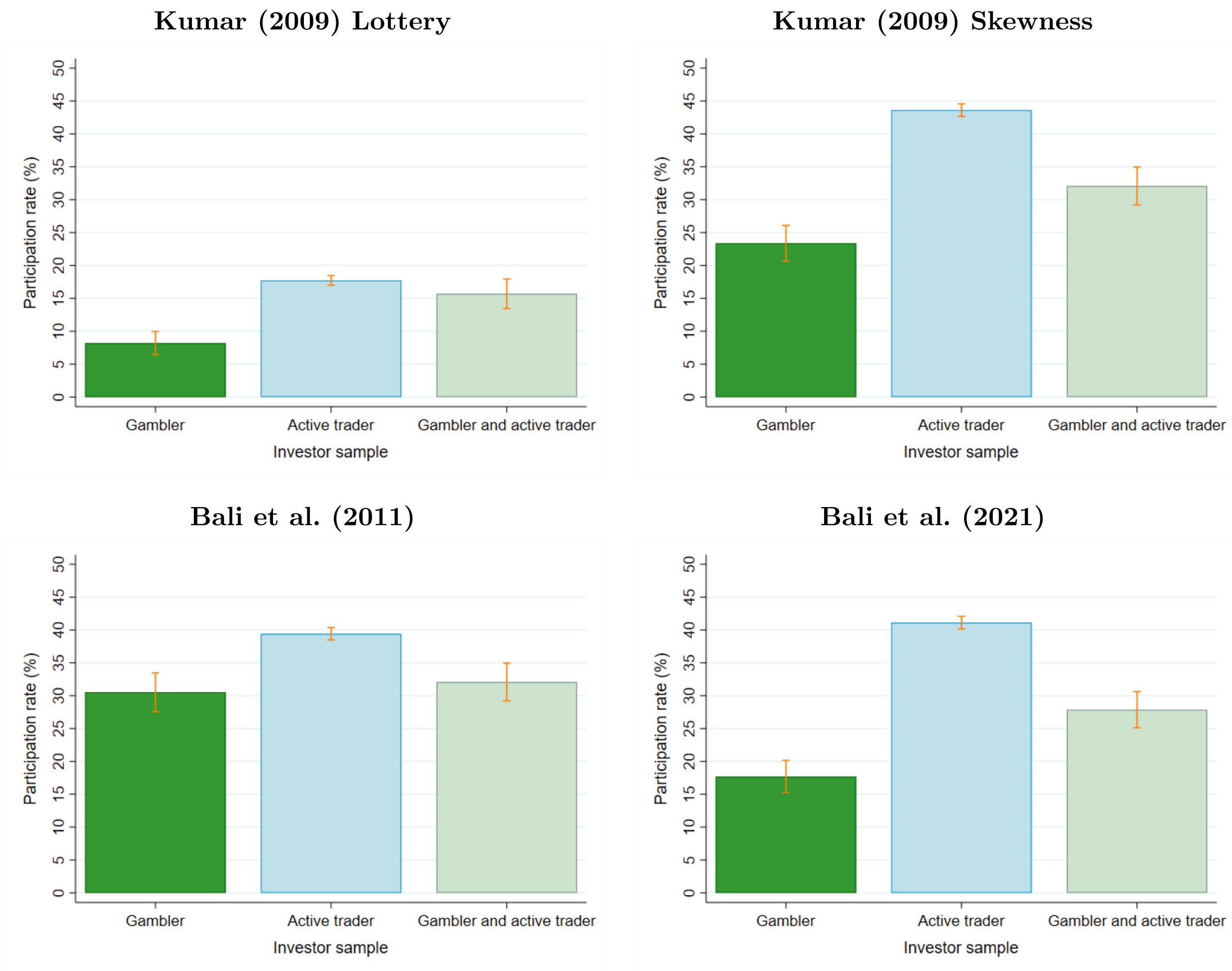

Figure 4 Participation rates in security type

Note. The above figures show average and 95% confidence intervals for participation rates in Kumar (2009) high-skewness and lottery, Bali et al. (2011) lottery, and Bali et al. (2021) high-media attention stocks. The respective labels for each stock are assigned following Kumar (2009), Bali et al. (2011), and Bali et al. (2021). We describe the assignment of stock labels in more detail in Section 2.3.

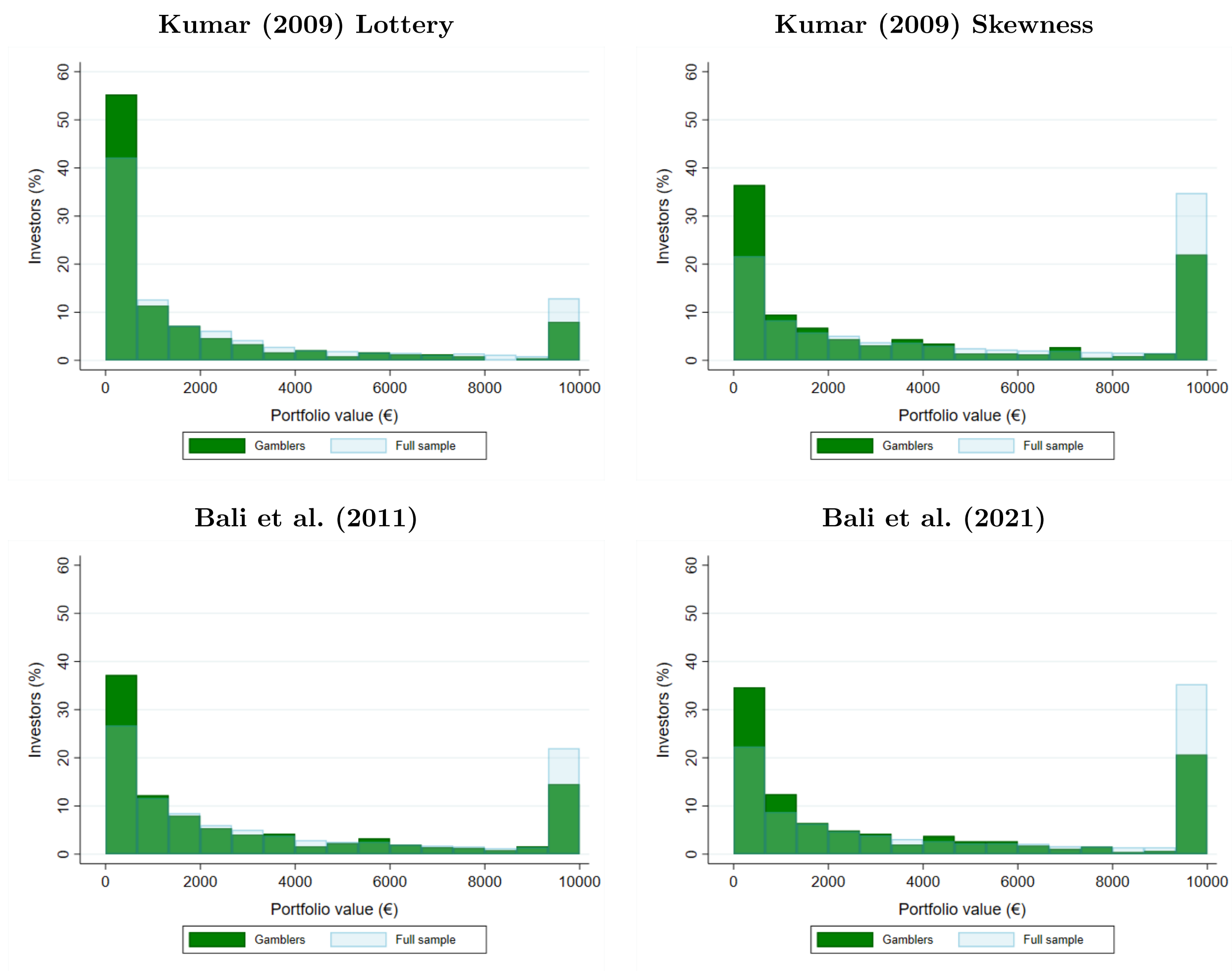

Figure 5 Distribution of portfolio value by security type: Overall sample

Note. The above figures show the distribution of portfolio values held in Kumar (2009) high-skewness and lottery, Bali et al. (2011) lottery, and Bali et al. (2021) high-media attention stocks. The respective labels for each stock are assigned following Kumar (2009), Bali et al. (2011), and Bali et al. (2021). We describe the assignment of stock labels in more detail in Section 2.3. Green bars present the distribution for gamblers, which is overlaid by transparent blue bars for the overall investor sample.

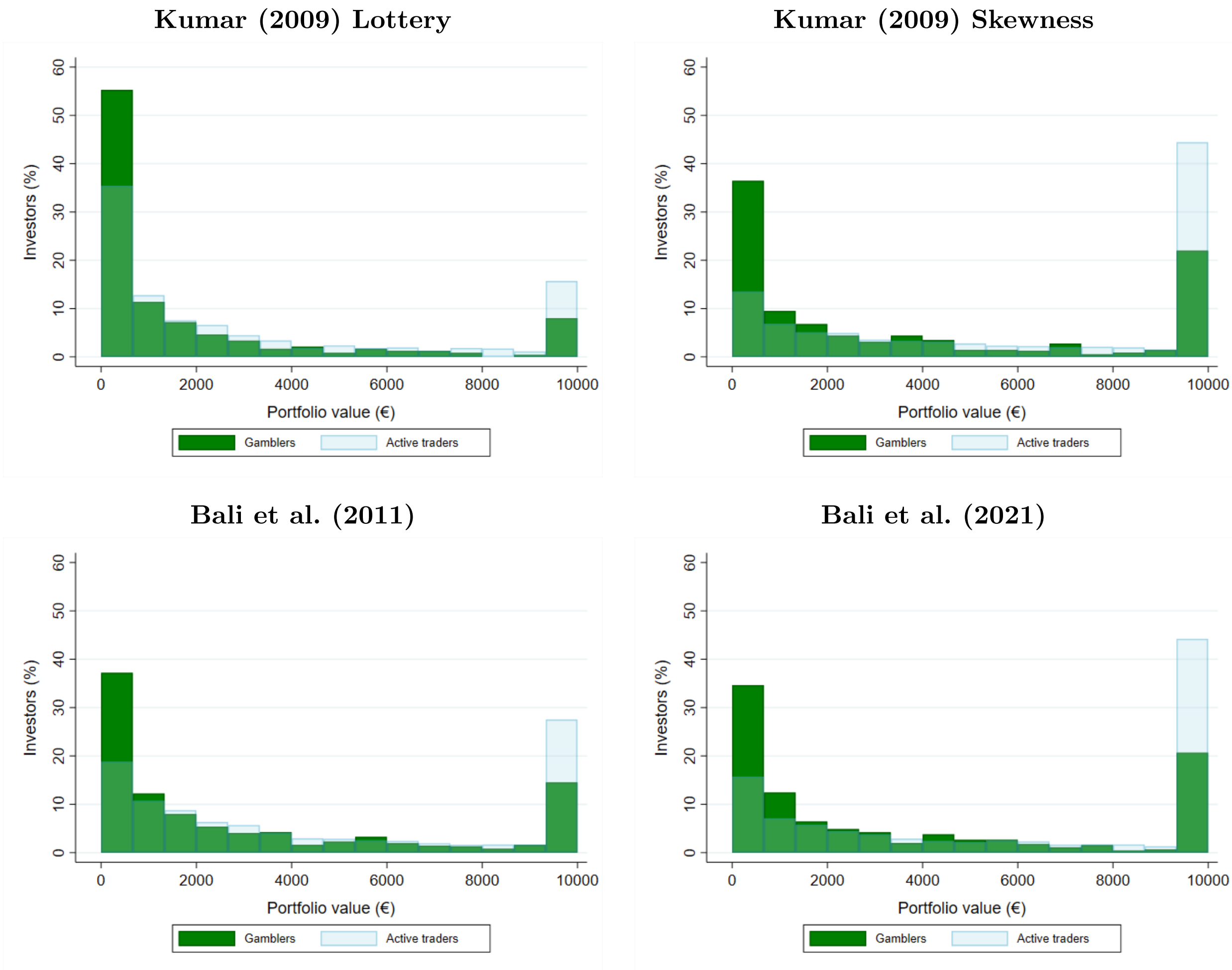

Figure 6 Distribution of portfolio value by security type: Active traders

Note. The above figures show the distribution of portfolio values held in Kumar (2009) high-skewness and lottery, Bali et al. (2011) lottery, and Bali et al. (2021) high-media attention stocks. The respective labels for each stock are assigned following Kumar (2009), Bali et al. (2011), and Bali et al. (2021). We describe the assignment of stock labels in more detail in Section 2.3. Green bars present the distribution for gamblers, which is overlaid by transparent blue bars for the active trader sample.

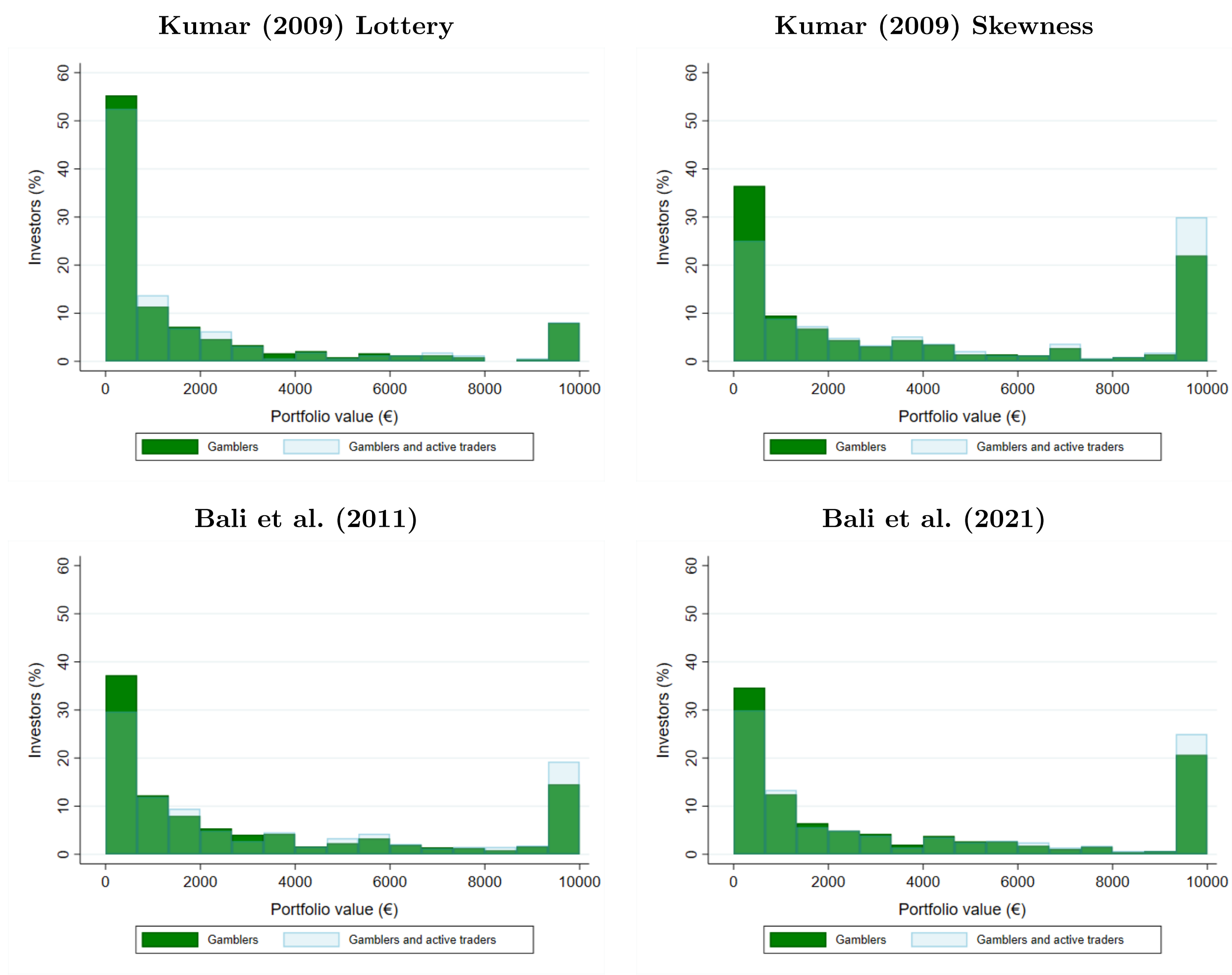

Figure 7 Distribution of portfolio value by security type: Gambler-active traders

Note. The above figures show the distribution of portfolio values held in Kumar (2009) high-skewness and lottery, Bali et al. (2011) lottery, and Bali et al. (2021) high-media attention stocks. The respective labels for each stock are assigned following Kumar (2009), Bali et al. (2011), and Bali et al. (2021). We describe the assignment of stock labels in more detail in Section 2.3. Green bars present the distribution for gamblers, which is overlaid by transparent blue bars for gamblers who are also active traders.

Tables

Table 1 Determinants of lottery stock investing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Participation					PF weight		
			$Pr(Y=1)$					(%)		
Gambler	0.022*** (0.006)	0.019** (0.007)	0.014* (0.006)	0.008 (0.006)	0.005 (0.006)	0.437* (0.191)	0.234 (0.205)	0.126 (0.204)	0.107 (0.205)	0.096 (0.206)
PF turnover (%)			0.004** (0.001)	0.006*** (0.001)	0.006*** (0.001)			0.182* (0.075)	0.199** (0.074)	0.203** (0.073)
PF value (std)			0.015*** (0.003)	0.030*** (0.003)	0.023*** (0.003)			0.091 (0.061)	0.163** (0.059)	0.149* (0.060)
Certificate part.			0.025*** (0.006)	0.036*** (0.005)	0.033*** (0.005)			-0.067 (0.074)	-0.020 (0.069)	-0.026 (0.069)
Active fund part.			0.122** (0.045)	0.098 (0.058)	0.123* (0.054)			1.462 (1.204)	1.366 (1.225)	1.435 (1.221)
Passive fund part.			-0.067*** (0.004)	-0.087*** (0.004)	-0.105*** (0.004)			-1.738*** (0.133)	-1.784*** (0.133)	-1.814*** (0.134)
Trading volume (std)			0.043*** (0.002)					0.198*** (0.053)		
No. of trades (std)				0.037*** (0.001)					0.121*** (0.029)	
Above-median number of trades					0.128*** (0.004)					0.291*** (0.076)
Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Pseudo-R^2/ $R^2_{adj.}$ (%)	0.06	2.81	11.06	11.39	13.24	0.03	0.28	1.82	1.79	1.81
Average (%)	9.90	9.90	9.90	9.90	9.90	0.75	0.75	0.75	0.75	0.75
Observations	28,152	28,152	28,152	28,152	28,152	28,152	28,152	28,152	28,152	28,152

Note. The above table presents results for regressions of Kumar (2009) lottery stock participation rates and portfolio weights. Estimates of participation rates are based on logistic regressions, and columns 1 through 5 present the resulting marginal effects, whereas portfolio weight regressions are based on OLS models and the displayed coefficients in columns 6 through 10 are given in percentage points. All variables with note *std* are standardized to have zero means and standard deviations of one. Columns 1 and 6 regress on a gambler dummy which is equal to one for gamblers and zero otherwise. Columns 2 and 7 add controls following Kumar (2009). These controls specifically include professions, marital status, age, and gender, as well as average monthly income and net wealth (both winsorized at the 0.1% level). Since we observe gambling preferences objectively and at the individual level, there is no need to include aggregate gambling proxies of religious and ethnic composition as suggested by Kumar (2009). In columns 3 through 5 and 8 through 10, we additionally include a set of portfolio and trading variables as independent variables, respectively. Robust standard errors are presented underneath coefficients in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% level (***).

Table 2 Gambling transactions

	Mean	P25	Median	P75	Min.	Max.	Std. Dev.	Obs.
	Transaction-level amounts (€)							
Bets	65.85	11.00	25.00	55.00	0.44	5,600.00	155.48	91,339
Wins	225.90	13.40	45.80	185.53	0.04	8,217.00	566.03	6,856
	Monthly bets and wins (€)							
Bets	151.04	22.10	50.00	105.85	0.45	16,850.00	478.08	39,820
Wins	334.87	17.50	55.00	220.00	0.04	16,413.47	963.71	4,625
Gamblers	12,783							

Note. The above table presents distributions of conditional Euro amounts bet and won gambling at the transaction and monthly level. We obtain gambling consumption by matching investor transactions to eleven German and European online casinos and sports betting platforms. These betting providers are *bet365*, *interwetten*, *bwin*, *tipico*, *William Hill*, a German online lottery provider, as well as the Austrian, Swiss, German, U.S.-American, and international subsidiaries of *bet-at-home*. We observe gambling transactions between July 1, 2020 and June 30, 2021 due to a regulary restriction that prohibits exact matching at the transaction level for a longer period than 13 consecutive months (PSD2).

Table 3 Lottery stock investment: Gambling and active investing

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)
	Kumar (2009)					
	Lottery			Skewness		
Gambler	0.019** (0.007)	0.082*** (0.007)	0.046*** (0.011)	0.015 (0.010)	0.112*** (0.010)	0.079*** (0.014)
Active trader		0.118*** (0.004)	0.118*** (0.004)		0.211*** (0.005)	0.211*** (0.005)
Gambler · active trader			0.107*** (0.008)			0.140*** (0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2 (%)	2.81	8.27	8.42	6.33	11.53	11.57
Average (%)	9.90	9.90	9.90	26.65	26.65	26.65
Observations	28,152	28,152	28,152	28,152	28,152	28,152

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Bali et al. (2011)			Bali et al. (2021)					
	Lottery			Attention			Any		
Gambler	0.064*** (0.009)	0.156*** (0.009)	0.154*** (0.012)	0.006 (0.010)	0.091*** (0.010)	0.037* (0.015)	0.038*** (0.011)	0.114*** (0.011)	0.131*** (0.015)
Active trader		0.204*** (0.005)	0.204*** (0.005)		0.187*** (0.005)	0.187*** (0.005)		0.187*** (0.005)	0.187*** (0.005)
Gambler · active trader			0.157*** (0.012)			0.138*** (0.012)			0.098*** (0.014)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2 (%)	4.65	9.80	9.80	6.92	11.17	11.27	5.54	8.43	8.43
Average (%)	24.44	24.44	24.44	25.51	25.51	25.51	35.92	35.92	35.92
Observations	28,152	28,152	28,152	28,152	28,152	28,152	28,152	28,152	28,152

Note. The above table presents results for logistic regressions of investment in Kumar (2009) lottery and high-skewness stocks, Bali et al. (2021) lottery, and Bali et al. (2021) attention stocks on three main variables of interest, which indicate whether investors are gamblers, active traders, or both. Columns titled *Any* present results for investment in any of the four stock types of interest, i.e., either of the Kumar (2009) lottery or skewness, Bali et al. (2011) lottery, or Bali et al. (2021) attention stocks. Controls include demographics (profession, age, gender, marital status), monthly income (average), and net wealth (median). Robust standard errors are presented underneath coefficients in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% level (***).

Table 4 Lottery stock investment: Number and volume of transactions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Kumar (2009)				Bali et al. (2011)		Bali et al. (2021)			
	Lottery		Skewness		Lottery		Attention		Any	
Panel A: Amounts										
Gambling amount	0.003*	0.003*	0.004	0.003	0.005	0.004	0.007*	0.005	0.005	0.004
	(0.001)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Trading amount		0.049***		0.192***		0.162***		0.166***		0.228***
		(0.002)		(0.007)		(0.006)		(0.005)		(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2 (%)	2.80	9.00	6.33	14.07	6.93	13.41	4.53	12.28	5.52	11.19
Average (%)	9.90	9.90	26.65	26.65	25.51	25.51	24.44	24.44	35.92	35.92
Observations	28,152	28,152	28,152	28,152	28,152	28,152	28,152	28,152	28,152	28,152
Panel B: Number of transactions										
Gambling transactions	0.003*	0.002	0.003	0.001	0.007**	0.005	0.012***	0.010***	0.011***	0.009**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Trading transactions		0.036***		0.078***		0.072***		0.075***		0.074***
		(0.001)		(0.003)		(0.003)		(0.003)		(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2 (%)	2.78	7.30	6.33	9.67	6.94	10.06	4.59	8.14	5.55	7.43
Average (%)	9.90	9.90	26.65	26.65	25.51	25.51	24.44	24.44	35.92	35.92
Observations	28,152	28,152	28,152	28,152	28,152	28,152	28,152	28,152	28,152	28,152

Note. The above table presents results for logistic regressions of investment in Kumar (2009) lottery and high-skewness stocks, Bali et al. (2021) lottery, and Bali et al. (2021) attention stocks on transaction amounts spent on gambling and investing (Panel A) as well as the number of gambling and trading transactions (Panel B). Amounts and transactions are defined as individual-investor averages of annual sums, standardized, and winsorized at the 0.1% level. Coefficients therefore show decimal changes in propensities to invest for a one standard deviation change in betting and trading amounts (number of transactions), respectively. Columns titled *Any* present results for investment in any of the four stock types of interest, i.e., either of the Kumar (2009) lottery or skewness, Bali et al. (2011) lottery, or Bali et al. (2021) attention stocks. Controls include demographics (profession, age, gender, marital status), monthly income (average), and net wealth (median). Robust standard errors are presented underneath coefficients in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% level (***).

Table 5 Portfolio holdings at the intensive margin

	(1)	(2)	(3)	(4)	(5)	(6)
	Portfolio value			Portfolio weight		
Gambler	-1.908	1.621	-2.188*	8.874***	4.225**	15.120***
	(1.638)	(1.604)	(1.057)	(1.388)	(1.458)	(2.150)
Active trader		6.676***	6.699***		-9.153***	-9.294***
		(0.982)	(0.982)		(0.596)	(0.596)
Gambler · active trader			5.619*			-7.215***
			(2.784)			(1.485)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
PF size	No	No	No	Yes	Yes	Yes
$R^2_{adj.}$ (%)	39.27	39.50	39.52	9.10	11.11	12.17
Average (%)	25.24	25.24	25.24	25.09	25.09	25.09
Observations	10,112	10,112	10,112	10,112	10,112	10,112

Note. The above table presents results for regressions of portfolio shares (in percent) and portfolio values (in thsd. EUR) on two main variables, which indicate whether investors are gamblers, active traders, or both (interaction). Portfolio holdings are computed as the sum of investments (weights) in any of the four stock types of interest, i.e., either of the Kumar (2009) lottery or skewness, Bali et al. (2011) lottery, or Bali et al. (2021) attention stocks. All regressions present results at the intensive margin, i.e., conditional on investing in the respective stock type of interest. Controls include demographics (profession, age, gender, marital status), monthly income (average), and net wealth (median). Models with indicated *PF size* additionally control for total investor portfolio size. Robust standard errors are presented underneath coefficients in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% level (***).

Table 6 Neo-brokerage investment

	(1)	(2)	(3)	(4)	(5)	(6)
	Neo-broker			TradeRepublic		
Gambler	0.002	0.003	0.003	-0.001	-0.000	0.000
	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)
Active trader		0.004^{*}	0.004^{*}		0.001	0.001
		(0.002)	(0.002)		(0.001)	(0.001)
Gambler · active trader			0.004			-0.001
			(0.003)			(0.002)
Age (10Y)	-0.008^{***}	-0.008^{***}	-0.008^{***}	-0.006^{***}	-0.006^{***}	-0.006^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Male	0.018^{***}	0.018^{***}	0.018^{***}	0.007^{***}	0.007^{***}	0.007^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Married	-0.002	-0.002	-0.002	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Manager	-0.002	-0.002	-0.002	-0.006	-0.006	-0.006
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
Civil servant	-0.011^{**}	-0.011^{**}	-0.011^{**}	-0.004	-0.004	-0.004
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Blue-collar worker	-0.005	-0.005	-0.005	-0.004	-0.004	-0.004
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Homemaker	0.003	0.003	0.003			
	(0.017)	(0.017)	(0.017)			
Unemployed or N/A	-0.005^{*}	-0.005^{*}	-0.005^{*}	-0.004^{**}	-0.004^{**}	-0.004^{**}
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Student	-0.006^{*}	-0.005	-0.005	-0.003^{*}	-0.003^{*}	-0.003^{*}
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Retired	-0.002	-0.001	-0.001	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2 (%)	7.52	7.62	7.62	14.10	14.15	14.15
Average (%)	1.91	1.91	1.91	0.80	0.80	0.80
Observations	28,152	28,152	28,152	27,903	27,903	27,903

Note. The above table presents results for logistic regressions of investment in neo-brokerage accounts and at TradeRepublic specifically on a set of demographic indicators at the individual-investor level and two main variables of interest, which indicate whether investors are gamblers or active traders. Controls include monthly income (average) and net wealth (median). Robust standard errors are presented underneath coefficients in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% level (***).

Table 7 Portfolio performance statistics

	(1) S	(2) G	(3) AT	(4) GAT	(5) G – S	(6) G – AT	(7) G – GAT	(8) GAT – AT
Market beta	0.372	0.308	0.378	0.304	-0.064***	-0.067***	0.008	-0.082***
	(0.299)	(0.357)	(0.243)	(0.344)	[-7.631]	[-5.338]	[0.480]	[-7.348]
Expected PF return (investor)	0.057	0.048	0.058	0.047	-0.010***	-0.010***	0.001	-0.012***
	(0.042)	(0.050)	(0.035)	(0.048)	[-8.186]	[-5.511]	[0.615]	[-7.781]
Portfolio standard deviation	0.190	0.158	0.194	0.156	-0.033***	-0.034***	0.004	-0.042***
	(0.155)	(0.185)	(0.126)	(0.178)	[-7.573]	[-5.317]	[0.467]	[-7.301]
Sharpe ratio (investor)	0.297	0.295	0.297	0.295	-0.001***	-0.001***	0.000	-0.002***
	(0.006)	(0.007)	(0.005)	(0.007)	[-7.996]	[-5.457]	[0.566]	[-7.636]
RSRL (CCS 2007)	0.046	0.050	0.045	0.050	0.004***	0.005***	-0.001	0.006***
	(0.020)	(0.024)	(0.016)	(0.023)	[7.996]	[5.457]	[-0.566]	[7.636]
Diversification loss (CCS 2007)	0.048	0.054	0.048	0.054	0.005***	0.005***	-0.001	0.007***
	(0.025)	(0.030)	(0.020)	(0.029)	[7.342]	[5.232]	[-0.419]	[7.114]
HHI	0.230	0.316	0.124	0.168	0.087***	0.354***	0.310***	0.049***
	(0.338)	(0.372)	(0.206)	(0.241)	[9.878]	[25.265]	[19.547]	[6.124]
HHI (equity)	0.317	0.362	0.232	0.211	0.044***	0.293***	0.313***	-0.022**
	(0.385)	(0.402)	(0.307)	(0.312)	[4.664]	[20.397]	[18.221]	[-2.170]
Observations	26,439	1,905	11,106	992	28,344	12,019	1,905	11,106

Note. This table presents summary statistics for portfolio performance measures. We compute market betas, expected portfolio returns, and standard deviations based on a CAPM following Balakina (2022). Relative Sharpe ratio loss (RSRL) and diversification loss are computed following Calvet et al. (2007) as described in Balakina (2022). The Herfindahl-Hirschman-Index (HHI) refers to the sum of squared weights of all securities held in each investor portfolio at the monthly level and is a measure for portfolio diversification, where higher values of HHI indicate lower diversification. Diversification loss and relative Sharpe ratio loss measure losses from under-diversification compared to the well-diversified market portfolio. We use the DAX performance index as a benchmark, and the monthly EURIBOR as the risk-free rate. All statistics are computed at the investor-month level between September 1, 2018 and June 30, 2021 and averaged across months for each investor. Subsequently, we average across investor groups. Columns 1 through 4 present statistics for the overall sample (S), gamblers (G), active traders (AT), as well as the intersection (gamblers and active traders, GAT). Columns 5, 6, 7, and 8 test the difference between sample averages of gamblers against those of the overall sample (G–S), active traders (G–T), and gambler-active traders (G–GAT) using Welch's unequal variances t-test. Standard errors of sample averages are presented in brackets underneath estimates, and t-statistics for differences are presented in square brackets. Asterisks indicate statistical significance of these differences at the 10% (*), 5% (**), and 1% level (***).

Table 8 Portfolio quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Return					Sharpe ratio		
Unit	%	%	%	%	%	%	%	%	%	%
Gambler	-1.035***	-0.831***	-0.735***	-1.035***		-0.150***	-0.122***	-0.106***	-0.150***	
	(0.152)	(0.155)	(0.204)	(0.152)		(0.021)	(0.021)	(0.028)	(0.021)	
Active trader		0.521***	0.521***				0.072***	0.072***		
		(0.054)	(0.054)				(0.007)	(0.007)		
Gambler · active trader			-0.930***		-0.973***			-0.139***		-0.143***
			(0.190)		(0.184)			(0.026)		(0.025)
Lottery stock investor				-0.003	0.005				-0.005	-0.004
				(0.073)	(0.073)				(0.010)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$R^2_{adj.}$ (%)	0.52	0.80	0.80	0.52	0.41	0.66	0.93	0.94	0.65	0.53
Average (%)	5.43	5.43	5.43	5.43	5.43	29.68	29.68	29.68	29.68	29.68
Observations	27,841	27,841	27,841	27,841	27,841	27,841	27,841	27,841	27,841	27,841

Note. The above table presents results for cross-sectional regressions of annualized investor portfolio returns (log) and Sharpe ratios on indicator variables which are equal to one for gamblers, active traders, and Kumar (2009) lottery stock investors, and zero otherwise. Controls include demographic information on age, gender, marital status, and occupation, as well as average monthly income and median net wealth. Robust standard errors in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% level (***).

Appendix

Table A.1.A Socio-demographics

	(1) S	(2) G	(3) AT	(4) GAT	(5) G – S	(6) G – AT	(7) G – GAT	(8) GAT – AT
				Panel A: Demographics				
Male	53.44	77.77	67.18	83.48	24.32***	10.08***	-6.21***	17.95***
Age	43.34	38.85	50.94	40.07	-4.49***	-12.20***	-1.33***	-11.97***
Married	34.05	26.18	42.92	24.25	-7.87***	-16.58***	2.09	-20.56***
Employee	37.13	36.17	39.74	44.25	-0.96**	-4.29***	-8.80***	4.97***
Industr. worker	10.22	12.20	3.67	7.54	1.98***	8.93***	5.07***	4.26***
Civil servant	1.48	1.71	2.96	3.09	0.23*	-1.37***	-1.50***	0.14
Manager	0.97	0.84	2.96	1.35	-0.13	-2.17***	-0.56	-1.77***
Student	12.37	20.02	4.71	8.50	7.65***	16.32***	12.53***	4.17***
Retired	5.87	4.20	10.97	3.38	-1.66***	-6.70***	0.89	-8.36***
Unemployed	6.54	2.62	0.87	0.19	-3.92***	1.96***	2.64***	-0.75***
Prob. of default	0.97	1.29	0.36	0.72	0.32***	0.98***	0.62***	0.40***
Micro status	5.97	5.70	7.18	6.49	-0.27***	-1.55***	-0.86***	-0.75***
Years with bank	12.82	13.47	15.77	13.26	0.65***	-2.28***	0.23	-2.77***
N	166,376	12,783	11,246	1,035	179,159	22,994	12,783	11,246
				Panel B: Income				
Regular & trans. inc.	1,753.98	1,965.41	3,520.16	3,225.53	211.43***	-1,690.51***	-1,395.89***	-334.79**
P50	1,233.55	1,405.31	2,551.90	2,225.71				
Salary	1,657.20	1,836.04	3,245.52	2,974.40	178.83***	-1,532.61***	-1,261.50***	-310.25**
P50	1,202.57	1,356.61	2,411.73	2,062.31				
Perm. income	1,690.07	1,895.76	3,330.03	3,070.26	205.68***	-1,560.82***	-1,301.04***	-295.19**
P50	1,194.91	1,366.46	2,430.28	2,098.54				
Trans. income	68.91	70.38	153.28	118.75	1.47	-89.15***	-54.62***	-39.38***
P50	10.50	16.15	51.74	45.56				
N	126,655	6,580	5,334	640	133,235	11,274	6,580	5,334

Note. The above table presents summary statistics for demographic information on investor age, marital status, gender, occupation, micro status, length of the bank-client relationship, and income. All statistics are computed at the investor-month level between September 1, 2018 and June 30, 2021 and averaged across months for each investor. Subsequently, we average across investor groups. Columns 1 through 4 present statistics for the overall sample (S), matched gambler controls (C), gamblers (G), and active traders (T). Columns 5, 6, and 7 test the difference between sample averages of gamblers against those of the overall sample (G–S), matched controls (G–C), and active traders (G–T) using Welch's unequal variances t-test. Asterisks indicate statistical significance of these differences at the 10% (*), 5% (**), and 1% level (***).

Table A.1.B Financial assets

	(1) S	(2) G	(3) AT	(4) GAT	(5) G – S	(6) G – AT	(7) G – GAT	(8) GAT – AT
Net wealth (k€)	22.17	11.10	195.10	70.53	-11.08***	-189.24***	-64.67***	-137.20***
P50	1.33	1.23	59.23	10.13				
Deposits (k€)	13.67	11.16	48.12	29.14	-2.51***	-38.54***	-19.56***	-20.90***
P50	1.87	1.84	13.09	6.24				
Securities acct. (%)	16.11	15.70	100.00	100.00	-0.41	-91.73***	-91.73***	0.00
P50	0.00	0.00	100.00	100.00				
Neo-broker account (%)	1.15	2.71	2.27	4.54	1.57***	0.29	-1.99***	2.50***
P50	0.00	0.00	0.00	0.00				
TradeRepublic account (%)	0.54	1.75	0.92	2.03	1.21***	0.81***	-0.30	1.23***
P50	0.00	0.00	0.00	0.00				
Other neo-broker acccount	0.61	0.96	1.35	2.51	0.35***	-0.53***	-1.69***	1.28**
P50	0.00	0.00	0.00	0.00				
Sec. acct. bal. (k€)	16.09	5.51	154.45	49.35	-10.58***	-152.81***	-47.71***	-115.75***
P50	0.00	0.00	37.76	3.78				
Loan (%)	48.20	55.17	35.20	52.46	6.97***	20.20***	2.94*	19.01***
P50	0.00	100.00	0.00	100.00				
Installment loan (%)	10.84	12.60	7.62	11.59	1.76***	5.07***	1.10	4.38***
P50	0.00	0.00	0.00	0.00				
Property loan (%)	4.63	3.04	6.18	6.09	-1.59***	-3.41***	-3.32***	-0.10
P50	0.00	0.00	0.00	0.00				
Loan amount (k€)	8.13	6.33	11.28	10.25	-1.81***	-5.30***	-4.26***	-1.14
P50	0.00	0.00	0.00	0.00				
N	166,376	12,783	11,246	1,035	179,159	22,994	12,783	11,246

Note. The above table presents summary statistics for ownership of financial products (securities accounts; any, TradeRepublic, and other accounts on neo-brokerage platforms; loan types), and for net wealth, wealth held in deposits, securities accounts, and loans. All statistics are computed at the investor-month level between September 1, 2018 and June 30, 2021 and averaged across months for each investor. Subsequently, we average across investor groups. Columns 1 through 4 present statistics for the overall sample (S), matched gambler controls (C), gamblers (G), and active traders (T). Columns 5, 6, and 7 test the difference between sample averages of gamblers against those of the overall sample (G–S), matched controls (G–C), and active traders (G–T) using Welch's unequal variances t-test. Asterisks indicate statistical significance of these differences at the 10% (*), 5% (**), and 1% level (***).

Table A.1.C Trading and investment

	(1) S	(2) G	(3) AT	(4) GAT	(5) G – S	(6) G – AT	(7) G – GAT	(8) GAT – AT
					Panel A: Portfolio statistics			
Trading								
Online broker acct. (%)	22.07	25.85	26.71	24.15	3.79***	1.90	4.46**	-2.82**
P50	0.00	0.00	0.00	0.00				
Risk class	4.33	4.41	4.37	4.45	0.09***	-0.01	-0.09	0.08**
P50	5.00	5.00	5.00	5.00				
Monthly trades (#)	1.63	2.16	3.18	3.37	0.53***	-1.02***	-0.19***	0.21
P50	0.41	0.82	1.41	1.59				
Volumes (€, win. 1.5%)								
Transaction	4,438.52	3,045.72	7,424.55	4,529.97	-1,392.80***	-6,794.23***	-3,899.66***	-3,187.97***
P50	1,094.11	287.76	2,488.08	421.31				
Buy	2,422.35	1,615.66	4,034.07	2,399.15	-806.69***	-3,693.43***	-2,058.51***	-1,800.64***
P50	604.18	146.00	1,487.39	239.31				
Sell	1,725.49	1,286.85	2,928.15	1,928.24	-438.64***	-2,685.07***	-1,685.16***	-1,101.26***
P50	288.23	82.85	753.41	140.96				
Portfolio turnover (%, win 1%)								
Monthly mean	19.74	27.49	15.75	24.62	7.74***	16.41***	7.54***	9.77***
P50	7.90	13.10	5.51	11.15				
N	21,050	1,671	11,246	1,035	22,721	11,882	1,671	11,246
					Panel B: Participation rates (%)			
Asset classes								
Ordinary stock	55.58	54.45	59.72	43.87	-1.13	6.24***	22.09***	-17.44***
Bond	8.72	2.86	13.13	3.73	-5.85***	-11.20***	-1.81**	-10.34***
Certificate	12.03	4.35	19.11	6.28	-7.69***	-16.87***	-4.04***	-14.11***
ETF	21.12	14.57	40.85	21.59	-6.55***	-33.91***	-14.65***	-21.19***
Other (asset type not in Eikon)	38.63	42.54	57.96	59.18	3.90***	-33.52***	-34.74***	1.34
Lottery and attention stocks								
Upper skew	26.55	27.91	42.56	32.09	1.36	-19.18***	-8.72***	-11.52***
Lottery stock (Kumar, 2009)	9.73	12.12	17.55	15.70	2.39***	-9.33***	-7.48***	-2.03*
Lottery stock (Bali et al., 2011)	23.92	31.34	38.76	32.09	7.42***	-8.24***	-1.57	-7.34***
Attention stock (Bali et al., 2019)	25.70	23.01	39.91	27.87	-2.69***	-22.19***	-10.15***	-13.24***
N	26,196	1,956	11,169	1,019	28,152	12,106	1,956	11,169

Note. The above table presents summary statistics for trading risk classes, online brokerage ownership, the number of monthly trades, trading volumes, portfolio turnovers, as well as asset participation rates. Portfolio turnovers are computed following Dorn and Sengmueller (2009), and lottery, skewness, and attention stock labels are assigned as described in Section 2.3, following Kumar (2009), Bali et al. (2011), and Bali et al. (2021). All statistics are computed at the investor-month level between September 1, 2018 and June 30, 2021 and averaged across months for each investor. Subsequently, we average across investor groups. Columns 1 through 4 present statistics for the overall sample (S), matched gambler controls (C), gamblers (G), and active traders (T). Columns 5, 6, and 7 test the difference between sample averages of gamblers against those of the overall sample (G–S), matched controls (G–C), and active traders (G–T) using Welch's unequal variances t-test. Asterisks indicate statistical significance of these differences at the 10% (*), 5% (**), and 1% level (***).

Table A.2 Determinants of lottery stock investing: Bali et al. (2011) definition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Participation					PF weight		
			$Pr(Y = 1)$					(%)		
Gambler	0.069***	0.064***	0.057***	0.044***	0.036***	5.623***	4.676***	4.077***	4.024***	3.959***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.565)	(0.593)	(0.561)	(0.564)	(0.566)
PF turnover (%)			0.008***	0.017***	0.017***			0.910***	1.002***	1.012***
			(0.002)	(0.002)	(0.002)			(0.149)	(0.147)	(0.147)
PF value (std)			0.023***	0.074***	0.062***			-0.054	0.326**	0.254*
			(0.005)	(0.005)	(0.004)			(0.121)	(0.111)	(0.112)
Certificate part.			0.082***	0.123***	0.114***			-0.711***	-0.429**	-0.480***
			(0.008)	(0.007)	(0.007)			(0.145)	(0.139)	(0.141)
Active fund part.			0.068	0.016	0.066			2.145*	1.731	1.991
			(0.066)	(0.081)	(0.070)			(0.965)	(1.113)	(1.068)
Passive fund part.			-0.151***	-0.182***	-0.213***			-8.880***	-9.051***	-9.201***
			(0.005)	(0.005)	(0.005)			(0.302)	(0.300)	(0.299)
Trading volume (std)			0.149***					0.956***		
			(0.006)					(0.107)		
No. of trades (std)				0.076***					0.416***	
				(0.003)					(0.061)	
Above-median number of trades					0.212***					1.198***
					(0.005)					(0.164)
Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Pseudo-R^2/ $R^2_{adj.}$ (%)	0.16	4.65	15.58	13.99	16.07	0.88	1.52	8.93	8.77	8.83
Average (%)	24.44	24.44	24.44	24.44	24.44	3.76	3.76	3.76	3.76	3.76
Observations	28,152	28,152	28,152	28,152	28,152	28,152	28,152	28,152	28,152	28,152

Note. The above table presents results for regressions of Bali et al. (2011) lottery stock participation rates and portfolio weights. Estimates of participation rates are based on logistic regressions, and columns 1 through 5 present the resulting marginal effects, whereas portfolio weight regressions are based on OLS models and the displayed coefficients in columns 6 through 10 are given in percentage points. All variables with note *std* are standardized to have zero means and standard deviations of one. Columns 1 and 6 regress on a gambler dummy which is equal to one for gamblers and zero otherwise. Columns 2 and 7 add controls following Kumar (2009). These controls specifically include professions, marital status, age, and gender, as well as average monthly income and net wealth (both winsorized at the 0.1% level). Since we observe gambling preferences objectively and at the individual level, there is no need to include aggregate gambling proxies of religious and ethnic composition as suggested by Kumar (2009). In columns 3 through 5 and 8 through 10, we additionally include a set of portfolio and trading variables as independent variables, respectively. Robust standard errors are presented underneath coefficients in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% level (***).

Table A.3 Portfolio holdings at the intensive margin

	Panel A											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Lottery						Skewness					
	PF value			PF weight			PF value			PF weight		
Gambler	-1.135	-0.076	0.456	0.073	-5.880***	5.189	-0.991	1.755	-2.146*	4.202**	-1.045	8.604***
	(0.893)	(0.904)	(1.077)	(1.463)	(1.740)	(3.646)	(1.417)	(1.415)	(0.874)	(1.388)	(1.493)	(2.591)
Active trader		1.513**	1.511**		-8.698***	-8.768***		4.481***	4.495***		-8.822***	-8.897***
		(0.499)	(0.499)		(1.006)	(1.006)		(0.793)	(0.793)		(0.662)	(0.662)
Gambler · active trader			-0.350			-11.587***			4.545*			-7.950***
			(1.075)			(1.283)			(2.161)			(1.388)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PF size	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
$R^2_{adj.}$ (%)	14.08	14.26	14.23	4.47	8.48	9.98	29.76	29.96	30.00	8.60	11.04	11.78
Average (%)	5.55	5.55	5.55	8.60	8.60	8.60	17.82	17.82	17.82	17.93	17.93	17.93
Observations	2,786	2,786	2,786	2,786	2,786	2,786	7,502	7,502	7,502	7,502	7,502	7,502

	Panel B											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Lottery						Attention					
	PF value			PF weight			PF value			PF weight		
Gambler	-0.859	0.585	-1.465*	10.803***	4.093*	18.605***	-2.462*	-1.757	-2.523*	1.615	-3.919**	7.542**
	(0.855)	(0.841)	(0.578)	(1.538)	(1.662)	(2.572)	(1.157)	(1.204)	(1.010)	(1.219)	(1.326)	(2.620)
Active trader		2.389***	2.399***		-11.494***	-11.668***		1.149	1.152		-9.378***	-9.477***
		(0.491)	(0.491)		(0.733)	(0.733)		(0.747)	(0.747)		(0.559)	(0.559)
Gambler · active trader			2.495			-9.432***			-1.278			-11.089***
			(1.366)			(1.400)			(1.633)			(1.031)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PF size	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
$R^2_{adj.}$ (%)	13.49	13.71	13.77	10.86	14.44	16.87	36.30	36.32	36.31	4.97	9.25	10.44
Average (%)	9.14	9.14	9.14	16.53	16.53	16.53	16.33	16.33	16.33	12.95	12.95	12.95
Observations	6,879	6,879	6,879	6,879	6,879	6,879	7,182	7,182	7,182	7,182	7,182	7,182

Note. The above table presents results for regressions of portfolio shares (in percent) and portfolio values (in thsd. EUR) held in Kumar (2009) lottery and high-skewness (Panel A), Bali et al. (2011) lottery, and Bali et al. (2021) attention stocks (Panel B) on two main variables of interest, which indicate whether investors are gamblers, active traders, or both (interaction). All regressions present results at the intensive margin, i.e., conditional on investing in the respective stock type of interest. Controls include demographics (profession, age, gender, marital status), monthly income (average), and net wealth (median). Models with indicated *PF size* additionally control for total investor portfolio size. Robust standard errors are presented underneath coefficients in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% level (***).

Table A.4 Portfolio quality: Bali et al. (2011) lottery stocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Return					Sharpe ratio				
Unit	%	%	%	%	%	%	%	%	%	%
Gambler	-1.035***	-0.831***	-0.735***	-1.040***		-0.150***	-0.122***	-0.106***	-0.151***	
	(0.152)	(0.155)	(0.204)	(0.152)		(0.021)	(0.021)	(0.028)	(0.021)	
Active trader		0.521***	0.521***				0.072***	0.072***		
		(0.054)	(0.054)				(0.007)	(0.007)		
Gambler · active trader			-0.930***		-0.976***			-0.139***		-0.144***
			(0.190)		(0.184)			(0.026)		(0.025)
Lottery stock investor				0.092	0.084				0.008	0.007
				(0.055)	(0.055)				(0.008)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$R^2_{adj.}$ (%)	0.52	0.80	0.80	0.53	0.41	0.66	0.93	0.94	0.66	0.53
Average (%)	5.43	5.43	5.43	5.43	5.43	29.68	29.68	29.68	29.68	29.68
Observations	27,841	27,841	27,841	27,841	27,841	27,841	27,841	27,841	27,841	27,841

Note. The above table presents results for cross-sectional regressions of annualized investor portfolio returns (log) and Sharpe ratios on indicator variables which are equal to one for gamblers, active traders, and Kumar (2009) lottery stock investors, and zero otherwise. Controls include demographic information on age, gender, marital status, and occupation, as well as average monthly income and median net wealth. Robust standard errors in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% level (***).

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