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Talking About Stocks: Pathways into Financial Engagement

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Abstract

Before anyone buys a stock, they start paying attention. Where does that attention come from? We follow 6.8 million Reddit users across thousands of communities and reconstruct what each was talking about in the year before their first post about stocks. They arrive along distinct routes: from budgeting and retirement forums, from economics and politics, from crypto, and from gambling. The route stays visible in the language and stated motive of the first post, and in the securities that follow. Savers concentrate on index funds, crypto entrants on bitcoin proxies, gamblers on sportsbooks and casinos. Entry is uneven over time, and months of high uncertainty change who arrives more than how many. Composition appears to predict market reactions: gambling-dominated episodes show larger price and volume responses than saver-dominated ones. That difference is selection, not price impact. Three observable security characteristics absorb much of it, volatility above all, and it vanishes when the same company is compared with itself. Where people come from shapes what they look at, not how the market answers.

Keywords: retail investors, attention, uncertainty, social finance, Reddit, online communities

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1 Introduction

Household-finance research explains differences in stock-market participation through participation costs, information frictions, background risk, ambiguity, trust, financial literacy, advice, and social interactions (Haliassos and Bertaut, 1995; Vissing-Jørgensen, 2002; Campbell, 2006; Guiso et al., 2008; Guiso and Jappelli, 2005; van Rooij et al., 2011). That work begins with people who already hold accounts or make investment decisions, and it explains why they differ from one another. But before anyone opens a brokerage account or buys a stock, they must first begin paying attention to financial markets, seeking information, weighing potential investments, and talking with others about what they might do. This earlier stage is difficult to observe, because surveys and administrative records capture decisions rather than the process that leads to them, leaving the formation of financial interest largely outside the evidence base.

Reddit makes this stage visible. We use a public archive covering roughly 40,000 subreddits from June 2005 through July 2026, and we identify 6.8 million users whose first contribution to a stock-market subreddit falls between January 2015 and July 2026. Because the same accounts participate across thousands of communities, we can reconstruct what a user discussed in the year before they first said anything about stocks, giving us a view of the interests from which financial engagement emerges. We define entry as a user's first observed contribution to one of these stock-market communities. This is not a measure of stock ownership, since we do not observe whether a contributor invests or trades, but writing a post or comment is an active choice, and users enter a financial community to ask a question, seek advice, interpret an event, express a view, or respond to others. Public discussion therefore occupies a useful middle ground between passive attention, as measured by searches or browsing, and financial action, as measured by trading or portfolio choice (Barber and Odean, 2008; Da et al., 2011).

We use these histories to address three related questions. Which interests lead users into stock-market discussion? Under what conditions do different kinds of users enter? And does it matter for markets which kinds of users enter, or only which securities they attend to? The last of these admits two answers that are not easy to separate ex ante, since the path into markets could plausibly shape how strongly a person responds to a given security, or shape only which securities that person attends to in the first place.

Our answers are as follows. Users arrive along distinct routes that are visible a year before they say anything about stocks, and those routes remain legible in the language and the intent of their first posts. Entry is highly uneven over time, and periods in which markets become newly salient change the composition of who enters rather than only the number of entrants. And the route a user took matters for markets through which securities draw their attention, not through how markets respond to any given security.

We measure a user's route with the composition of their pre-entry activity. For each entrant we compare their activity shares across subreddit categories during the twelve months before entry with the contemporaneous Reddit-wide shares, and we assign the user the finance-adjacent category in which their excess activity is largest, standardizing the comparison to avoid favoring categories merely because they are large on the platform. This yields nine types, *Politics and News*, *Personal Finance*, *Productivity and Career*, *Home and Housing*, *Crypto*, *Economics*, *Law and Legal*, *Non-Stock Investing*, and *Gambling*, together with two residual groups for users whose prior activity is too sparse to classify or too diffuse to concentrate in any finance-adjacent category.

Future entrants are unusually active in finance-adjacent topics well before their first stock-market contribution, and this concentration rises steadily as entry approaches, making entry the culmination of a broader shift in attention rather than an isolated first post. Comparing entrants with otherwise active users who have not yet entered, we find that prior activity in *Non-Stock Investing*, *Economics*, *Personal Finance*, and *Crypto* predicts entry in the following month, while most non-financial categories carry small or negative associations.

The types capture differences that persist into what users say when they arrive. *Personal Finance* types are especially likely to use portfolio and household-investing language and to ask questions, *Economics* and *Politics and News* entrants use more economic and political language, *Crypto* entrants use more crypto vocabulary, and *Gambling* entrants use more terms related to trading and speculation. Annotating a sample of 100,000 first posts with a large language model, using a codebook that distinguishes learning, advice seeking, personal financial decisions, implementation problems, investment evaluation, event interpretation, view sharing, and social participation, we find that *Personal Finance* entrants more often seek advice and discuss personal decisions, while *Economics* and *Politics and News* entrants more often interpret external events. The types also predict which securities users discuss once they arrive, with *Personal Finance* entrants concentrating on broad-market index funds, *Crypto* entrants on bitcoin proxies such as MicroStrategy, and *Gambling* entrants on sportsbooks and casinos, an association 27.5 times what independence would produce. Because the types are assigned from pre-entry activity alone and carry no market information, misclassification can only weaken that association, making the figure a lower bound.

Entry into stock-market discussion varies sharply over time. The largest surge occurs during the GameStop episode in early 2021, with smaller increases around other periods in which markets became especially salient or volatile, including the Brexit referendum, the onset of the COVID-19 pandemic, and the period following Donald Trump's 2024 election and subsequent tariff announcements. Different types respond to different episodes, with *Gambling* entry concentrated in the speculative environment of early 2021 and *Economics* entry rising during the macroeconomic and policy episodes of 2020 and 2025.

We show that about 17 percent more users enter in months with unusually high economic policy uncertainty. This aggregate relationship masks important differences across user types. Users with prior interests in *Politics and News*, and to a lesser extent *Economics*, are especially likely to enter during high-uncertainty months. Taken together, the results suggest that stock-market discussion often provides a place to seek information, advice, or interaction with others interested in markets. Periods of heightened uncertainty appear to draw in particular users whose prior attention already lies in *Economics* and politics, when events make financial markets newly salient.

We then ask what this heterogeneity means for markets. Identifying episodes in which a security is discussed unusually heavily, and measuring returns and trading volume around them, we find that larger episodes go with larger absolute abnormal returns, higher abnormal volume, and mild subsequent reversal. Composition predicts these reactions as well, with episodes dominated by *Gambling* entrants showing larger absolute abnormal returns than episodes dominated by *Personal Finance* entrants, a gap of about half the sample mean.

Strikingly, none of this reflects how markets respond to a given company. Three observable security characteristics, and return volatility above all, account for two thirds of that gap on their own, and it disappears entirely once we compare episodes within the same security. Entry types do not react differently to the same company. They attend to different companies, and those companies differ in volatility, so the link from who enters to what happens in markets runs through where attention is directed.

Two objections deserve a direct answer. The first is that the types are an argmax over a standardized score, and that such a rule can manufacture apparent separation when categories differ in size on the platform. Near ties are uncommon, with the share of users whose top two scores differ by less than half a standard unit running from 1.1 percent to 7.6 percent across types, and the labels are stable, since splitting each user's pre-entry history at random into two halves and classifying each half separately yields agreement for 88.8 percent of users who receive a substantive label in both halves. Because each half uses only half of the available history, that figure understates the reliability of the labels we use.

The second objection is that our central market result is a null estimated on a constructed regressor, and that the within-security specification removes the variation common to a security, which is the part most likely to be signal, raising the possibility that the disappearance of the composition effect is mechanical rather than economic. We address this by instrumenting one composition measure with the other, using the two independent classifications just described, which cover the same authors over the same event windows and differ only in the labels they assign. The instrumented within-security estimate is -0.0034, with a confidence interval that excludes the across-security estimate, and correcting for measurement error moves the coefficient by less than fifteen percent.

Our analysis speaks first to the literature on household participation in financial markets (Mankiw and Zeldes, 1991; Haliassos and Bertaut, 1995; Vissing-Jørgensen, 2002; Hong et al., 2004; Campbell, 2006; van Rooij et al., 2011; Brown et al., 2008; Fagereng et al., 2017; Giannetti and Wang, 2016; Duraj et al., 2025), which explains why households differ in whether and how they invest, but which takes as its starting point people who already own stocks or hold brokerage accounts. We observe a margin that comes earlier, following users before their first public engagement with the stock market, and we show that this margin resolves into several distinct routes through which financial markets enter people's attention.

Second, the paper connects to work on investor attention and social finance, in which attention, social interactions, communication, and narratives shape investor beliefs and behavior (Barber and Odean, 2008; Da et al., 2011; Hirshleifer, 2020; Shiller, 2019; Kuchler and Stroebel, 2021). Studies using social-media data have examined sentiment, disagreement, information transmission, and behavior among users already active in financial communities (Tumarkin and Whitelaw, 2001; Antweiler and Frank, 2004; Bollen et al., 2011; Chen et al., 2014; Sprenger et al., 2014; Bartov et al., 2018; Cookson and Niessner, 2020; Giannini et al., 2019; Cookson et al., 2023, 2024), and related work documents attention-induced trading among retail brokerage users (**?**). We shift the object of study from communication within these communities to selection into them, which Reddit's multi-community structure makes observable.

Third, we show that the information environment is related not only to how many users enter financial discussion, but also to who enters. Aggregate measures of searches, social-media activity, or trading capture changes in attention, yet they cannot reveal the prior interests of the people behind those changes. Following the same users across Reddit communities makes this compositional margin visible, and our time-series evidence shows that episodes of uncertainty draw users into stock-market discussion who differ systematically from those who enter in ordinary months.

Finally, we connect the composition of entry to market outcomes. A large literature relates social-media activity to prices, volume, and retail trading (Antweiler and Frank, 2004; Chen et al., 2014; Cookson et al., 2023, 2024), taking the membership of a financial community as given and studying what its members say. We show that this membership is itself systematic, and that it maps onto the securities the community discusses. Our results also caution against reading compositional shifts as differences in price impact, since holding the security fixed the mix of entry types carries no information about the market reaction, a finding that survives correcting the composition measure for classification error.

Section 2 describes the data. Section 3 studies users' interests before they engage with stock-market discussions and defines user types. Section 4 examines the timing of entry. Section 5 connects entry types to market outcomes. Section 6 concludes.

2 Data

2.1 Reddit Archive and User Histories

We use a public archive of 26,121,553,873 comments and submissions posted to the 40,000 largest subreddits between June 2005 and July 2026 (Watchful1, 2026), a source that prior work has used to study social organization, user life cycles, movement across communities, and specific financial episodes.[1] For each contribution the archive records the public username, subreddit, timestamp, available text and a unique identifier, and we refer to comments and submissions jointly as posts, linking them over time by username.

Reddit's organization into topic-specific communities is the main advantage of the data for our setting, since the platform hosts stock-market forums alongside communities devoted to *Personal Finance*, *Economics*, politics, entertainment, local issues, and thousands of unrelated topics. The same account can participate in all of them. We can therefore reconstruct what users discussed elsewhere on Reddit before their first contribution to a stock-market community, observing a transition that would be unobservable in data collected only within financial forums such as StockTwits. Appendix A illustrates the platform's structure.

The main analysis covers users who entered a stock-market subreddit between January 2015 and July 2026. We nevertheless use all available pre-2015 activity to determine whether a contribution is a user's first observed stock-market post, preventing accounts already active before the window opens from being counted as new entrants. Stock-market activity before 2015 accounts for 5.3% of all stock-market posts in the archive.

2.2 Subreddit Taxonomy and Stock-Market Entry

To impose some structure on the data, we assign each of the 40,000 subreddits to one of 38 mutually exclusive categories, building on *r/ListOfSubreddits*.[2] The categories most relevant

[1] See Baumgartner et al. (2020); Waller and Anderson (2021); Hamilton et al. (2017); Zhang et al. (2017); Kumar et al. (2018); Semenova and Winkler (2021); Anand and Pathak (2022); Warkulat and Pelster (2024).

[2] https://www.reddit.com/r/ListOfSubreddits/wiki/listofsubreddits/

to our analysis are Stock Market, *Personal Finance*, *Economics*, *Crypto*, *Non-Stock Investing*, *Gambling*, *Politics and News*, *Productivity and Career*, *Law and Legal*, and *Home and Housing*. We refer to them as finance related or adjacent because they capture activity that has a direct relationship with the stock market (*Personal Finance*, *Economics*), represents relevant behavior (*Gambling*) or is related to a person's other financial decisions (*Productivity and Career*, *Law and Legal*, *Home and Housing*).

Each post inherits the category assigned to its subreddit, giving us a measure of participation in communities rather than of isolated references to stocks elsewhere on Reddit. A mention of a company in a general news forum does not count as stock-market participation, while a contribution to a stock-market subreddit does.

We use GPT-5.6 Luna to assign each subreddit to a category, giving the model the subreddit's name, the full taxonomy, the subreddit's self-description, and the title and text of eight randomly sampled submissions. It assigns exactly one category and reports a confidence score between zero and one. The final taxonomy includes all 40,000 subreddits, of which 320 are classified as Stock Market, and these communities account for 0.98% of all posts in the archive.

We assess the taxonomy against independent annotations of a fixed random sample of 250 subreddits, where GPT-5.6 Luna's agreement with the human annotator is substantial (Cohen's $\kappa = 0.734$) and the mean pairwise agreement across the human annotator and four language models is 0.795. Appendix B reports the full prompt, Table 12 lists category counts, post shares, and confidence scores, and Appendix E.3 describes the validation exercise.

We define entry as a user's first observed contribution to any of the 320 stock-market subreddits, and because the definition uses the full available history, each account has at most one first entry even if it later participates in several stock-market communities. The resulting ledger contains 6,804,621 users whose first observed entry occurs between January 2015 and July 2026. Entry therefore measures the beginning of public engagement with stock-market discussions on Reddit, not a user's first exposure to financial information or the date on which the user first invests.

2.3 Market Data and Security Mentions

We measure market outcomes with daily closing prices and trading volumes from LSEG, covering 5,686 securities between January 2015 and December 2025 in a panel of 10.7 million security-day observations. We compute daily returns from closing prices and benchmark abnormal returns against the daily factor returns of Fama and French (1993) over the same period.

Market coverage ends in December 2025, while the Reddit archive runs through July 2026. The analyses of entry and its timing in Sections 3 and 4 therefore use the full Reddit window, while the market analysis in Section 5 covers January 2015 to December 2025.

We also build a panel of security mentions from the text of every submission and comment in the 320 stock-market subreddits, using the matching rule described in Appendix G. The rule gives priority to explicit cashtags and otherwise accepts uppercase tokens that are valid ticker symbols and are not common English words. The procedure yields 44.7 million mentions, each carrying the author and the posting date, which lets us merge mentions to the pre-entry user types. Appendix G.2 describes the screen that removes symbols used in this corpus as ordinary abbreviations rather than as securities.

3 Pre-Entry Activity and Stock-Market Engagement

This section studies users' activity in the year before their first engagement with a stock-market subreddit, tracing how that activity changes as entry approaches and which parts of it predict who enters. We then show that prior activity is substantially heterogeneous, with users approaching stock-market subreddits from different parts of the platform. We use this heterogeneity to define user types, and we show that the types differ in the way their members first engage with the stock-market part of Reddit.

3.1 How Activity Changes Before Entry

As entry approaches, users shift more of their activity toward finance-adjacent categories. For each user, category, and month in the year before entry, we divide the share of the user's activity in that category by the corresponding platform-wide share of Reddit activity. A value of one means that the user allocates the same share of their activity to the category as the average Reddit user, and values above one indicate relatively greater activity there.

Figure 1 shows that finance-adjacent activity among future entrants already exceeds the Reddit benchmark twelve months before entry and rises further as entry approaches, with *Non-Stock Investing* and *Personal Finance* carrying the largest ratios, followed by *Crypto*, *Economics*, and *Gambling*. The plot depicts the average pattern for the 47.4% of users in our sample for whom we observe sufficient prior activity, meaning at least ten non-stock posts in the year before entry. Table 13 formally tests whether this excess attention changes systematically as entry approaches, relative to users' own average activity and contemporaneous Reddit-wide trends in each category.

One caveat governs how much of this pattern is behavioral. Entry is a user's first *observed* stock-market contribution and the archive records activity rather than account creation, leaving us with observed Reddit tenure rather than account age. Among the 6,804,621 entrants, 30.8 percent make their first stock-market contribution in the same month as their first observed activity anywhere on the platform, while 33.6 percent have at least 24 months of observed tenure at entry. For the first group the pre-entry window is mechanically short, making part of the rise in Figure 1 a matter of composition rather than a change in behavior, though the ten-post requirement removes most of these users from the figure. We cannot separate short observed tenure from a recently created account with these data, since the archive carries no account-creation date. These descriptive patterns show how activity changes before entry but not whether prior activity predicts who enters, which leads us to compare entrants with otherwise active users who have not yet entered.

3.2 Pre-Entry Activity Predicts Entry

We next test whether users' recent interests predict entry into stock-market discussion, estimating a monthly risk-set model that compares users who enter in a given month with otherwise similar users who do not. For computational tractability we draw deterministic samples of 300,000 eventual entrants and 300,000 non-entrants and follow them through July 2026. In each month the risk set contains sampled users who have not yet made an observed stock-market contribution and whose recent non-stock Reddit activity is observed, including both users who enter later in the sample and users for whom we never observe entry. A user leaves the risk set after their first observed stock-market contribution.

We estimate

$$\text{Entry}_{im} = \alpha_m + \sum_c \beta_c \, \text{PriorShare}_{ic,m-12:m-1} + X'_{i,m-1}\gamma + \varepsilon_{im}, \tag{1}$$

Here Entry_{im} equals one if user i makes their first observed contribution to any stock-market community in month m, and $\text{PriorShare}_{ic,m-12:m-1}$ is the share of the user's non-stock Reddit activity in category c during the preceding twelve months. The vector $X_{i,m-1}$ contains predetermined measures of the user's prior Reddit activity. Calendar-month fixed effects, α_m, absorb changes over time in aggregate Reddit activity and in the overall probability of entry.

Because category shares sum to one, coefficients are interpreted relative to the omitted category, Other Hobbies, and each coefficient measures how a ten-percentage-point reallocation of prior activity from Other Hobbies to category c is associated with the probability of entry in the following month.

Entrants are deliberately oversampled relative to their frequency in the population, so all estimates are inverse-probability weighted to target population quantities. Eligible eventual entrants are sampled with probability 0.104 and carry a weight of 9.61, while never-entrants are sampled with probability 0.0437, with one quarter of each sampled user's months retained, giving an inclusion probability of 0.0109 and a weight of 91.62. The percentage-point magnitudes below are therefore population-targeting estimates rather than unweighted case-control slopes.

Figure 2 shows that prior activity in finance-adjacent categories strongly predicts subsequent entry. The largest association is for *Non-Stock Investing*, where a ten-percentage-point higher share of activity in the category is associated with a 1.3-percentage-point higher monthly probability of entering stock-market discussion. The corresponding estimates are also large for *Economics* and *Personal Finance*, at about one percentage point, and for *Crypto*, at about 0.8 percentage points. Prior activity in *Gambling*, *Home and Housing*, *Politics and News*, *Law and Legal*, and *Productivity and Career* also predicts entry, though less strongly, while most non-financial categories carry small or negative associations.

These results show that future entrants are not simply unusually active Reddit users, the composition of their earlier activity instead carrying substantial information about whether and when they first join stock-market discussion.

3.3 Classifying Entrants by Their Prior Activity

The analysis so far describes average patterns among future entrants, and those averages may conceal substantial heterogeneity in the interests that lead users to stock-market discussion. We therefore define user types to characterize the distinct pre-entry pathways through which users arrive.

We assign each entrant a type using only activity during the twelve months before their first stock-market contribution, comparing the user's activity share in each finance-adjacent category with the contemporaneous Reddit-wide share and taking the category with the largest standardized excess activity as the user's type.

$$R_{ic} = \frac{n_{ic}/\sum_d n_{id}}{(1/12)\sum_{s=-12}^{-1} q_{c,t_i+s}}, \tag{2}$$

A value of $R_{ic} = 1$ means that the user's share equals the platform benchmark, while values above one indicate overrepresentation. Here n_{ic} counts user i's posts in category c during months $t_i - 12$ through $t_i - 1$, $N_i = \sum_d n_{id}$ is the user's total activity in the non-stock categories, $q_{c,m}$ is the platform-wide share of category c in calendar month m, and t_i is the user's first observed stock-market contribution month. For users with $N_i \geq 10$, we select the category with the largest standardized excess activity:

$$S_{ic} = \frac{p_{ic} - q_{ic}}{\sqrt{q_{ic}(1 - q_{ic})/N_i}}, \qquad p_{ic} = \frac{n_{ic}}{N_i}, \qquad q_{ic} = \frac{1}{12} \sum_{s=-12}^{-1} q_{c,t_i+s}.$$

The baseline rule also requires at least two posts in the category selected as a user's type. Users with at least ten pre-entry posts but fewer than two posts in the finance-adjacent category with the highest excess attention are classified as *Enough history, not finance-related*, while users with fewer than ten pre-entry posts are classified as *Not enough prior history*. These rules distinguish users for whom the data provide too little prior activity to assign a meaningful type from users with sufficient activity whose interests do not concentrate in the finance-adjacent categories used to define types.

Because the assignment is an argmax, two questions arise about how much it leaves to chance, the first being whether the winning category is typically clear. It is. Across the eight of nine substantive types for which the diagnostic is currently available, the share of users whose top two standardized scores differ by less than 0.50 runs from 1.1 percent for *Gambling* to 7.6 percent for *Politics and News*, against median gaps between 5.3 and 21.8.

The second is whether the label is stable, which we measure directly by splitting each user's pre-entry history at random into two halves and running the same assignment separately on each. The two labels agree for 88.8 percent of users who receive a substantive label in both halves. Each half uses only half of a user's history, making this a lower bound on the reliability of the labels we actually use, which are built from the full pre-entry window. Stability varies across types in a way that tracks the score gaps, running highest for *Crypto* at 93.3 percent and *Politics and News* at 93.1 percent, and lowest for *Economics* at 80.4 percent and *Law and Legal* at 80.0 percent. Appendix C reports both diagnostics by type.

Figure 3 describes both the prevalence of types and the shared activity between them. Panel A shows that a little over one quarter of the 6,804,621 entrants receive a substantive type, with *Politics and News* the largest, followed by *Personal Finance* and *Productivity and Career*. *Home and Housing*, *Crypto*, *Economics*, *Law and Legal*, *Non-Stock Investing*, and *Gambling* each account for smaller shares of entrants. The remaining users fall into one of the two residual groups, either lacking sufficient pre-entry history or holding sufficient activity that does not meet the minimum threshold in any finance-adjacent category.

Panel B shows that these labels capture dominant rather than exclusive interests, reporting for each assigned type the share of users whose activity is also elevated relative to Reddit-wide benchmarks in each other category.

Users assigned to one type often show elevated interest in several other categories as well, an overlap that is natural because the defining category is simply the one that stands out most. Users assigned to the *Personal Finance* type, for example, are also unusually active in

Productivity and Career and in *Home and Housing*, and there is substantial co-interest between the *Economics* type and the *Politics and News* category. The types therefore summarize the most distinctive component of users' pre-entry activity rather than partitioning users into mutually exclusive groups. Appendix C reports type coverage and label stability under alternative classification cutoffs.

3.4 Where User Types Enter

As a first test of whether our pre-entry types capture distinct online personas, we examine where users first enter stock-market discussion, since types that reflect meaningful differences in users' interests and motivations should predict which stock-market communities attract them. We focus on five large communities with distinct orientations: *r/WallStreetBets*, *r/Bogleheads*, *r/Options*, *r/StockMarket*, and *r/PennyStocks*.

Table 1 shows that entry is far from random, since the community a user first posts in lines up closely with what they were talking about beforehand, and the clearest split is between risk-seeking and risk-averse dispositions carried over from outside contexts. *Gambling* users, who are typically over-represented in casino and sports-betting content before entry, funnel into *r/WallStreetBets*, *r/Options*, and *r/PennyStocks*, three communities organized around leverage, volatility, or lottery-like payoffs, and they are the only type overrepresented in *r/PennyStocks*. *Personal Finance* users show the opposite pattern, entering *r/Bogleheads* at more than four times the average rate, essentially treating their first stock-market post as an extension of the budgeting and saving discussions they were already having. *Home and Housing* and *Productivity and Career* users, whose pre-entry interests also skew toward long-horizon financial planning, follow a similar though less pronounced path into *r/Bogleheads*.

A second pattern involves users drawn in by current events rather than by a settled investing philosophy. *Politics and News* users are overrepresented in both *r/WallStreetBets* and *r/StockMarket*, where the former likely reflects the wave of news-driven users who arrived during the GameStop squeeze, while the latter suggests that politically and economically engaged users are pulled into stock-market discussion more broadly whenever markets become newsworthy. *Economics* users follow a related but more specialized path, concentrating almost exclusively in *r/StockMarket*, a community whose framing is closer to market commentary than to portfolio strategy or speculation. *Crypto* users, meanwhile, pattern with the risk-tolerant group, appearing disproportionately in *r/WallStreetBets*, consistent with a shared taste for speculative assets that carries over from one domain to the other.

Together, these results offer an initial form of external validation, since types built solely from what users discussed before ever mentioning stocks nonetheless predict through which subreddits users enter.

3.5 Which Stocks User Types Discuss

The evidence in Section 3.4 is internal to Reddit, since entry community is itself a platform outcome, and a skeptical reader could argue that both the types and the communities reflect the same underlying activity data. A stronger test asks whether the types predict which individual securities users discuss, since securities are external to the platform and can be matched to market data.

This question does double duty, testing the classification against data the types never saw and forming the first stage of the market analysis in Section 5. If the path into stock-market discussion matters for markets, the first thing it must do is direct attention toward different securities.

We extract ticker mentions from every submission and comment in the stock-market subreddits over the sample period, using the matching rule and the screening described in Appendix G. Attaching to each mention the pre-entry type of its author yields 16.3 million mentions of 4,410 securities from users we can classify. The types were built from pre-entry subreddit activity alone and contain no information about securities.

Types Attend to Different Securities

We measure attention with the same standardized enrichment used in Section 3 to define types, now applied to securities rather than to subreddit categories. For type g and ticker k,

$$S_{gk} = \frac{p_{gk} - q_k}{\sqrt{q_k(1 - q_k)/N_g}}, \qquad p_{gk} = \frac{n_{gk}}{N_g},$$

where n_{gk} counts mentions of ticker k by users of type g, N_g is type g's total mentions, and q_k is ticker k's share of all classified mentions, with positive values indicating that a type discusses a security more than the average classified user does.

Table 2 reports the most over-represented securities for each type, and the pattern follows the pre-entry interests closely. *Personal Finance* entrants concentrate on broad-market index funds, their four strongest securities being VXUS and BND, Vanguard's total international stock and total bond funds, and QQQM and QQQ, two Nasdaq-100 trackers. These are instruments of diversified long-horizon saving, aligning with the budgeting and retirement discussions these users came from.

Crypto entrants concentrate on the equity market's bitcoin proxies, with MicroStrategy their strongest security by a wide margin and the spot bitcoin fund IBIT also among their most over-represented, suggesting that these users are reaching for bitcoin exposure through instruments available in an ordinary brokerage account.

Gambling entrants concentrate on sports betting and casinos, with DraftKings and MGM Resorts their two strongest securities. This is the same disposition documented in Section 3.4, where these users funnel into *r/WallStreetBets* and *r/PennyStocks*, now visible in the individual companies they discuss.

Non-Stock Investing entrants stand apart in a different way, their strongest securities being small, little-known names such as FLNT, AEHR and PERI rather than any recognizable category of large company. *Productivity and Career* and *Home and Housing* entrants resemble *Personal Finance*, consistent with the co-interest structure in Figure 3.

Politics and News is the exception, and informatively so, being the least thematically coherent of the nine types. Its most over-represented securities mix mega-cap technology names, TSLA, PLTR and AAPL, with securities tied to particular episodes of retail attention, RKT, ICLN and CRSR, and no single category organizes the list in the way sportsbooks organize *Gambling* or index funds organize *Personal Finance*. This is what the label implies, since users who arrive from political and news communities attend to whatever is prominent at the time rather than to a standing interest.[3]

The Sorting Exceeds Chance

Enrichment rankings are informative but do not establish that the distributions differ, so we compare each pair of types by the total variation distance between their ticker distributions. This is the share of one type's mentions that would have to move to a different security for the two types to attend identically.

Any finite sample produces some separation by chance, and thin securities produce more of it, so we build a null by drawing mention counts under independence while preserving the expected margins, leaving each type with its total mentions and each security with its total mentions but the two unrelated. Table 3 reports the observed distances alongside this null.

The observed distances run from 3.6 to 7.3 times the null, with a median of about five. *Gambling* and *Personal Finance* are the most separated pair among the types, at 0.224 against a null of 0.047, meaning that nearly a quarter of gambling entrants' attention would have to move to different securities to match where personal-finance entrants look. *Crypto* separates from both *Politics and News* and *Personal Finance* by similar margins.

[3]One caveat applies to this type in particular. *Politics and News* contributes the largest share of classified mentions, and the benchmark q_k includes the type's own mentions, which shrinks its enrichment values relative to smaller types. Comparisons of enrichment magnitudes across types of very different size should be read with that in mind.

We also summarize the whole table with the normalized mutual information between type and security, $I(g;k)/H(g)$. Knowing which security a mention concerns resolves 2.8 percent of the uncertainty about the author's entry type, against 0.102 percent under the null, making the observed value 27.5 times chance.

Taken together, these results establish the first stage of the market question. The types are constructed from what users discussed before they ever mentioned a stock, using no market data, yet they predict which securities users go on to discuss, and they predict them in the direction their labels imply. Savers discuss index funds, crypto entrants discuss bitcoin proxies, and gamblers discuss sportsbooks. Entry paths direct attention toward different parts of the market, and Section 5 asks what that does to prices.

These magnitudes are lower bounds. Types are assigned from pre-entry Reddit activity and use no market data, so classification error is independent of which securities a user later mentions, and a noisy label can therefore carry no more information about a security than the true label carries, leaving the measured association an understatement of the true one.[4] Misclassification works against these findings rather than for them, which is the opposite of its role in the within-security comparison of Section 5.

3.6 Entry Motives Across User Types

If prior activity reflects the concerns that bring users to financial discussion, users from different types should differ systematically in what they say, and in what they appear to seek, when they first arrive. We test this prediction by comparing the language of users' first stock-market posts across types.

For each user we analyze their first observed stock-market post, applying six short, concept-specific dictionaries to measure whether the post discusses *Economics*, politics, portfolio and household-investing decisions, trading and speculation, *Crypto*, or advice and help, and recording whether the post contains a question mark and how long it is. Our main text outcomes indicate whether a post contains at least one dictionary term or complete phrase, rather than relying on word densities that can be mechanically sensitive to the length of short comments. Appendix F reports the dictionaries and matching rules.

Table 4 reports the raw feature prevalence by entrant type and the full first-post benchmark. The displayed type rows exclude users with not enough prior history and those with enough history but no finance-related activity. The clearest differences align with the pre-entry type labels: *Politics and news* and *Economics* users use substantially more political language,

[4] If $\hat{g}$ is a noisy label satisfying $\hat{g} \perp k \mid g$, then $\hat{g}$, g and k form a Markov chain and the data processing inequality gives $I(\hat{g};k) \leq I(g;k)$. The same logic applies to the total variation distances, since misclassification mixes two types' security distributions toward one another, which can only reduce the distance between them.

Personal finance users use more portfolio language and are more likely to seek advice or ask questions, and *Crypto* users use far more crypto language. *Gambling* users have the highest prevalence of trading language, while *Economics* users are most likely to use economic terms, showing that differences observed before entry remain visible in users' first stock-market contributions.

The semantic features show that pre-entry pathways are associated with systematically different forms of initial engagement with stock-market discussion, revealing what users discuss but providing only limited evidence on why users enter or whether their first post concerns a personally consequential financial decision.

We therefore annotate a sample of 100,000 first posts, drawn proportionally across the nine defined user types, using GPT-5.6 Luna and a prespecified codebook (Appendix B.2), which assigns each post a primary motive and separately identifies whether the user expresses a personal financial stake or contemplates a concrete action. These measures allow us to distinguish posts aimed at learning, seeking advice, discussing events, evaluating investments, or participating socially, and to identify whether entry is connected to a stated financial decision or plan. Figure 4 reports the raw distribution of primary motives in users' first stock-market posts, separately for comments and submissions.

Figure 4 shows that entry motives broadly align with users' types. *Personal Finance*, *Law and Legal*, and *Non-Stock Investing* users frequently seek advice or validation and address implementation problems in their first post. *Home and Housing* users are most likely to describe a concrete financial decision in a submission (19%), while *Personal Finance* users also do so frequently (17%). *Politics and News* users are distinctively conversational and reactive, with social reactions accounting for 46% of their comments, whereas *Economics* users are especially likely to enter to learn or interpret external events. *Crypto* users are the most information-oriented group, with view or information motives accounting for 24% of submissions and 33% of comments. These descriptive results are consistent with what one would expect from each type: household-finance, legal, and general-investing interests lead to practical questions; political and economic interests lead to discussion of events and information; and *Crypto* interest leads to information-oriented engagement.

Table 5 then reports the prevalence of stated financial stakes and contemplated actions. *Personal Finance* entrants are most likely to express a personal stake (27.8%), contemplate a concrete action (21.3%), and do both (16.3%). These patterns show that a meaningful share of first contributions concerns concrete financial choices.

Taken together, the first-post evidence shows that the user types capture meaningful differences in how people arrive at stock-market discussion, with users' stated motives and financial concerns at entry systematically aligning with the interests that characterized their earlier activity on the platform. More broadly, the results in this section suggest that interest in financial markets does not emerge through a single path, since some users arrive through household-finance concerns and others through economic and political events, investing, *Crypto*, or related interests.

4 Uncertainty and the Timing of Engagement

Section 3 showed that future entrants differ substantially in their activity before they enter stock-market discussions and in the intentions with which they enter. We now turn from this cross-sectional heterogeneity to the timing of entry, asking whether there are patterns in when users enter and whether those patterns differ between types.

4.1 Entry Timing Across User Types

The first fact we document is that entry is highly uneven over time, with Figure 5 showing by far the largest increase during the GameStop short squeeze in early 2021. Smaller increases occur around the onset of COVID-19 in early 2020 and the rise in U.S. policy uncertainty in late 2024 and early 2025. The data suggest that people enter stock-market discussions all the time, but that entry rises sharply when either the platform (GameStop) or the market itself (COVID crash) becomes more salient to the public.

Aggregate entry conceals substantial differences in when different user types enter, a contrast that Figure 6 illustrates for *Gambling* and *Economics* users. Entry among *Gambling* users is concentrated during the speculative market environment of early 2021, whereas entry among *Economics* users rises more visibly during the macroeconomic and policy episodes of 2020 and 2025. While entry therefore seems to be connected to external events, an event that draws one type of user into stock-market discussion need not have the same relationship with other types.

4.2 Economic Policy Uncertainty and Entry

The variation in aggregate entry suggests that users may join stock-market discussion when external events make financial markets more salient and harder to interpret, and unexpected increases in economic policy uncertainty provide one way to formalize such episodes. If these increases draw broader attention to financial markets, aggregate entry should rise in months with large positive uncertainty innovations, and if users' prior interests shape how they respond, the same increases should also change the composition of entrants across user types. Users with prior interests in *Economics* or politics may be especially likely to enter when such events prompt a need to understand or discuss their implications, whereas users whose activity is concentrated in *Crypto* or *Gambling* may respond less strongly.

We identify these episodes using innovations in economic policy uncertainty from a vector autoregression (VAR) defined in Appendix D, which separates the unexpected component of monthly uncertainty from its predictable part. We define an uncertainty-shock month as one in which the estimated positive innovation exceeds one standard deviation. The estimation sample covers May 2015 through July 2026, comprising 135 monthly observations and 18 shock months.

We estimate aggregate entry using

$$\log(1 + \text{Entrants}_t) = \alpha + \beta\,\text{EPUShock}_t + \rho\,\log(1 + \text{Entrants}_{t-1}) + f(t) + \mu_m + \varepsilon_t. \quad (3)$$

Here Entrants_{t-1} is the lagged monthly entry count, $f(t)$ is a quadratic time trend, and μ_m denotes month-of-year fixed effects, with the coefficient β capturing the conditional difference in log entry between uncertainty-shock and other months. To examine whether high-uncertainty months also change the composition of entry, we stack the type-by-month series and estimate

$$\log(1+\text{Entrants}_{pt}) = \alpha_p + \beta_p\,\text{EPUShock}_t + \rho_p\,\log(1+\text{Entrants}_{p,t-1}) + \delta_{1p}t + \delta_{2p}t^2 + \mu_{p,m} + \varepsilon_{pt}. \quad (4)$$

Here p indexes user types, the lagged outcome, time trend, and month-of-year fixed effects are each allowed to differ by type, and each β_p measures the conditional difference in log entry for type p between shock and non-shock months. Because the uncertainty innovation is common to all types within a month, we cluster standard errors by calendar month in the stacked model, while the aggregate model uses HAC standard errors with a three-month lag length. Finally, we test the null hypothesis that the type-specific shock coefficients are equal across all eleven groups.

Figure 7 shows that entry is higher in months with unexpectedly high economic policy uncertainty. Conditional on lagged entry, a quadratic time trend, and month-of-year fixed effects, aggregate entry is about 17% higher when the EPU innovation exceeds one standard deviation. High-uncertainty months also change who enters. The largest estimated increase is among *Politics and News* users, while *Economics* users and several other types with prior economic or financial interests also show relatively large increases. By contrast, the association is smaller for users with too little pre-entry activity to receive a substantive type and comparatively modest for *Crypto* users. The type-specific coefficients are jointly unequal (Wald $\chi^2(10) = 23.88$, $p = 0.0079$), rejecting the hypothesis that uncertainty has the same association with entry for every group. High-uncertainty months are therefore associated with both more entry overall and a different composition of entrants. These results are not an artifact of the archive gap documented in Appendix H. Excluding March, April and May 2018 outright leaves the aggregate estimate at 16.7 percent ($p = 0.024$) against a baseline of 17.1 percent, with the type-specific coefficients still jointly unequal ($p = 0.006$).

Entry into stock-market discussion is substantial in ordinary months, but it can rise sharply when external events make Reddit or financial markets unusually salient. The GameStop short squeeze illustrates the first case, when attention focused directly on Reddit and its stock-market communities. Episodes such as Brexit, the onset of COVID-19, and the 2025 tariff announcements illustrate the second, where periods of heightened economic-policy uncertainty are associated with higher aggregate entry and a different mix of entrants. In these months, users with prior interests in *Politics and News*, and to a lesser extent *Economics*, enter at relatively higher rates.

5 From Entry Types to Market Outcomes

Section 3.5 shows that entry types sort across securities, with different kinds of entrants attending to different companies in ways their pre-entry interests predict. This section asks what that sorting means for markets.

We separate the question into two stages. The first stage asks whether Reddit attention is associated with market outcomes at all, and the second asks whether the composition of that attention matters beyond its level, that is, whether it matters who is talking and not merely how much talk there is. The distinction is important for interpretation, and ex ante it is unclear which way it runs. On the one hand, entry paths may shape behavior, with users who arrive from gambling communities trading more aggressively and herding more than users who arrive from budgeting communities, in which case the composition of attention carries information about price impact beyond the securities involved. On the other hand, entry paths may shape only the allocation of attention, with every group responding to a given security in much the same way and the apparent differences between groups reflecting which securities each one looks at. The evidence favors the second reading.

5.1 Event Construction

We identify attention spikes from the daily count of mentions of each security in stock-market subreddits. A day is a spike day if the security receives at least five mentions and the count exceeds three times the trailing 90-day median of its own daily mentions. The rolling median makes the threshold adapt to how much a security is normally discussed, making a count that is routine for a heavily discussed company a spike for a rarely discussed one. During the first 90 days of a security's series the median is undefined and the five-mention floor applies alone. Spike days separated by five or fewer calendar days are merged into a single event, a gap of six days or more begins a new one, and we date each event at its day of peak mentions. The median event covers a single day, and the most sustained episodes extend to 69 days.

We match events to daily prices and volumes from LSEG, estimating for each event a factor model over trading days -120 to -11 relative to the event day and requiring at least 90 of the 110 possible observations. We then cumulate abnormal returns over days 0 to 5 and report results for the three-factor specification of Fama and French (1993), taking as our return outcome the absolute cumulative abnormal return, since Reddit attention need not predict the direction of a move.

We use three further outcomes. Log abnormal volume is $\log(\bar{V}_{0,5}/\bar{V}_{-120,-11})$, where $\bar{V}$ denotes mean daily share volume over the indicated window. Volume decay is $\log(\bar{V}_{0,5}/\bar{V}_{-120,-11}) - \log(\bar{V}_{6,20}/\bar{V}_{-120,-11})$, where a larger value means volume falls back further after the event window, and reversal is the cumulative abnormal return over days 6 to 20.

We drop events on the 96 symbols that Appendix G.2 adjudicates as non-securities, which matters here because several of those symbols are themselves listed tickers, so spikes in the token `DRS` or `CDC` generate events whose mentions have nothing to do with the company. These events behave as one would expect of noise, with a mean absolute abnormal return of 0.034 against 0.059 for the retained events and a mean abnormal volume that is slightly negative. The screened sample contains 34,476 events on 2,602 securities.

5.2 Specification

Let e index events, $j(e)$ the security and $t(e)$ the event day. The first stage estimates

$$y_e = \beta \log M_e + \alpha_{t(e)} + \left[\alpha_{j(e)}\right] + \eta_e, \tag{5}$$

where y_e is one of the four outcomes, M_e is the total number of mentions in the event window, α_t is an event-day fixed effect and α_j is a security fixed effect included in the second specification only.

The composition stage adds the mix of authors:

$$y_e = \sum_{g \neq g_0} \gamma_g \, s_{ge} + \delta \, c_e + \phi \log M_e + \alpha_{t(e)} + \left[\alpha_{j(e)}\right] + \left[\mathbf{x}'_{j(e)} \boldsymbol{\lambda}\right] + \eta_e. \tag{6}$$

Here s_{ge} is the share of window mentions written by authors of type g, and g_0 is the omitted reference group. In Panel A of Table 7 the shares run over three groups defined by pre-entry history, with users having fewer than ten pre-entry posts as the reference. In Panel B they run over the nine focal types among classified mentions, with *Politics and News* as the reference, and c_e is the share of all window mentions that are classified. The vector $\mathbf{x}_j$ collects three time-invariant security characteristics and enters only where indicated, and standard errors are two-way clustered by security and event day throughout.

5.3 Attention Spikes and Market Reactions

Table 6 relates the size of an attention spike to the market outcomes around it.[5] The results are what a first stage requires: larger spikes go with larger absolute abnormal returns and higher abnormal volume, that volume falls back further over the following two weeks, and returns partly reverse. All four relationships hold with event-day fixed effects, so they are not driven by market-wide days on which both Reddit activity and volatility are high, and all four survive the addition of security fixed effects, so they reflect variation within a security over time rather than a comparison between heavily discussed and lightly discussed companies. Reversal is the weakest of the four and is significant only at the 10 percent level once security fixed effects are included.

The magnitudes are moderate, with a one log point increase in window mentions associated with a 0.0128 increase in the absolute abnormal return, against a sample mean of 0.059. The reversal coefficient is negative and small, with larger spikes followed by lower returns over days 6 to 20, consistent with partial reversal of an attention-driven price move rather than with the incorporation of lasting news.

5.4 Composition Matters, But Only Across Securities

We now ask whether it matters who is talking, computing for each event the composition of mentions in the spike window by the pre-entry type of the author.

Panel A of Table 7 splits mentions by how much pre-entry Reddit history the author has, and events dominated by users with at least ten pre-entry posts show smaller reactions on all three outcomes. The pattern survives security fixed effects for the share of authors who receive a type, though for authors whose history is not finance-related it weakens and is no longer significant for abnormal volume. The finding is about the presence of a history rather than its content, since we cannot reject that the two coefficients are equal on any outcome, with

[5] We measure spike size by the total number of mentions in the event window. The peak single-day count is an alternative measure, but it correlates 0.92 with the window total, and including both produces unstable coefficients whose signs flip across specifications. We therefore use the window total throughout.

the tests giving $p = 0.171$ for absolute abnormal returns, $p = 0.102$ for abnormal volume and $p = 0.342$ for volume decay. We therefore read this as an account-maturity result rather than a sophistication result, with authors who have fewer than ten pre-entry posts concentrating in the episodes with the largest reactions.[6]

Panel B turns to the nine types, where composition predicts market outcomes strongly among classified mentions. The eight type shares are jointly significant at $p = 2.5 \times 10^{-11}$ for absolute abnormal returns and $p = 4.7 \times 10^{-9}$ for abnormal volume once we include event-day fixed effects. Two types carry the result, since relative to *Politics and News* a higher *Gambling* share predicts larger reactions and a higher *Personal Finance* share predicts smaller ones. The gap between them is economically large, at 0.0271 in absolute abnormal return, roughly half the sample mean, and 0.176 in log abnormal volume, roughly the size of the mean itself.

The result disappears once we add security fixed effects, with the joint tests becoming $p = 0.492$ and $p = 0.311$, leaving no evidence that within a given security the mix of entry types discussing it predicts how the market responds.

This is a null, so it is worth stating what the data can and cannot rule out. The within-security gap between *Gambling* and *Personal Finance* is 0.0035 with a 95 percent confidence interval of $[-0.0040, 0.0110]$ for absolute abnormal returns, an interval that excludes the across-security estimate of 0.0271. The smallest effect the test would detect at 80 percent power is 0.0124, less than half the across-security estimate, so measured against the type shares as we observe them the design is powered to find an effect of the size that exists between securities, and it does not find one. The corresponding figures for abnormal volume are a gap of 0.0424 with an interval of $[-0.0102, 0.0950]$ against an across-security estimate of 0.176, and a detectable effect of 0.0752.

Two qualifications matter. First, the comparison has variation to work with, since for the difference between the *Gambling* and *Personal Finance* shares 82 percent of the total variance is within security rather than between, and 1,519 of the 2,135 securities in this sample contribute more than one event. A high within-security variance share is also what one would observe if much of the event-to-event variation were classification noise, however, leaving this on its own no evidence that the specification retains signal.

Second, and more seriously, the type shares are built from a classifier and are measured with error, and the within transformation removes the variation that is common to a security, which is the part most likely to be signal, raising the noise share of what remains. Classical

[6] The reference group is defined by a threshold on observed posts, not by the absence of any Reddit history. A user with nine pre-entry posts falls in it. We use the group as a proxy for account maturity and note that it is a noisy one.

measurement error of that kind shrinks the within-security coefficients toward zero whether or not a true within-security effect exists. The power calculation does not settle this, since it establishes that the design would reject an effect of a given size in the measured share, not in the true one.

These estimates cannot separate the two readings on their own, and the next subsection separates them directly, using two independent classifications of every author.

5.5 Is the Null Measurement Error?

The concern is specific. If the type shares are noisy measures of the true composition, the within-security coefficients are attenuated whether or not a true within-security effect exists, and the null in Table 7 would be an artifact of the classifier rather than a fact about markets.

The concern is also testable. We obtain two independent classifications of every author. For each user we split their pre-entry posting history at random into two halves and run the identical assignment procedure separately on each, which yields two labels for the same person.[7]

Aggregating each set of labels over the same event window gives two composition measures, s^1_{ge} and s^2_{ge}. They are computed over an identical set of authors with an identical denominator. Only the labels differ. Writing $s^k_{ge} = s^*_{ge} + \varepsilon^k_{ge}$, the two measurement errors are independent conditional on the true composition, so s^2 satisfies the requirements for an instrument for s^1: it is correlated with the signal and uncorrelated with the other measure's error. Because the labels are built from pre-entry Reddit activity and the split is a seeded random draw, neither error can be related to market outcomes except through the true composition.

Table 8 reports the result. The first stage is very strong, with F statistics on the excluded instruments between 7,164 and 25,846, which is what two readings of the same underlying history should produce. The sample is 25,419 events on 2,001 securities, close to the 28,400 events used in Table 9.

Three things follow. First, correcting for measurement error does not restore the effect. The instrumented within-security gap between *Gambling* and *Personal Finance* is -0.0034 with a 95 percent confidence interval of $[-0.0111, 0.0044]$, which excludes the across-security estimate of 0.0249 from the same sample. The joint test on the eight type shares gives $p = 0.65$.

Second, the correction is small. The ratio of the ordinary least squares estimate to the

[7]The split is implemented as an independent Binomial$(n_c, 0.5)$ draw on each pre-entry category count, which is equivalent to randomly assigning the user's individual posts to two halves. Both halves use the same Reddit-wide benchmark and the same ten-post and two-winning-post rules. Appendix C reports the agreement rates.

instrumented estimate is 0.94 with event-day fixed effects and 0.85 with security fixed effects, so classification error was costing between six and fifteen percent of the coefficient. To lift -0.0034 to 0.0249 would require a reliability near 0.18, and attenuation shrinks estimates toward zero in any case rather than reversing their sign. The reason the correction is so modest is that the regressor is a share averaged over many mentions, so errors in individual labels largely cancel before they reach the event level.

Third, the two halves are exchangeable by construction, and reversing the roles of instrument and regressor changes nothing: the within-security gap moves from -0.0034 to -0.0032 for absolute abnormal returns.

One limitation remains. The instrument purges the component of classification error that depends on which posts fell in which half. It cannot purge error common to both halves, which arises when a user's pre-entry history is genuinely ambiguous between two categories. The correction is therefore partial, and the instrumented coefficient is a lower bound in absolute value. Given that the measured correction is at most fifteen percent, the common component would have to be both far larger and sign-reversing to overturn the conclusion.

We read the evidence as ruling out measurement error as the explanation for the within-security null.

5.6 The Composition Effect Operates Through Security Selection

The mechanism can be tested directly, without relying on the within-security comparison at all, by adding three observable security characteristics to the event-day specification in Table 9: return volatility, dollar volume and price. If types differ because they select different kinds of companies, these characteristics should absorb the type coefficients.

They do. Volatility enters with a coefficient of 2.13 and is the dominant channel, with the three characteristics together absorbing 68 percent of the gap between *Gambling* and *Personal Finance* in absolute abnormal returns and 34 percent of the gap in abnormal volume. Security fixed effects, which absorb everything fixed about a company rather than only these three observables, remove 87 percent and 76 percent respectively. Three observable characteristics therefore recover most of what a full set of security fixed effects recovers, which is what a selection account predicts and what a behavioral account does not.

This is our central evidence on the second stage, and it does not share the vulnerability of the preceding subsection. The specification carries event-day fixed effects only, and the composition variable is never transformed within security, leaving the attenuation described above with nothing to operate on. Measurement error in the type shares would shrink every type coefficient toward zero, in all three columns alike, and would not explain why adding return volatility in particular is what closes the gap between *Gambling* and *Personal Finance*.

The reading is direct. *Gambling* entrants do not move prices more than *Personal Finance* entrants when they discuss the same company. They discuss different companies, and DraftKings and MGM Resorts are more volatile than Vanguard's total international stock and total bond funds, while volatile securities respond more to attention. The composition variable is informative about the market reaction because it is informative about the security, not because it identifies a group of users with unusual price impact.

Taken together, the two stages describe a chain rather than a direct effect, in which pre-entry interests are associated with which securities new participants attend to, and the characteristics of those securities are associated with how markets respond to that attention. Our contribution is the first link, which has not previously been observable, and we take the second from an established literature on retail attention and prices (Barber and Odean, 2008; Da et al., 2011; Cookson et al., 2023). Attention and prices are jointly determined and we do not identify a causal effect in either link, so the evidence does not establish that some entry paths carry more price impact than others, and we do not claim it.

6 Conclusion

Before people open a brokerage account or buy a stock, they must first begin paying attention to financial markets, seeking information, discussing current events, considering an investment, or asking others what to do. This early stage is usually difficult to observe because surveys and administrative data tend to reveal people only once they hold an account or make a financial decision.

Using the cross-community histories of 6.8 million Reddit users, we study how interest in financial markets develops before users first contribute to a stock-market community, who enters, and under which conditions. Future entrants already devote unusually large shares of their activity to finance-adjacent topics one year before entry, and this concentration rises as their entry approaches. Prior activity in *Personal Finance*, *Economics*, *Non-Stock Investing*, *Crypto*, and related categories predicts entry relative to comparable users who do not enter. These average patterns conceal substantial heterogeneity.

Users arrive with different pre-entry interests, enter through different stock-market communities, and express different motives in their first posts. *Personal Finance*, *Law and Legal*, and *Non-Stock Investing* users often seek advice or help with practical problems; *Politics and News* and *Economics* users more often discuss events or try to understand their implications; and *Crypto* users enter with a comparatively information-oriented profile. Some first posts also disclose a personal financial stake or contemplated action, showing that users discuss economically meaningful decisions with the community.

Entry is substantial in ordinary months but rises sharply when Reddit or financial markets become especially salient, the largest increase occurring during the GameStop episode, when attention focused directly on Reddit's stock-market communities. Entry is also about 17% higher in months with unexpectedly high economic policy uncertainty, and these months change not only the number of entrants but also their composition, with users with prior interests in *Politics and News* and *Economics* entering at relatively higher rates. This is consistent with the idea that political and economic events draw users who already follow these topics into stock-market discussion when financial markets become newly relevant to their existing interests.

We also ask what this heterogeneity means for markets. Episodes in which a security is discussed unusually heavily are followed by larger absolute abnormal returns, higher abnormal trading volume, and mild reversal over the following weeks. Who is talking predicts these reactions, with episodes dominated by *Gambling* entrants showing larger reactions than episodes dominated by *Personal Finance* entrants, by about half the sample mean. Observable security characteristics, volatility above all, account for two thirds of that difference on their own, and it vanishes entirely once we compare episodes within the same security, a null that survives instrumenting one composition measure with a second, independent classification of the same authors. Entry types do not appear to react differently to the same company. They attend to different companies, and those companies differ in volatility, making the path into stock-market discussion related to market outcomes through which securities draw attention rather than through groups of users with unusual price impact.

The results have implications for both policy and research, and efforts to broaden financial-market participation should not assume that all potential participants can be incentivized in the same way. Some people approach financial markets through household-finance decisions, while others arrive through an interest in economic and political events, careers and housing, cryptocurrencies, or other forms of investing. Periods in which markets become unusually salient may offer opportunities for timely financial education, but they may also be moments when new users are especially vulnerable to confusion, poor advice, or speculative narratives. For researchers, public discussion provides an observable intermediate stage between passive attention and financial action, one that can complement surveys, search data, and brokerage records. Linking this stage to subsequent account opening, portfolio choice, and trading would help establish when public engagement develops into financial participation, and when it does not.

Several limitations bound these conclusions. We observe public discussion rather than portfolios or trades, so we cannot say whether the users we follow go on to invest. Our entry measure records a user's first contribution to a stock-market community, which need not be the moment they first became interested in markets. The subreddit taxonomy and the first-post motive labels are assigned by a language model and checked against a single human annotator on a limited subsample, so we cannot report a human-to-human agreement benchmark for either. The market evidence is associational, since attention and prices are jointly determined, and we do not claim that Reddit discussion causes the reactions we document. The within-security result is a null on shares measured with error, though instrumenting one classification with a second, independent classification of the same authors moves the coefficient by less than fifteen percent and leaves it far from the across-security estimate. Our market data end in December 2025, so the final months of the Reddit sample inform the analysis of entry but not the analysis of returns. Finally, Reddit users are not a representative sample of households, and the platform's own composition shifted over our sample, most visibly around the GameStop episode.

Understanding how people arrive at financial markets, and not only what they do once they are there, is a useful step toward explaining who participates and who does not.

References

Anand, A. and Pathak, J. (2022). The role of Reddit in the GameStop short squeeze. *Economics Letters*, 211:110249.

Antweiler, W. and Frank, M. Z. (2004). Is all that talk just noise? The information content of Internet stock message boards. *The Journal of Finance*, 59(3):1259–1294.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636.

Barber, B. M. and Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, 21(2):785–818.

Bartov, E., Faurel, L., and Mohanram, P. S. (2018). Can Twitter help predict firm-level earnings and stock returns? *The Accounting Review*, 93(3):25–57.

Baumgartner, J., Zannettou, S., Keegan, B., Squire, M., and Blackburn, J. (2020). The Pushshift Reddit dataset. In *Proceedings of the Fourteenth International AAAI Conference on Web and Social Media*, volume 14, pages 830–839.

Bollen, J., Mao, H., and Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, 2(1):1–8.

Brown, J. R., Ivković, Z., Smith, P. A., and Weisbenner, S. (2008). Neighbors matter: Causal community effects and stock market participation. *The Journal of Finance*, 63(3):1509–1531.

Campbell, J. Y. (2006). Household finance. *The Journal of Finance*, 61(4):1553–1604.

Chen, H., De, P., Hu, Y. J., and Hwang, B.-H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *The Review of Financial Studies*, 27(5):1367–1403.

Cookson, J. A., Engelberg, J. E., and Mullins, W. (2023). Echo chambers. *The Review of Financial Studies*, 36(2):450–500.

Cookson, J. A., Lu, R., Mullins, W., and Niessner, M. (2024). The social signal. *Journal of Financial Economics*, 158:103870.

Cookson, J. A. and Niessner, M. (2020). Why don't we agree? Evidence from a social network of investors. *The Journal of Finance*, 75(1):173–228.

Da, Z., Engelberg, J., and Gao, P. (2011). In search of attention. *The Journal of Finance*, 66(5):1461–1499.

Duraj, K., Grunow, D., Haliassos, M., Laudenbach, C., and Siegel, S. (2025). Rethinking the stock market participation puzzle: A qualitative approach. Technical report, CESifo Working Paper.

Fagereng, A., Gottlieb, C., and Guiso, L. (2017). Asset market participation and portfolio choice over the life-cycle. *The Journal of Finance*, 72(2):705–750.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Giannetti, M. and Wang, T. Y. (2016). Corporate scandals and household stock market participation. *The Journal of Finance*, 71(6):2591–2636.

Giannini, R., Irvine, P., and Shu, T. (2019). The convergence and divergence of investors' opinions around earnings news: Evidence from a social network. *Journal of Financial Markets*, 42:94–120.

Guiso, L. and Jappelli, T. (2005). Awareness and stock market participation. *Review of Finance*, 9(4):537–567.

Guiso, L., Sapienza, P., and Zingales, L. (2008). Trusting the stock market. *The Journal of Finance*, 63(6):2557–2600.

Haliassos, M. and Bertaut, C. C. (1995). Why do so few hold stocks? *The Economic Journal*, 105(432):1110–1129.

Hamilton, W. L., Zhang, J., Danescu-Niculescu-Mizil, C., Jurafsky, D., and Leskovec, J. (2017). Loyalty in online communities. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 11.

Hirshleifer, D. (2020). Presidential address: Social transmission bias in economics and finance. *The Journal of Finance*, 75(4):1779–1831.

Hong, H., Kubik, J. D., and Stein, J. C. (2004). Social interaction and stock-market participation. *The Journal of Finance*, 59(1):137–163.

Kuchler, T. and Stroebel, J. (2021). Social finance. *Annual Review of Financial Economics*, 13(1):37–55.

Kumar, S., Hamilton, W. L., Leskovec, J., and Jurafsky, D. (2018). Community interaction and conflict on the web. In *Proceedings of the 2018 World Wide Web Conference*, pages 933–943.

Mankiw, N. G. and Zeldes, S. P. (1991). The consumption of stockholders and nonstockholders. *Journal of Financial Economics*, 29(1):97–112.

Semenova, V. and Winkler, J. (2021). Social contagion and asset prices: Reddit's self-organised bull runs. *arXiv preprint arXiv:2104.01847*.

Shiller, R. J. (2019). *Narrative Economics: How Stories Go Viral and Drive Major Economic Events*. Princeton University Press, Princeton, NJ.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica*, 48(1):1–48.

Sprenger, T. O., Tumasjan, A., Sandner, P. G., and Welpe, I. M. (2014). Tweets and trades: The information content of stock microblogs. *European Financial Management*, 20(5):926–957.

Tumarkin, R. and Whitelaw, R. F. (2001). News or noise? Internet postings and stock prices. *Financial Analysts Journal*, 57(3):41–51.

van Rooij, M., Lusardi, A., and Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial Economics*, 101(2):449–472.

Vissing-Jørgensen, A. (2002). Towards an explanation of household portfolio choice heterogeneity: Nonfinancial income and participation cost structures. *NBER Working Paper*, (8884).

Waller, I. and Anderson, A. (2021). Quantifying social organization and political polarization in online platforms. *Nature*, 600:264–268.

Warkulat, S. and Pelster, M. (2024). Social media attention and retail investor behavior: Evidence from r/wallstreetbets. *International Review of Financial Analysis*, 96:103721.

Watchful1 (2026). Subreddit comments/submissions 2005-06 to 2025-12. Academic Torrents. Watchful1 is the data-collector handle; based on the Pushshift Reddit dumps; zstandard-compressed ndjson files for the 40,000 largest subreddits.

Zhang, J., Hamilton, W. L., Danescu-Niculescu-Mizil, C., Jurafsky, D., and Leskovec, J. (2017). Community identity and user engagement in a multi-community landscape. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 11.

Tables

Table 1: Relative Entry-Community Deviations by Pre-Entry User Type

User type	*r/WallStreetBets*	*r/Bogleheads*	*r/Options*	*r/StockMarket*	*r/PennyStocks*
Politics and News	+38.5%	-58.2%	-69.0%	+33.3%	-37.4%
Personal Finance	-27.6%	+308.2%	-39.3%	-12.4%	-36.1%
Productivity and Career	-1.4%	+70.9%	-38.1%	+21.9%	-30.3%
Home and Housing	-11.6%	+137.8%	-49.5%	+57.6%	-36.5%
Crypto	+17.5%	-51.7%	-23.3%	+33.2%	-20.4%
Economics	-15.3%	+0.0%	-32.3%	+66.8%	-45.0%
Law and Legal	-14.5%	+31.2%	-53.3%	+23.2%	-38.6%
Non-Stock Investing	-6.6%	+72.8%	-29.1%	+19.0%	-28.2%
Gambling	+22.0%	-7.5%	+7.3%	-4.2%	+33.6%

Notes: Each cell reports $100 \times [(\text{type-specific share}/\text{overall share}) - 1]$, where shares refer to entrants whose first stock-market contribution is in the indicated community. Thus, +50% means that the type enters through the indicated community 50% more often than the average entrant, while -50% means half as often. The table uses the full first-post file for the January 2015–July 2026 window; user types are assigned from pre-entry activity.

Table 2: Most Over-Represented Securities by Pre-Entry User Type

User type	Securities, ordered by standardized enrichment					
Politics and News	TSLA (79)	PLTR (62)	RKT (54)	ICLN (50)	CRSR (50)	AAPL (42)
Personal Finance	VXUS (205)	BND (114)	QQQM (62)	QQQ (55)	ATO (50)	BLNE (50)
Productivity and Career	VXUS (56)	FTWO (50)	PLTR (38)	ASTS (38)	QQQM (35)	QQQ (35)
Home and Housing	VXUS (69)	PULS (63)	BGM (42)	BND (36)	ICLN (25)	TMC (25)
Crypto	MSTR (189)	TSLA (63)	NVDA (50)	QQQ (43)	IBIT (43)	USO (41)
Economics	AVD (33)	TSLA (33)	EPI (28)	VXUS (27)	BYD (23)	ACHR (23)
Law and Legal	LYV (60)	PK (27)	DXC (27)	PLBY (27)	IFF (26)	ICLN (25)
Non-Stock Investing	FLNT (57)	AEHR (51)	PERI (40)	RCMT (30)	IONQ (29)	HIMX (29)
Gambling	DKNG (89)	MGM (51)	PTON (29)	PLTR (27)	BTU (27)	TSLA (26)

Notes: Each cell reports a ticker and, in parentheses, its standardized enrichment $S_{gk} = (p_{gk} - q_k)/\sqrt{q_k(1-q_k)/N_g}$, where p_{gk} is the share of type g's mentions that concern ticker k, q_k is ticker k's share of all classified mentions, and N_g is type g's total mentions. Higher values indicate that the type discusses the security more than the average classified user does. The sample covers all submissions and comments in the stock-market subreddits from January 2015 to July 2026, restricted to securities with at least 100 classified mentions and at least 250 trading days of price data, giving 16,302,391 mentions of 4,410 securities. Ticker mentions are identified by the rule in Appendix G; mentions from accounts flagged by the screening in Appendix H are excluded, as are the 96 symbols adjudicated not to be securities in this corpus. User types are assigned from pre-entry activity only and use no market data.

Table 3: Separation Between User Types in the Securities They Discuss

Type A	Type B	Observed	Null	Excess
Gambling	Not enough prior history	0.236	0.043	0.192
Gambling	Personal Finance	0.224	0.047	0.177
Gambling	Politics and News	0.161	0.045	0.116
Crypto	Politics and News	0.162	0.029	0.133
Crypto	Personal Finance	0.182	0.032	0.150
Politics and News	Personal Finance	0.174	0.024	0.150
Economics	Politics and News	0.130	0.034	0.095
Productivity and Career	Enough history, not finance	0.096	0.027	0.069
Normalized mutual information $I(g;k)/H(g)$		0.0281	0.00102	27.5×

Notes: Total variation distance between the ticker distributions of the two types, equal to half the sum of absolute differences in mention shares across securities. A value of 0.20 means that 20 percent of one type's mentions would have to move to different securities for the two distributions to coincide. The null column reports the mean over 40 draws in which mention counts are generated under independence between type and security while preserving the expected row and column margins, so each type keeps its total mentions and each security keeps its total mentions. The final row reports the mutual information between type and security, normalized by the entropy of the type distribution, with the ratio of observed to null in the last column. The sample is the same as in Table 2.

Table 4: Raw First-Post Features by Entrant User Type

User type	N	Economic	Political	Portfolio	Trading	Crypto	Advice	Question	Words
Overall first-post sample	6,804,360	1.6	2.2	4.7	2.5	2.5	3.7	25.3	25.6
Politics and news	657,490	2.3	5.4	2.1	3.3	1.1	1.9	22.1	23.0
Personal finance	282,970	2.3	2.1	**9.9**	3.1	1.6	**3.9**	**29.9**	**32.8**
Productivity and career	278,910	2.1	3.3	5.7	3.2	1.6	3.6	27.2	28.1
Home and housing	165,586	2.1	4.6	5.6	2.6	1.3	2.8	26.0	27.3
Crypto	157,229	1.8	1.5	3.5	4.5	**9.1**	2.6	24.2	23.9
Economics	156,934	**2.9**	**6.1**	3.8	3.0	1.6	2.9	25.3	28.7
Law and legal	107,380	1.9	4.5	4.7	2.8	1.4	3.3	27.6	29.1
Non-stock investing	56,795	2.8	2.9	5.4	3.8	1.8	3.0	25.5	28.2
Gambling	40,761	1.3	2.0	4.4	**4.7**	2.1	3.5	27.1	23.8

Notes: Economic, Political, Portfolio, Trading, Crypto, Advice, and Question are percentages of first posts containing at least one term or phrase from the respective dictionary. Words is the mean alphabetic word count. The Overall row uses non-deleted first observed stock-market contributions in the January 2015–July 2026 main analysis window; type rows exclude Not enough prior history and Enough history, not finance-related.

Table 5: Personal Financial Engagement at Stock-Market Entry

User type	N	Personal stake	Contemplated action	Stake + action
Politics and News	34,531	14.4	11.4	8.2
Personal Finance	14,862	27.8	21.3	16.3
Productivity and Career	14,648	22.1	17.1	12.9
Home and Housing	8,696	19.7	14.8	11.2
Crypto	8,257	18.5	16.1	10.6
Economics	8,242	15.2	12.3	8.5
Law and Legal	5,640	21.6	16.9	13.0
Non-Stock Investing	2,983	20.9	16.4	11.7
Gambling	2,141	22.2	19.0	14.3

Notes: Cells are raw within-type percentages. "Stake + action" equals one only when the author both discloses a personal financial stake and contemplates a concrete financial action. The annotation uses only the first contribution's text and is not used to construct types.

Table 6: Attention Spikes and Market Outcomes

Outcome	Event-day FE	Event-day + security FE
$\lvert$CAR$\rvert$, three-factor, days 0–5	0.0128***	0.0083***
	(0.0014)	(0.0010)
Log abnormal volume, days 0–5	0.1586***	0.1464***
	(0.0113)	(0.0094)
Volume decay	0.0632***	0.0595***
	(0.0080)	(0.0068)
CAR, days 6–20 (reversal)	−0.0042**	−0.0034*
	(0.0017)	(0.0017)
Events	34,476	34,476
Securities	2,602	2,602
Event days	3,541	3,541

Notes: Each cell is from a separate regression of the stated outcome on the log number of mentions in the event window, following equation (5). Cluster-robust standard errors are in parentheses, two-way clustered by security and event day. Abnormal returns are cumulated over trading days 0 to 5 relative to the event day, using the three-factor model of Fama and French (1993) estimated over days −120 to −11 with at least 90 of 110 observations. $\lvert$CAR$\rvert$ is the absolute value of that cumulative abnormal return. Log abnormal volume is $\log(\bar{V}_{0,5}/\bar{V}_{-120,-11})$, where $\bar{V}$ is mean daily share volume over the window. Volume decay is $\log(\bar{V}_{0,5}/\bar{V}_{-120,-11}) - \log(\bar{V}_{6,20}/\bar{V}_{-120,-11})$, so a larger value means volume falls back further after the event. Reversal is the cumulative abnormal return over days 6 to 20. The sample is all spike events on securities with LSEG price coverage, excluding events on the 96 symbols adjudicated as non-securities in Appendix G.2. Each specification also absorbs the log peak single-day mention count. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table 7: Composition of Attention and Market Outcomes

	No FE	Event-day FE	Event-day + security FE
Panel A. Pre-entry history. Reference: fewer than ten pre-entry posts. $N = 34{,}407$.			
Outcome: $\lvert CAR \rvert$, three-factor			
Share with an assigned type	-0.0318^{***}	-0.0307^{***}	-0.0080^{***}
	(0.0032)	(0.0027)	(0.0021)
Share with history, not finance	-0.0216^{***}	-0.0197^{***}	-0.0043^{*}
	(0.0043)	(0.0035)	(0.0025)
Difference			-0.0037
95% CI			[-0.0090, 0.0016]
Test of equality (p)			0.171
Outcome: log abnormal volume			
Share with an assigned type	-0.1568^{***}	-0.1764^{***}	-0.0716^{***}
	(0.0234)	(0.0209)	(0.0192)
Share with history, not finance	-0.0960^{***}	-0.1150^{***}	-0.0305
	(0.0289)	(0.0244)	(0.0226)
Difference			-0.0411
95% CI			[-0.0904, 0.0082]
Test of equality (p)			0.102
Outcome: volume decay			
Share with an assigned type	-0.1694^{***}	-0.1798^{***}	-0.0909^{***}
	(0.0179)	(0.0154)	(0.0150)
Share with history, not finance	-0.1617^{***}	-0.1568^{***}	-0.0716^{***}
	(0.0246)	(0.0186)	(0.0178)
Difference			-0.0194
95% CI			[-0.0593, 0.0205]
Test of equality (p)			0.342
Panel B. Nine entry types. Reference: *Politics and News.* $N = 28{,}413$.			
Outcome: $\lvert CAR \rvert$, three-factor			
Gambling share	0.0169^{***}	0.0131^{***}	0.0026
	(0.0045)	(0.0043)	(0.0038)
Personal Finance share	-0.0122^{***}	-0.0140^{***}	-0.0009
	(0.0024)	(0.0021)	(0.0015)
Gambling minus Personal Finance	0.0290	0.0271	0.0035
95% CI	[0.0203, 0.0377]	[0.0184, 0.0358]	[-0.0041, 0.0110]
Detectable at 80% power	0.0124	0.0124	0.0107
Joint test, eight shares (p)	3.0e-11	2.5e-11	0.492
Outcome: log abnormal volume			
Gambling share	0.1092^{***}	0.0951^{***}	0.0217
	(0.0325)	(0.0317)	(0.0265)
Personal Finance share	-0.0674^{***}	-0.0809^{***}	-0.0207
	(0.0173)	(0.0158)	(0.0137)
Gambling minus Personal Finance	0.1766	0.1760	0.0424
95% CI	[0.1138, 0.2393]	[0.1129, 0.2391]	[-0.0102, 0.0949]
Detectable at 80% power	0.0897	0.0902	0.0752
Joint test, eight shares (p)	7.2e-07	4.7e-09	0.311

Notes: Estimates of equation (6), with cluster-robust standard errors two-way clustered by security and event day in parentheses. Composition is the share of mentions in the event window written by authors of each pre-entry type. Panel A omits the share written by authors with fewer than ten pre-entry posts, so coefficients are relative to that group and the equality test is a Wald test on the two reported coefficients. Panel B restricts to windows with at least one classified mention, uses shares of classified mentions, omits *Politics and News*, and adds the classified share as a control; the joint test covers the eight included shares, whose full vector appears in Table 9. All specifications control for the log number of window mentions and the log peak single-day count. Intervals are 95 percent, and the detectable-effect row reports the smallest difference rejectable at 80 percent power against a two-sided 5 percent alternative. Sample restrictions as in Table 6. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table 8: Split-Sample Instrumental Variables Estimates of the Composition Effect

	Event-day FE	Event-day + security FE
Outcome: $\lvert CAR \rvert$, three-factor		
OLS, half-one labels	0.0234	−0.0029
	(0.0042)	(0.0037)
OLS, half-two labels	0.0229	−0.0031
	(0.0041)	(0.0036)
2SLS	0.0249	−0.0034
	(0.0044)	(0.0039)
95% CI	[0.0163, 0.0336]	[−0.0111, 0.0044]
2SLS, roles reversed	0.0253	−0.0032
	(0.0045)	(0.0039)
Joint test, eight shares (p)	3.0e−08	0.655
First-stage F, min–max	7,164–25,846	7,271–24,856
OLS / 2SLS	0.94	0.85
Outcome: log abnormal volume		
OLS, half-one labels	0.1455	0.0045
	(0.0299)	(0.0257)
OLS, half-two labels	0.1403	−0.0023
	(0.0300)	(0.0257)
2SLS	0.1526	−0.0027
	(0.0324)	(0.0279)
95% CI	[0.0890, 0.2161]	[−0.0574, 0.0520]
2SLS, roles reversed	0.1578	0.0045
	(0.0318)	(0.0276)
Joint test, eight shares (p)	1.6e−05	0.961
Events	25,419	25,419
Securities	2,001	2,001

Notes: Each entry is the difference between the *Gambling* and *Personal Finance* coefficients in equation (6), estimated on composition shares built from two independent classifications of the same authors. Cluster-robust standard errors are in parentheses, two-way clustered by security and event day. Each author's pre-entry history is split at random into two halves and the identical assignment procedure is run on each, so the two composition measures cover the same authors over the same event window and differ only in the labels. The 2SLS rows instrument the half-one shares with the half-two shares; the reversed rows exchange their roles, which is legitimate because the halves are exchangeable by construction. The first-stage F range covers the eight endogenous type shares. The sample is restricted to events containing at least one mention by an author who receives a substantive label in both halves, which requires enough pre-entry history to survive being divided, giving 25,419 of the 28,400 events in Table 9. The composition measured here is therefore the mix among authors with well-documented pre-entry histories. All specifications control for the log number of window mentions, the log peak single-day count, and the share of mentions contributed by two-label authors. Sample screening as in Table 6.

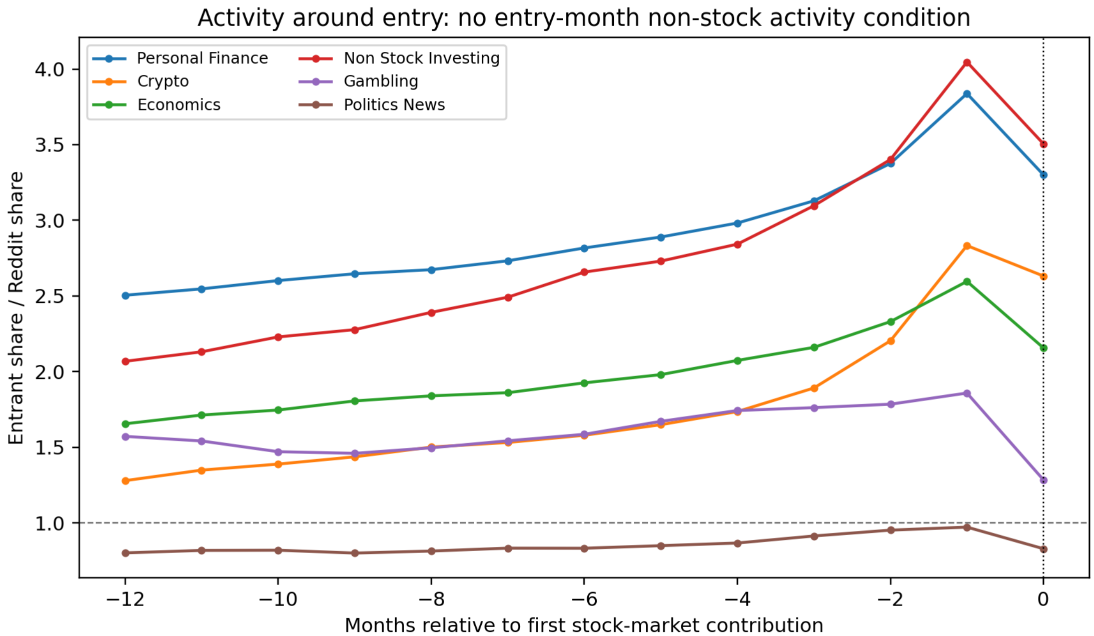
Table 9: The Composition Effect Runs Through Security Characteristics

	Event-day FE	+ characteristics	+ security FE
Outcome: $\lvert CAR \rvert$, three-factor			
Personal Finance	-0.0141^{***}	-0.0061^{***}	-0.0009
	(0.0021)	(0.0016)	(0.0015)
Productivity and Career	-0.0060^{**}	-0.0047^{**}	-0.0025
	(0.0025)	(0.0021)	(0.0019)
Home and Housing	-0.0091^{***}	-0.0088^{***}	-0.0059^{**}
	(0.0033)	(0.0028)	(0.0027)
Crypto	-0.0012	-0.0042^{*}	0.0005
	(0.0030)	(0.0023)	(0.0022)
Economics	-0.0065^{**}	-0.0042	-0.0006
	(0.0030)	(0.0026)	(0.0023)
Law and Legal	-0.0021	-0.0043	-0.0012
	(0.0038)	(0.0032)	(0.0031)
Non-Stock Investing	0.0013	-0.0032	0.0007
	(0.0043)	(0.0038)	(0.0038)
Gambling	0.0131^{***}	0.0025	0.0026
	(0.0043)	(0.0037)	(0.0038)
Return volatility		2.1321^{***}	
		(0.0714)	
Log dollar volume		-0.0022^{***}	
		(0.0004)	
Gambling minus Personal Finance	0.0272	0.0086	0.0035
95% CI	[0.0185, 0.0358]	[0.0012, 0.0160]	[-0.0040, 0.0110]
Share of the gap absorbed		68%	87%
Joint test, eight shares (p)	2.3e$-$11	0.0031	0.513
Outcome: log abnormal volume			
Personal Finance	-0.0809^{***}	-0.0546^{***}	-0.0208
	(0.0158)	(0.0165)	(0.0137)
Productivity and Career	0.0161	0.0219	0.0093
	(0.0201)	(0.0197)	(0.0174)
Home and Housing	0.0177	0.0190	0.0201
	(0.0282)	(0.0279)	(0.0250)
Crypto	-0.0134	-0.0242	-0.0239
	(0.0213)	(0.0208)	(0.0184)
Economics	-0.0401^{*}	-0.0332	-0.0273
	(0.0239)	(0.0232)	(0.0210)
Law and Legal	-0.0077	-0.0162	-0.0078
	(0.0310)	(0.0298)	(0.0278)
Non-Stock Investing	0.0101	-0.0050	0.0080
	(0.0353)	(0.0355)	(0.0326)
Gambling	0.0953^{***}	0.0622^{**}	0.0216
	(0.0317)	(0.0302)	(0.0265)
Return volatility		7.8258^{***}	
		(0.6332)	
Log dollar volume		-0.0171^{***}	
		(0.0044)	
Gambling minus Personal Finance	0.1761	0.1168	0.0424
95% CI	[0.1130, 0.2393]	[0.0557, 0.1780]	[-0.0102, 0.0950]
Share of the gap absorbed		34%	76%
Joint test, eight shares (p)	6.5e$-$09	0.0009	0.310

Notes: Estimates of equation (6) on the $N = 28{,}400$ events for which all three security characteristics are available, with cluster-robust standard errors two-way clustered by security and event day in parentheses. Each coefficient is on the stated type's share of classified mentions in the event window, relative to the omitted *Politics and News* share. The middle column adds three time-invariant characteristics computed over the full LSEG panel for securities with at least 250 trading days: the standard deviation of daily returns, the log of median daily dollar volume, and the log of median closing price, the last included but not reported. All specifications control for the log number of window mentions, the log peak single-day count, and the share of all mentions that are classified. The gap row is the difference between the *Gambling* and *Personal Finance* coefficients, the widest among the nine types, and the absorbed row is the share of the event-day-FE gap that each column removes. Joint tests differ slightly from Panel B of Table 7, which retains 13 further events that lack characteristics. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Figures

Figure 1: Activity Around Stock-Market Entry



Notes: The figure plots the year before a user's first observed stock-market contribution, plus the entry month itself (months −12 through 0), as the average ratio of entrants' category shares to the corresponding platform-wide category shares. The sample comprises 3,224,789 users whose first observed stock-market contribution is to any stock-market destination and who made at least 10 non-stock posts during months −12 to −1. We impose no requirement of activity outside stock-market subreddits in the entry month, because that activity is realized at the entry date. Appendix C reports the earlier version of the figure, which imposed that condition and covered 2,883,824 users. Stock market category activity is excluded from both user-level and platform-wide denominators.

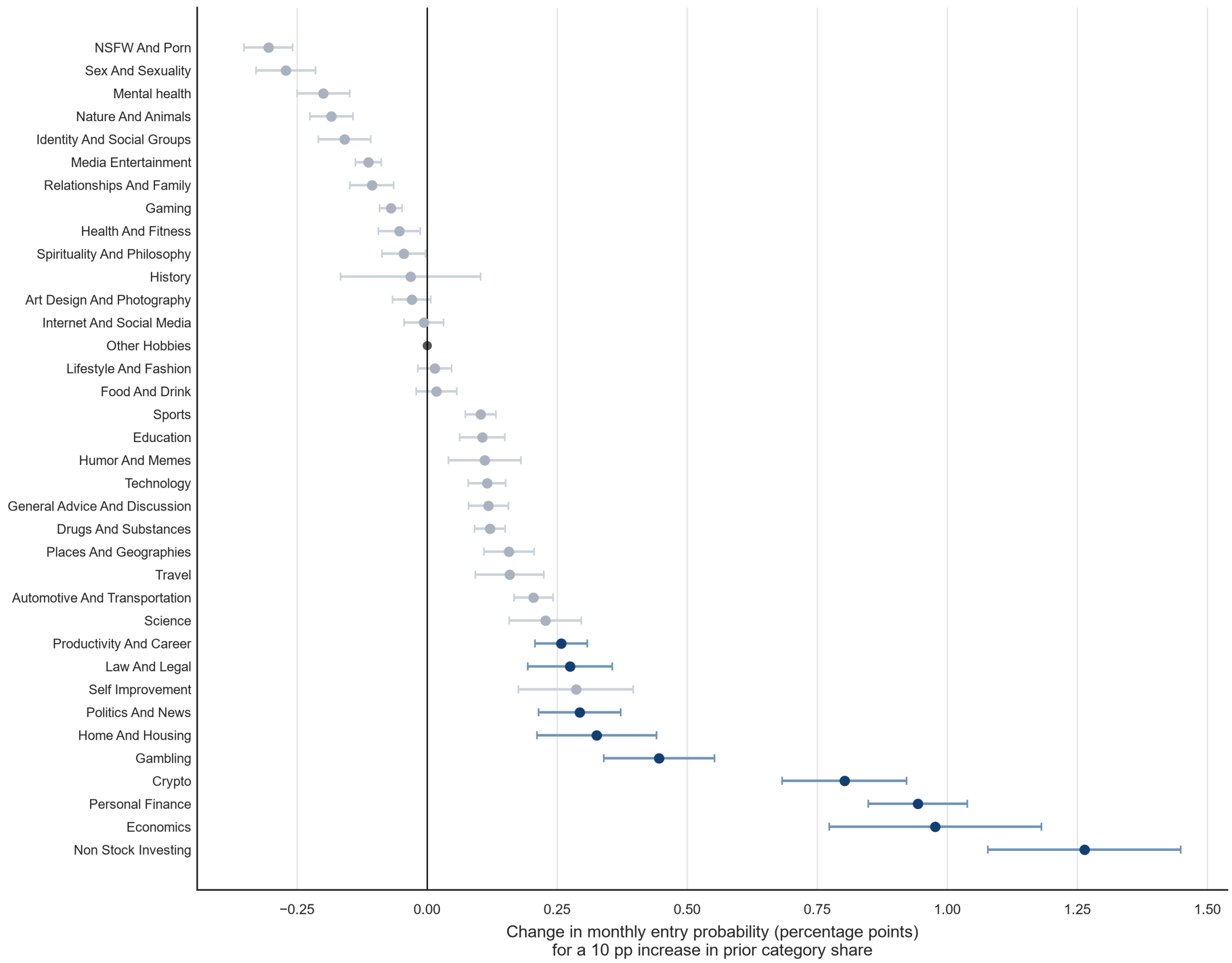


Figure 2: Risk-Set Model Estimates

Notes: The figure reports estimated associations between a user's category shares over the preceding twelve months and entry in the following month from the monthly risk-set model in Equation 1. Each point shows the change in monthly entry probability, in percentage points, associated with a ten-percentage-point increase in the prior share of activity in the indicated category, relative to Other Hobbies. Estimates are inverse-probability weighted for the choice-based sampling design, with weights of 9.61 for entrants and 91.62 for control user-months. Whiskers show 95% confidence intervals based on two-way clustering by user and calendar month.

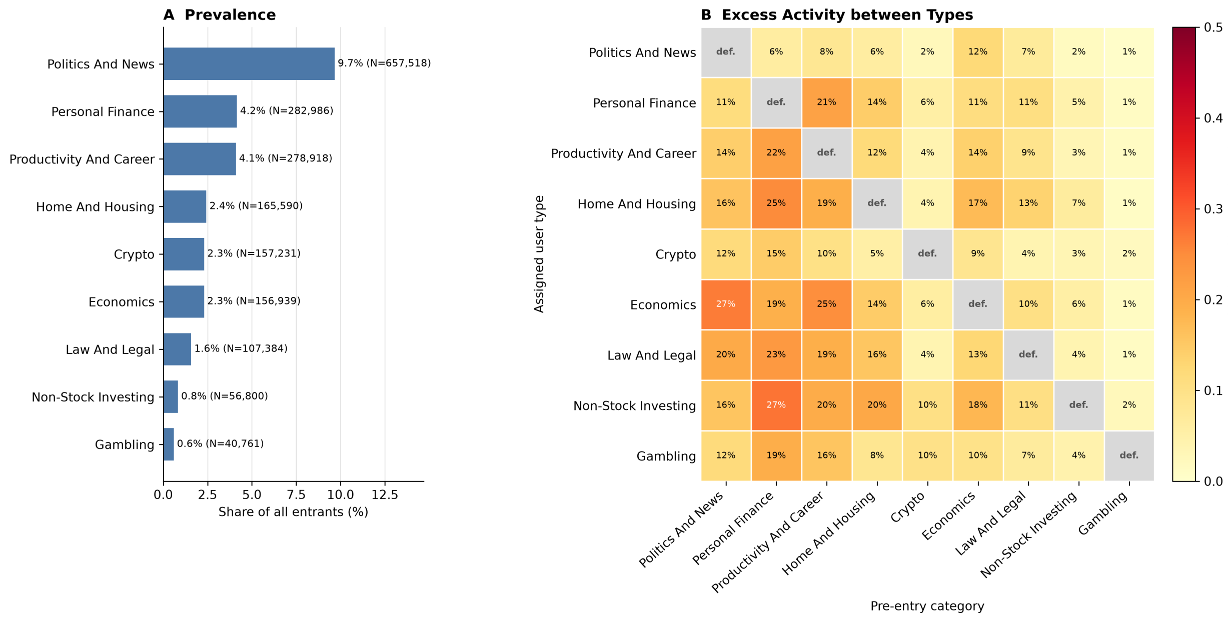


Figure 3: User-Type Prevalence and Pre-Entry Co-Interest Profiles

Notes: Panel A reports the number and share of all 6,804,621 entrants assigned to each substantive type. Panel B reports, for each row type, the percentage of users whose activity in the column category exceeds the contemporaneous Reddit-wide benchmark ($R_{ic} > 1$). Gray "def." cells indicate the category used to define the type and are therefore not independent validation outcomes. The two residual groups, Not enough prior history ($N = 3{,}579{,}832$) and Enough history, not finance-related ($N = 1{,}320{,}662$), are omitted.

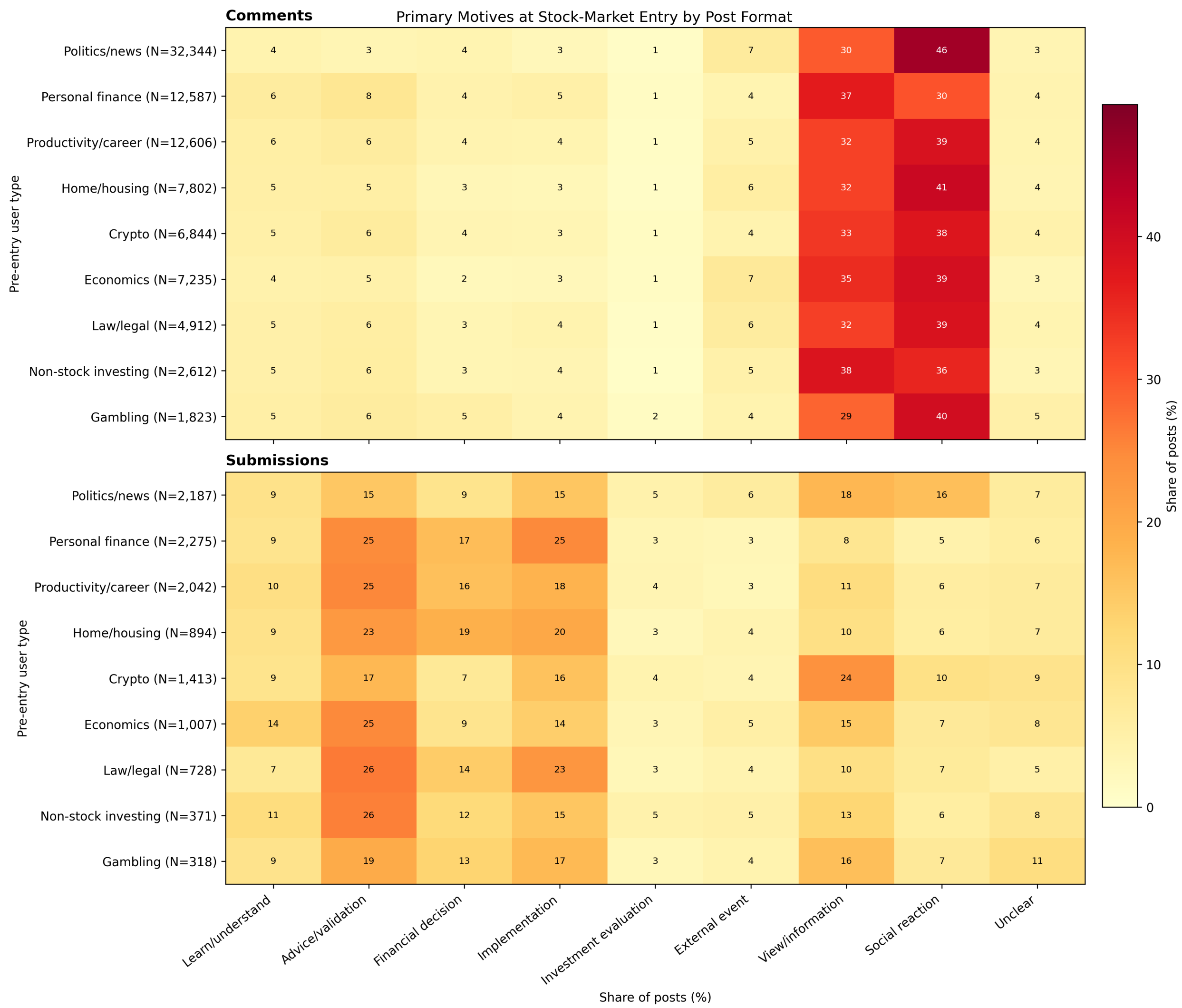
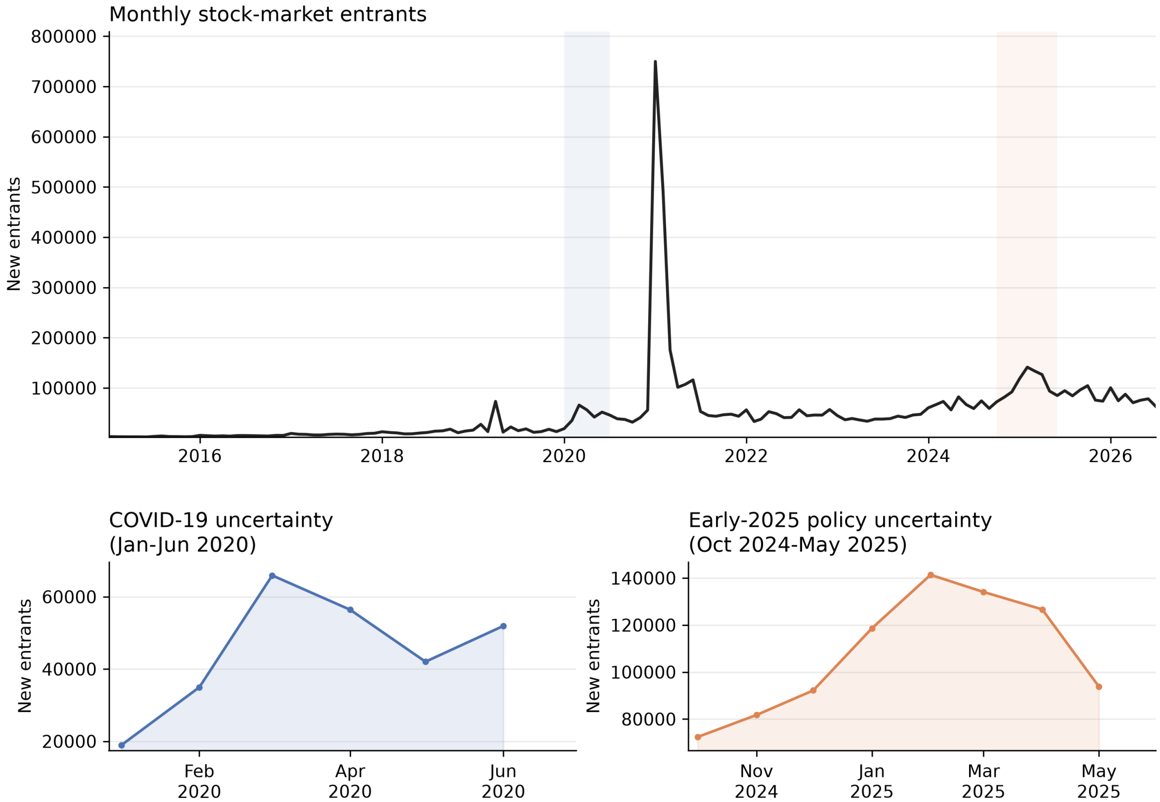


Figure 4: Primary Motives at Stock-Market Entry, by User Type and Post Format

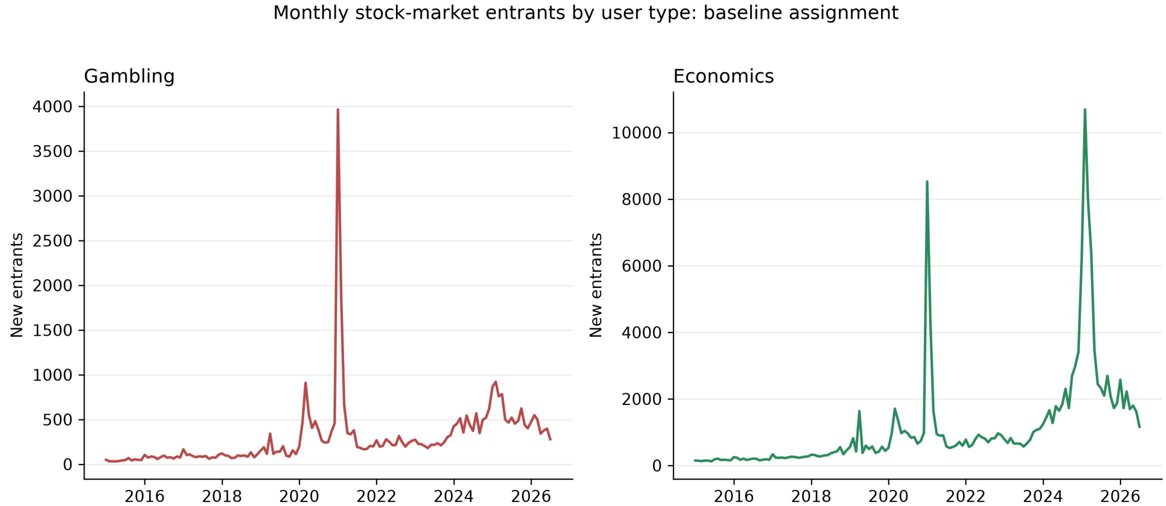
Notes: The figure reports raw within-type percentages for 100,000 first stock-market posts, drawn proportionally across the nine defined user types. Panels separately report comments and submissions. Each post receives one primary motive from the prespecified LLM codebook. The model observes at most the first 1,000 characters of the available title, self-text, or comment body.

Figure 5: Aggregate Monthly Entry into Stock-Market Discussion



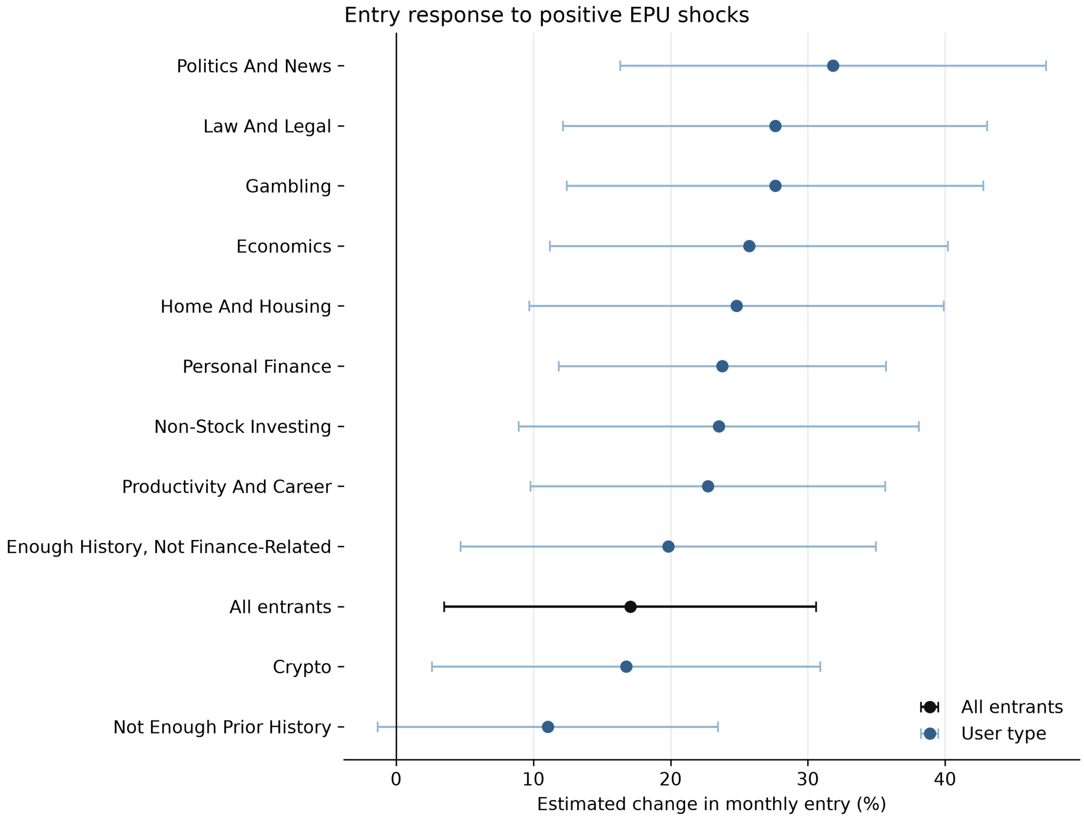
Notes: The upper panel plots monthly first-time entry into stock-market discussion from January 2015 through July 2026. The lower panels zoom in on the COVID-19 episode (January–June 2020) and the rise in U.S. policy uncertainty surrounding tariff announcements (October 2024–May 2025); each uses its own vertical scale. Entry is a user's first observed contribution to any stock-market subreddit.

Figure 6: Monthly Entry for *Gambling* and *Economics* User Types



Notes: Each panel plots monthly entry for the indicated pre-entry user type: *Gambling* ($N = 40{,}761$) and *Economics* ($N = 156{,}939$). Vertical scales differ across panels.

Figure 7: Entry Response to Positive EPU Shocks by User Type

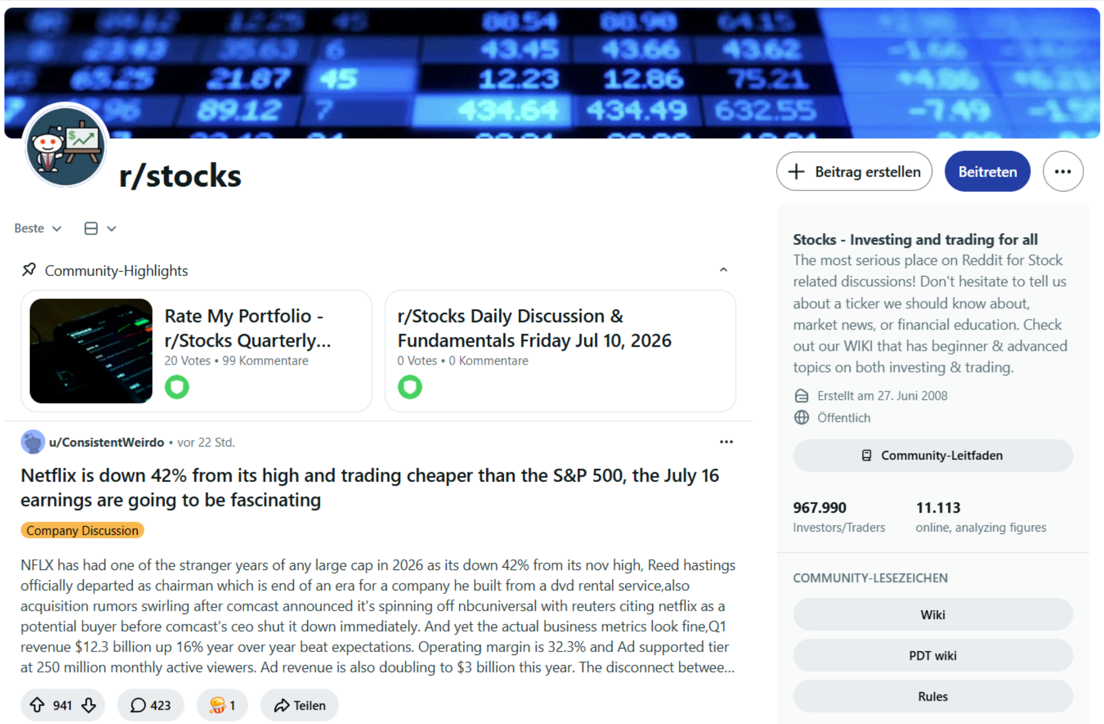


Notes: Points show the percentage change in monthly entry implied by an EPU innovation exceeding one standard deviation, $100[\exp(\hat{\beta}) - 1]$. The black point is the aggregate estimate; blue points are type-specific estimates from the stacked model. Confidence intervals use HAC(3) standard errors for the aggregate estimate and standard errors clustered by calendar month for type-specific estimates. The sample covers May 2015 through July 2026 (135 months, including 18 EPU-shock months).

A Structure of Reddit

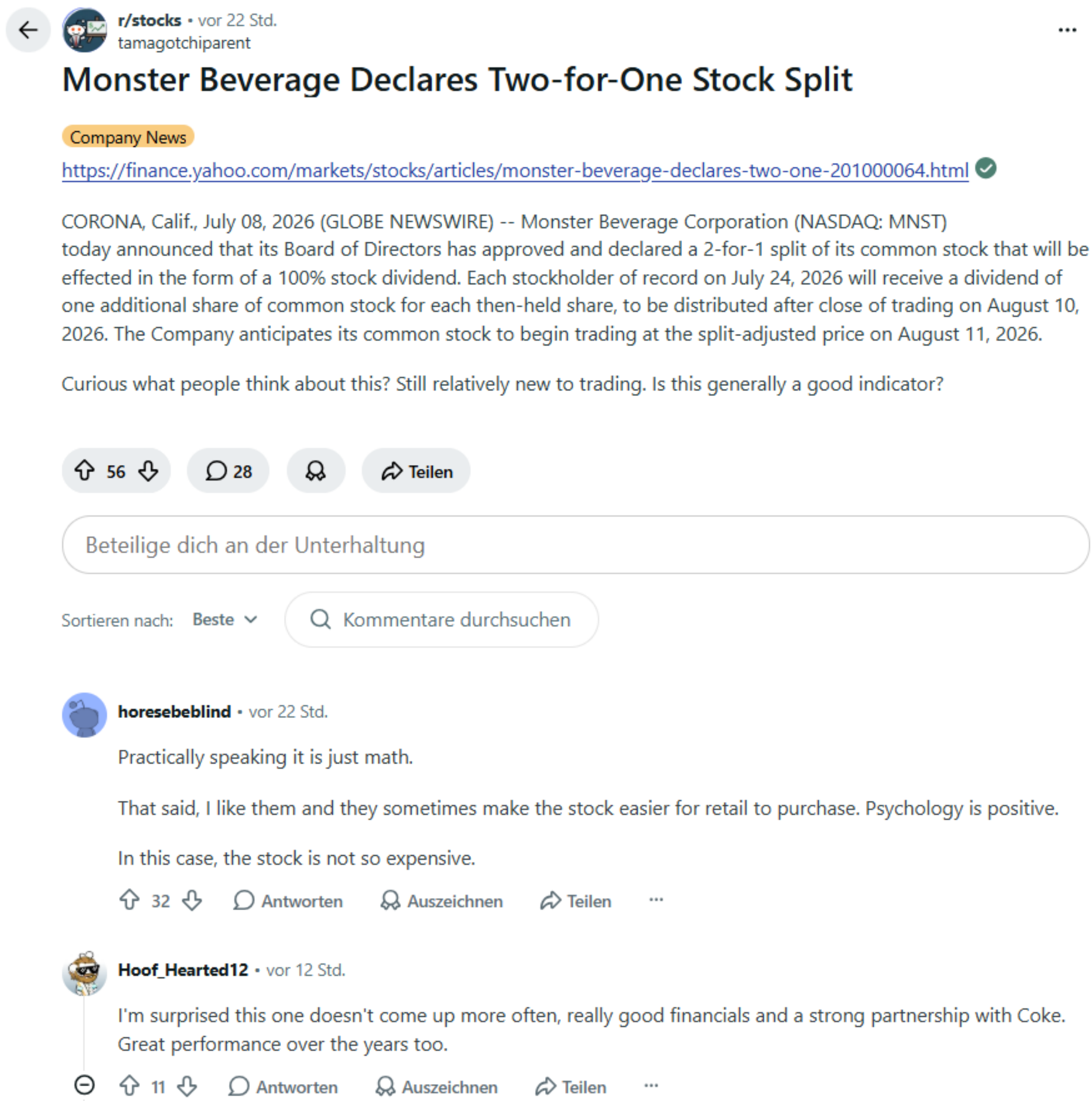
Reddit is organized into topic-specific communities called subreddits. Each subreddit has a front page that collects submissions and comments around the community's topic, while individual submissions can open into threaded discussions with nested replies. The two examples below illustrate these two levels of organization: a subreddit front page and a discussion tree.

Figure 8: Example Subreddit Front Page



Notes: Illustrative screenshot of a subreddit front page; it is not part of the analytical sample. Interface captured in July 2026; the displayed interface language is German.

Figure 9: Example Discussion Tree



Notes: Illustrative screenshot of a threaded discussion; it is not part of the analytical sample. Interface captured in July 2026; the displayed interface language is German.

B LLM Prompts

B.1 Taxonomy Prompt

Subreddits are assigned to taxonomy categories using GPT-5.6 Luna. For each subreddit, the model receives the subreddit name, its self-description when available, and eight representative submissions with their titles. It is instructed to assign one primary category to each subreddit. The operative instruction is:

> Assign each subreddit to exactly one category. For each subreddit, you receive its name, its self-description when available, and eight representative submissions with their titles. Use all of this information to identify the subreddit's overall topic; prefer consistent evidence across the description and submissions over incidental words in a single post. If evidence is weak, use `other_unknown` and a low confidence. Return JSON only.
>
> **Categories:**
>
> - `stock_market`: public equity investing, stock trading, ETFs, options, stock analysis, company valuation, portfolio management, and WallStreetBets-style investing.
> - `non_stock_investing`: investing outside public equities or cryptocurrencies, including bonds, fixed income, commodities, precious metals, private equity, venture capital, collectibles, alternative investments, real estate investing, rental properties, house flipping, and REITs.
> - `crypto`: cryptocurrencies, blockchain, NFTs, DeFi, tokens, mining, wallets, and crypto investing or trading.
> - `personal_finance`: budgeting, saving, debt, taxes, retirement planning, FIRE, banking, insurance, credit cards, mortgages, home buying, rent-versus-buy decisions, and household financial decisions.
> - `economics`: economics, macroeconomics, economic policy, business strategy, entrepreneurship, industries, firms, labor markets, and business or economic news.
> - `politics_news`: politics, government, elections, public policy, political ideology, current events, and news.
> - `technology`: programming, software, hardware, artificial intelligence, cybersecurity, consumer technology, operating systems, engineering, and software tools.
> - `science`: academic research, natural sciences, medicine as a scientific discipline, mathematics, physics, chemistry, biology, and scientific discussion.
> - `gaming`: video games, tabletop games, game-specific communities, esports, game development, and gaming culture.
> - `sports`: sports teams, athletes, leagues, competitions, sporting events, and sports discussion.

- `health_and_fitness`: exercise, fitness, nutrition, physical health, healthy lifestyles, sports training, recovery from physical injury, and general wellness.
- `mental_health_support`: mental health support, emotional wellbeing, therapy, anxiety, depression, ADHD, trauma, addiction recovery, crisis support, peer support, and communities focused on coping with psychological distress.
- `drugs_and_substances`: drug use, harm reduction, recovery, sobriety, psychoactive substances, cannabis, and communities focused on substance use or its consequences.
- `automotive_and_transportation`: cars, motorcycles, trucks, aviation, trains, bicycles, public transport, vehicle ownership, and transportation.
- `other_hobbies`: recreational hobbies and enthusiast communities including DIY, woodworking, crafts, model building, collecting, outdoor recreation, musical instruments, firearms, guns, shooting sports, weapons collecting, and other leisure activities.
- `art_design_and_photography`: visual arts, illustration, graphic design, photography, architecture, drawing, painting, and creative design.
- `food_and_drink`: cooking, recipes, baking, restaurants, beverages, coffee, tea, food culture, and culinary discussion.
- `lifestyle_and_fashion`: fashion, beauty, skincare, grooming, interior lifestyle, personal style, and aesthetics.
- `travel`: travel, tourism, destinations, trip planning, digital nomads, and travel advice.
- `productivity_and_career`: jobs, careers, resumes, interviews, workplace issues, studying for careers, professional development, certifications, productivity, and time management.
- `relationships_and_family`: dating, marriage, parenting, friendships, family relationships, and interpersonal relationships.
- `self_improvement`: habits, motivation, self-discipline, personal growth, life improvement, and non-clinical self-development.
- `sex_and_sexuality`: sexuality, sexual health, sexual relationships, sexual identity, and non-explicit sexual discussion outside adult-content communities.
- `spirituality_and_philosophy`: religion, spirituality, philosophy, ethics, belief systems, and existential discussion.
- `gambling`: sports betting, casinos, poker, lotteries, betting strategies, and gambling communities.
- `media_entertainment`: movies, television, music, anime, books, comics, podcasts, celebrities, and entertainment media.
- `humor_and_memes`: memes, jokes, satire, comedy, humorous images, shitposting,

and parody communities.

- `education`: schools, universities, learning resources, studying, teaching, academic life, and educational discussion.
- `history`: historical events, periods, people, archives, historiography, and discussion of the past.
- `identity_and_social_groups`: communities organized around identity, culture, ethnicity, nationality, gender, sexual orientation, disability, or shared social experience.
- `internet_and_social_media`: online communities, websites, social-media platforms, internet culture, content creators, and digital social interaction.
- `nature_and_animals`: pets, animals, wildlife, gardening, plants, environmental topics, and nature.
- `home_and_housing`: housing and home-related communities, including renting, apartments, roommates, home improvement, DIY renovation, appliances, interior design, and everyday housing issues not primarily focused on financial decisions or investment returns.
- `law_and_legal`: law, legal advice, courts, legal professions, law school, and legal discussion.
- `nsfw_and_porn`: adult content, pornography, explicit sexual content, and NSFW communities.
- `places_and_geographies`: countries, cities, regions, local communities, languages, and location-based subreddits.
- `general_advice_and_discussion`: general discussion, question-and-answer communities, AskReddit-style forums, advice, AMAs, support, and broad conversation.
- `other_unknown`: cannot be confidently assigned to any substantive category.

Output for each subreddit: `subreddit`, `primary`, `llm_confidence` from 0 to 1, and `llm_reason` as a short phrase.

B.2 First-Post Annotation Prompt

We separately annotate a fixed sample of users' first contributions to stock-market discussion. The model sees the post identifier and the first 1,000 characters formed from the title, self-text, and comment body. It is asked to classify the purpose of the contribution rather than its topic. The operative instruction is:

> You are classifying users' first contributions to a stock-market discussion forum.
>
> The input contains multiple posts. Return one annotation for every post, preserving input order. The id is only for alignment and must be copied exactly.

The goal is to identify why the user appears to be participating: what they want to achieve, learn, decide, or express. Do not classify the post merely by topic or keywords. Use only information explicitly stated or strongly implied by the text. Do not infer motives that are not supported.

Assign exactly one `primary_motive`, optionally one different `secondary_motive` (otherwise the string `none`), `personal_stake`, and `contemplated_action`. The two Boolean fields must be JSON `true` or `false`, not strings.

Primary-motive codebook:

`learn_understand`
: Wants to understand an investing concept, financial mechanism, market phenomenon, or how something works.

`seek_advice_validation`
: Wants others to recommend, evaluate, or validate a plan, idea, strategy, or possible choice.

`make_financial_decision`
: Is actively deciding what to do with their own money or investments, such as buying, selling, holding, allocating, investing, or changing a position. Prefer this over advice or validation when a concrete personal decision is central.

`solve_implementation_problem`
: Wants practical help executing an action, such as using a brokerage account, transferring funds, handling taxes, placing an order, or resolving platform or account mechanics.

`evaluate_investment`
: Wants to assess the attractiveness, value, prospects, or risk of a particular stock, asset, company, or investment opportunity.

`interpret_external_event`
: Wants to understand or discuss the financial implications of a current market, macroeconomic, political, geopolitical, or company-specific event.

`share_view_information`
: Primarily contributes an opinion, analysis, thesis, information, or advice rather than asking for something.

`social_reaction`
: Primarily jokes, agrees, disagrees, reacts, or participates conversationally without a clear informational or financial objective.

`other_unclear`
: No motive can be identified confidently.

Decision rules: classify purpose, not subject matter; classify a question about the author's own concrete financial choice as `make_financial_decision`; classify a request for feedback without a clear concrete action as `seek_advice_validation`; classify a conceptual question as `learn_understand`; and classify a post prompted by a recent event as `interpret_external_event`. Use `secondary_motive` only when a second motive is clearly present. `personal_stake` and `contemplated_action` are independent of the motive labels.

Boolean codebook: Set `personal_stake=true` only when the text states or strongly implies that the author or the author's household has money, income, debt, holdings, gains, losses, an account, or another direct financial exposure at issue. Generic discussion of an amount, ticker, or hypothetical investor is not sufficient. Set `contemplated_action=true` only when the author states or strongly implies a current or planned action involving money or an investment, such as buying, selling, holding, allocating, opening or changing an account, or paying a financial obligation. A general question about what investors might do, without an author-specific plan or decision, is false. If the text is too incomplete to support either flag, use false rather than infer the field.

Return JSON only as an object with an `items` array. Each item must contain the copied id and exactly the four annotation keys `primary_motive`, `secondary_motive`, `personal_stake`, and `contemplated_action`. `secondary_motive` must be `none` or a different value from the primary-motive codebook. Do not include explanations, confidence scores, or any other keys. Return items in the same order as the input posts.

C Robustness of Finance-Related User-Type Assignments

The user-type classification rests on two thresholds: the minimum pre-entry history required for a user to be classified at all, and the minimum number of posts the winning category must contain for its label to be assigned. Both are somewhat arbitrary, so this appendix asks whether a different reasonable choice would materially change the resulting types. We use the same nine finance-adjacent categories as the main text (politics/news, personal finance, crypto, economics, non-stock investing, gambling, law/legal, productivity/career, and home/housing) and the same standardized-enrichment procedure: each user is compared against the contemporaneous Reddit-wide benchmark over the twelve months before entry; users below the history threshold are labeled *Not enough prior history*, and users above it whose top category fails to clear the winning-post threshold are labeled *Enough history, not finance-related*.

The baseline rule requires at least ten pre-entry posts and at least two posts in the winning category. Under this rule, just under 28% of entrants receive a focal-category label, a little over half lack sufficient history, and the remainder have history but no qualifying category. Politics/news is the largest type, followed by personal finance and productivity/career, with the remaining six categories forming a longer tail (exact shares in the main text).

Table 10 varies both thresholds, and optionally adds a minimum raw enrichment ratio, and reports the resulting typed share alongside label agreement with the baseline. The classification is stable under sensible variation: raising the history requirement to fifteen or twenty posts, or the winning-post requirement to three or five, leaves most baseline labels unchanged among users typed at baseline. Adding a raw-enrichment floor shrinks the typed population but does not disturb the labels of users who remain typed. Tightening any threshold mainly moves marginal users into the two unclassified categories rather than reshuffling them across finance-adjacent types, which is the pattern expected if the labels track real, if noisy, differences in pre-entry behavior rather than artifacts of where the cutoffs happen to sit.

These checks support the ten-post/two-winning-post rule as a transparent compromise between coverage and conservatism: stricter raw-ratio cutoffs trade one for the other without changing the underlying story. As throughout the main text, every assignment uses only pre-entry activity, so classification is fixed before, and cannot be influenced by, entry timing, first-post content, or post-entry behavior.

Table 10: Robustness to User-Type Assignment Cutoffs

Min. history	Min. winner	Min. raw ratio	Typed share	Not enough history	Agreement†
5	2	–	29.43%	46.37%	–
10	1	–	34.80%	52.61%	86.9%
10	2	–	27.98%	52.61%	100.0%
10	3	–	24.32%	52.61%	86.9%
10	5	–	19.92%	52.61%	71.2%
15	2	–	26.78%	56.65%	95.7%
20	2	–	25.73%	59.70%	91.9%
30	2	–	23.96%	64.18%	85.6%
10	2	1.25	23.79%	52.61%	85.0%
10	2	1.50	23.01%	52.61%	82.2%
10	2	2.00	21.60%	52.61%	77.2%

†Share of baseline-typed users retaining their label.

Assignment Stability

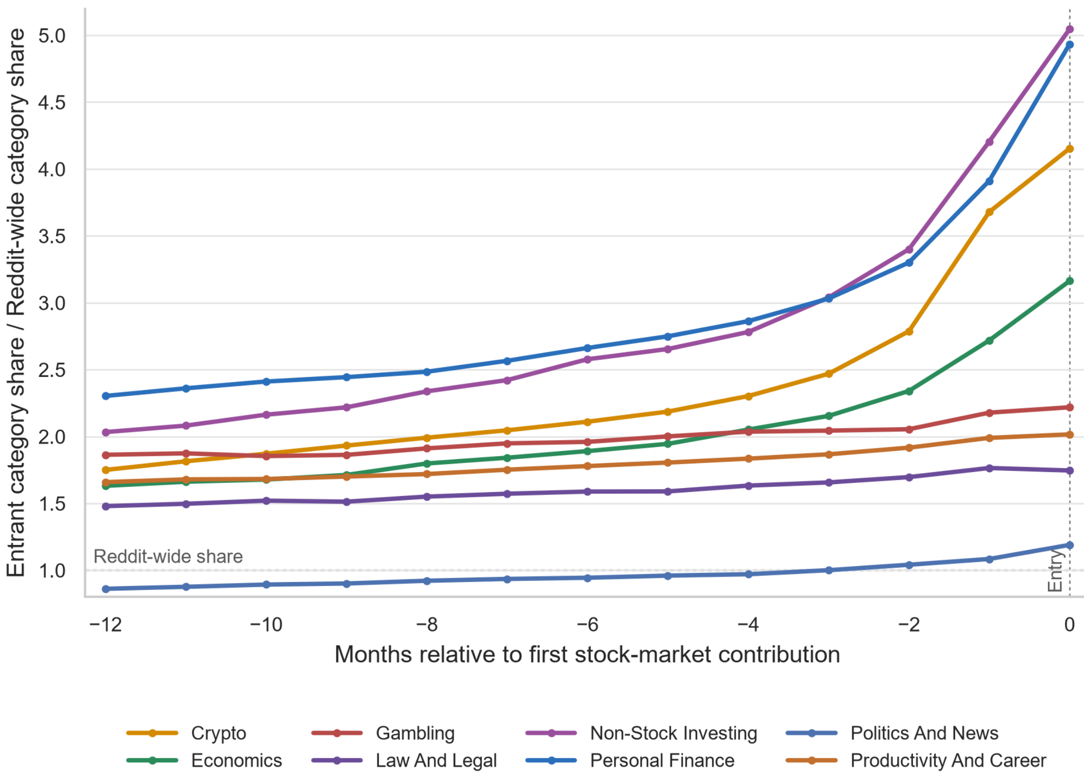
Two diagnostics bear on the hard-assignment rule. The first is the gap between a user's top two standardized category scores, which measures how close the argmax came to selecting a different label. The second splits each user's pre-entry history at random into two halves, runs the identical assignment procedure on each half, and reports how often the two labels agree.

Table 11: Assignment Stability by Pre-Entry Type

Type	Users	Median score gap	Near-tie share	Split-half agreement
Crypto	157,237	16.78	2.6%	93.3%
Economics	167,142	5.88	5.8%	80.4%
Gambling	41,470	21.77	1.1%	92.0%
Law and Legal	115,001	5.92	5.5%	80.0%
Non-Stock Investing	60,550	16.91	1.7%	86.6%
Personal Finance	301,398	7.29	4.6%	87.1%
Politics and News	525,201	5.26	7.6%	93.1%
Productivity and Career	285,568	5.87	6.2%	86.7%

Notes: The table covers eight of the nine substantive types, together 1,653,567 entrants under the baseline ten-post and two-winning-post rule. Home and Housing is absent from the diagnostic file and is not shown. The median score gap is the difference between a user's largest and second-largest standardized excess-activity score S_{ic}. The near-tie share is the fraction of users for whom that gap falls below 0.50. Split-half agreement divides each user's pre-entry category counts into two independent halves by a Binomial$(n_c, 0.5)$ draw with a fixed seed, which is equivalent to randomly assigning the user's individual posts to two halves, then runs the identical assignment on each half using the same Reddit-wide benchmark. The column reports the share of users whose two half-history labels coincide, conditional on both halves yielding a substantive label. Because each half uses half the history, these rates understate the reliability of the full-history labels used throughout the paper. Agreement across all users including the two residual groups is 89.3 percent.

Figure 10: Activity Around Stock-Market Entry, Conditional Sample



Notes: This is the earlier version of Figure 1, which additionally required users to be active outside stock-market subreddits in the entry month. That condition selects on behavior realized at the entry date, so the main text uses the unconditioned version. The conditional sample covers 2,883,824 users against 3,224,789 in the main figure. The pre-entry gradients are positive and significant in both.

D VAR Specification and Uncertainty Shock Measure

This appendix describes the construction of the monthly uncertainty shocks used in Section 4. We estimate a reduced-form vector autoregression (VAR) following Sims (1980) to isolate unexpected innovations in economic policy uncertainty after controlling for the joint dynamics of macroeconomic and financial variables.

Let

$$y_t = \begin{bmatrix} \log(\mathrm{EPU}_t) \\ \log(\mathrm{VIX}_t) \\ r_t^{SP500} \\ g_t^{IP} \\ \pi_t \\ u_t \\ ff_t \\ cs_t \end{bmatrix},$$

where EPU_t denotes the U.S. Economic Policy Uncertainty index (Baker et al., 2016), VIX_t is the CBOE Volatility Index, r_t^{SP500} is the monthly S&P 500 return, g_t^{IP} is industrial production growth, π_t is inflation, u_t is the unemployment rate, ff_t is the effective federal funds rate, and cs_t is the Baa–Treasury credit spread.

The EPU series is the U.S. news-based index supplied with the Baker–Bloom–Davis data (FRED series USEPUINDXM). The VIX, industrial-production index, CPI, unemployment rate, effective federal funds rate, and Moody's Baa corporate-yield/10-year Treasury spread are downloaded from FRED as VIXCLS, INDPRO, CPIAUCSL, UNRATE, FEDFUNDS, and BAA10Y, respectively. The S&P 500 level is the daily close for Yahoo Finance symbol `^GSPC`, aggregated to the last available observation in each month. These are the exact inputs saved in the replication file `var_monthly_input_201501_202607.csv`.

The transformed variables are

$$\begin{aligned} r_t^{SP500} &= 100\,\Delta\log(\mathrm{SP500}_t), \\ g_t^{IP} &= 100\,\Delta\log(\mathrm{IP}_t), \\ \pi_t &= 1200\,\Delta\log(\mathrm{CPI}_t), \end{aligned}$$

while $\log(\mathrm{EPU}_t)$, $\log(\mathrm{VIX}_t)$, u_t, ff_t, and cs_t enter in levels. All series are observed monthly over January 2015–July 2026.

The VAR is given by

$$y_t = c + \sum_{j=1}^{p} A_j y_{t-j} + \varepsilon_t,$$

where c is a vector of intercepts, A_j are coefficient matrices, and ε_t is the vector of reduced-form innovations. The lag length is selected using the Akaike Information Criterion over candidate specifications with one to six lags. For the baseline sample, the AIC selects $p = 3$.

Our measure of uncertainty shocks is based on the innovation in the EPU equation. Let $\hat{\varepsilon}_t^{EPU}$ denote the estimated residual from that equation and define the standardized innovation as

$$z_t = \frac{\hat{\varepsilon}_t^{EPU}}{\widehat{\sigma}(\hat{\varepsilon}_t^{EPU})},$$

where $\widehat{\sigma}(\hat{\varepsilon}_t^{EPU})$ is the sample standard deviation of the residuals. We classify month t as an uncertainty shock whenever

$$\text{Shock}_t = \mathbf{1}\{z_t > c\},$$

where c is a threshold parameter. Our baseline specification sets $c = 1$.

This approach provides a simple reduced-form measure of unusually large positive uncertainty innovations after accounting for the persistence and comovement of macroeconomic and financial conditions. It is not intended to identify structural policy shocks but rather to identify months characterized by exceptionally large unexpected increases in policy uncertainty.

E Taxonomy Categories: Coverage, Pre-Entry Trends, and Reliability

E.1 Taxonomy Counts and Confidence

Table 12 reports the number of subreddits, post prevalence, and average classifier confidence for each taxonomy category.

Table 12: Subreddit taxonomy counts, post prevalence, and user activity

Category	N	Posts (%)	Users ever (%)	Posts/active month	Posts/subreddit	Mean conf.
NSFW and porn	7,428	8.51%	24.2%	14.2	274,953	0.988
Gaming	5,134	16.36%	30.2%	12.0	764,650	0.987
Media entertainment	4,565	10.33%	26.1%	6.5	543,048	0.972
Humor and memes	1,834	7.57%	20.0%	7.2	991,017	0.949
Technology	1,785	3.35%	17.0%	5.0	450,005	0.973
Places and geographies	1,505	5.42%	16.2%	6.3	864,864	0.970
Other hobbies	1,412	2.83%	13.7%	7.0	481,145	0.952
Sex and sexuality	1,381	1.64%	11.6%	7.2	284,947	0.966
Internet and social media	1,190	2.01%	12.2%	6.3	405,724	0.922
Politics and news	1,182	4.82%	10.1%	9.1	979,155	0.929
Sports	1,148	6.53%	8.8%	14.6	1,366,012	0.981
Health and fitness	903	1.47%	9.2%	4.8	391,253	0.965
Automotive and transportation	879	1.56%	7.3%	6.2	424,772	0.989
Nature and animals	862	1.59%	12.5%	5.1	442,808	0.982
Lifestyle and fashion	817	1.35%	10.4%	6.2	396,338	0.951
Education	775	1.45%	11.2%	4.3	448,147	0.971
Art, design, and photography	687	1.61%	10.9%	4.0	562,314	0.945
General advice and discussion	683	7.82%	20.0%	7.6	2,746,454	0.830
Identity and social groups	599	2.12%	9.4%	7.8	849,482	0.937
Productivity and career	550	1.01%	9.5%	5.5	439,102	0.952
Food and drink	501	0.82%	7.0%	4.3	395,076	0.981
Drugs and substances	472	1.01%	4.9%	7.1	512,728	0.979
Crypto	462	0.75%	3.8%	10.5	389,004	0.989
Spirituality and philosophy	402	0.96%	4.9%	6.8	573,653	0.961
Relationships and family	397	1.69%	11.8%	5.1	1,023,978	0.955
Mental health support	326	0.81%	6.4%	4.3	597,725	0.967
Stock market	320	1.01%	2.4%	12.1	753,906	0.973
Personal finance	286	0.66%	5.1%	4.6	552,238	0.948
Other unknown	270	0.43%	3.9%	5.4	378,145	0.552
Science	265	0.46%	4.0%	4.2	417,819	0.928
Home and housing	171	0.35%	4.1%	4.6	490,212	0.958
History	168	0.35%	3.2%	3.7	495,786	0.942
Economics	154	0.33%	3.8%	5.3	518,474	0.915
Law and legal	150	0.29%	3.3%	5.4	464,084	0.964
Travel	149	0.24%	4.3%	4.1	389,651	0.974
Self improvement	76	0.22%	4.0%	3.4	687,861	0.907
Gambling	68	0.14%	0.8%	9.0	499,131	0.968
Non-stock investing	44	0.13%	0.9%	4.5	696,630	0.920

Notes: The table covers 40,000 uniquely classified subreddits. Posts (%) uses all observed posts as its denominator. Users ever (%) is the percentage of all observed Reddit users with at least one post in the category. Posts/active month is total category posts divided by the estimated number of active user–month observations in the category, where a user–month is active if the user makes at least one post in that category during that calendar month. Thus, it measures the average number of posts per active user per month, not posts per active calendar month.

E.2 Pre-Entry Trends by Category

This appendix reports the full set of category-specific pre-entry trends summarized in the main text. The sample is the same cohort used in Figure 1: users whose first contribution is to any stock-market destination, who made at least ten non-stock posts in the twelve months before entry, and who were active outside stock-market subreddits in the entry month. This yields 2,883,824 users. Because users appear only in months with observed non-stock activity, the resulting panel is unbalanced.

For each non-stock category c, we estimate a within-user linear trend in excess attention over the twelve months before entry. Let $\tau \in \{-12, \ldots, -1\}$ index event time, with $\tau = -1$ denoting the month immediately preceding entry, and let $\text{Proximity}_{i\tau} = \tau + 12$ increase linearly as entry approaches. The dependent variable, $y_{i\tau c}$, is user i's activity share in category c in event month τ, net of the platform-wide share of category c in the same calendar month; stock-market activity is excluded from both shares. We estimate

$$y_{i\tau c} = \alpha_i + \lambda_{m(i,\tau)} + \beta_c \, \text{Proximity}_{i\tau} + \varepsilon_{i\tau c},$$

where α_i are user fixed effects and $\lambda_{m(i,\tau)}$ are calendar-month fixed effects, so β_c is identified from within-user changes in category c activity as entry approaches, net of aggregate seasonal patterns. We interpret β_c as the average monthly increase in excess attention to category c over the year before entry.

Table 13 reports β_c for every category, with standard errors clustered by user. To make magnitudes comparable across categories of very different overall size, coefficients are scaled by each category's mean platform-wide prevalence.

Table 13: Relative Pre-Entry Pathway Slopes by Category

Category	Monthly slope	Category	Monthly slope
Personal Finance	12.709*** (0.277)	Other Hobbies	−0.187*** (0.070)
Non-Stock Investing	7.132*** (0.575)	Media and Entertainment	−0.329*** (0.027)
Economics	4.020*** (0.262)	Spirituality and Philosophy	−0.411*** (0.100)
Crypto	3.148*** (0.282)	Self-Improvement	−0.431 (0.277)
Politics and News	2.310*** (0.044)	Technology	−0.490*** (0.084)
Home and Housing	1.828*** (0.238)	Lifestyle and Fashion	−0.499*** (0.098)
Law and Legal	1.704*** (0.240)	Gaming	−0.516*** (0.021)
Travel	1.630*** (0.308)	Internet and Social Media	−0.521*** (0.058)
Places and Geographies	1.513*** (0.052)	Art, Design, and Photography	−0.675*** (0.091)
Automotive and Transportation	1.333*** (0.114)	Education	−0.900*** (0.117)
Sports	1.137*** (0.040)	Nature and Animals	−0.912*** (0.086)
Productivity and Career	1.005*** (0.150)	Health and Fitness	−1.005*** (0.113)
Gambling	0.547 (0.444)	Drugs and Substances	−1.066*** (0.129)
Science	0.323* (0.193)	Relationships and Family	−1.145*** (0.076)
History	0.295* (0.163)	NSFW and Porn	−1.726*** (0.014)
Other/Unknown	0.234 (0.157)	Sex and Sexuality	−1.879*** (0.047)
Food and Drink	0.145 (0.139)	Mental Health and Support	−2.159*** (0.121)
Humor and Memes	0.103*** (0.032)		
General Advice and Discussion	−0.052 (0.038)		
Identity and Social Groups	−0.101** (0.050)		

Notes: Each entry reports the all-users monthly slope in excess attention, scaled by the category's typical platform prevalence; standard errors are in parentheses. A positive coefficient indicates that attention to the category rises as stock-market entry approaches. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

E.3 Human and LLM Annotation Agreement

We assess the reliability of the main subreddit taxonomy in a two-stage validation exercise. In Stage 1, a human annotator assigns a fixed random sample of 250 subreddits to the mutually exclusive categories of the full taxonomy. For each subreddit, the annotator observes its name, the category definitions, and eight randomly sampled submissions, including titles and self-text.

We repeat this task independently using GPT-5.6 Luna, Gemini, OpenAI GPT-5 mini, and DeepSeek. Each model receives the same subreddit-level information, taxonomy definitions, and sampled submissions as the human annotator. This common information set ensures that differences in labels reflect differences across annotators rather than differences in the material available to them.

Table 14 reports pairwise Cohen's kappa coefficients across the 250 sampled subreddits. Agreement is high: the unweighted mean kappa across the ten distinct annotator pairs is 0.795 for the full taxonomy.[8]

Table 14: Pairwise Cohen's kappa: full taxonomy

	Human	GPT-5.6 Luna	Gemini	OpenAI GPT-5 mini	DeepSeek
Human	1.000	0.734	0.733	0.707	0.736
GPT-5.6 Luna	0.734	1.000	0.870	0.810	0.839
Gemini	0.733	0.870	1.000	0.831	0.843
OpenAI GPT-5 mini	0.707	0.810	0.831	1.000	0.848
DeepSeek	0.736	0.839	0.843	0.848	1.000

Notes: Each cell reports Cohen's kappa for the corresponding pair of annotators across 250 subreddits. Cohen's kappa adjusts observed agreement for the agreement expected from the annotators' marginal label distributions. Diagonal entries equal one by construction.

[8]Cohen's kappa is defined for a pair of annotators. We therefore summarize overall agreement using the unweighted mean across the ten distinct pairs formed by the five annotators.

F Text Feature Construction

This appendix documents the transparent first-post features used in Section 3.6. The goal is to test whether user types defined exclusively from pre-entry Reddit activity differ in the structure and content of their first stock-market contribution. These features are not used in the type assignment.

For submissions, the document is the title plus selftext; for comments, it is the body. We normalize whitespace and exclude documents that are empty, `[deleted]`, or `[removed]`. Word counts use alphabetic tokens. Text is lowercased for dictionary matching. We use whole-word and complete phrase matching, with longer phrases placed first within each dictionary. Thus, for example, a match to *interest rates* is not separately counted as *interest rate*. The principal dictionary outcomes are binary indicators equal to one if at least one term or phrase is present. This avoids mechanically inflating dictionary scores for short comments. Matches-per-100-words results are retained in the replication output as a robustness check.

Table 15: Dictionaries Used in the First-Post Semantic Validation

Economic terms.
economy; economic; macro; macroeconomic; inflation; deflation; stagflation; cpi; core cpi; ppi; pce; federal reserve; the fed; fomc; Jerome Powell; interest rates; rate hikes; rate cuts; quantitative easing; quantitative tightening; unemployment; labor market; jobs report; nonfarm payrolls; gdp; recession; soft landing; hard landing; economic growth; monetary policy; fiscal policy; yield curve; treasury yields; business cycle; consumer confidence; housing market; mortgage rates; debt ceiling; stimulus; national debt.

Political terms.
election; president; presidential; congress; congressional; senate; democrat; republican; gop; maga; trump; biden; administration; white house; supreme court; scotus; midterms; primary; government shutdown; executive order; tariff; trade war; sanctions; immigration policy.

Portfolio and household-investing terms.
asset allocation; portfolio allocation; diversification; diversified; rebalance; rebalancing; index fund; index funds; etf; etfs; mutual fund; mutual funds; expense ratio; target date fund; risk tolerance; time horizon; dollar cost averaging; dca; buy and hold; roth ira; traditional ira; 401k; brokerage account; taxable account; retirement account; tax advantaged; tax loss harvesting; cost basis; net worth; emergency fund; compound interest; hsa; 529; fiduciary; financial advisor; fee-only; asset class; S&P 500; spy; vti; voo; bond fund; bonds; total market fund.

Trading and speculation terms.
call option; call options; put option; put options; options trading; strike price; implied volatility; IV

crush; 0dte; leverage; short selling; short squeeze; margin call; day trading; swing trading; stop loss; technical analysis; yolo; gamble; stonks; tendies; diamond hands; paper hands; to the moon; wsb; meme stock; penny stock; theta; delta; gamma; pump and dump; rug pull; loss porn; gain porn; ape.

Crypto terms.

crypto; cryptocurrency; bitcoin; btc; ethereum; eth; blockchain; altcoin; altcoins; stablecoin; defi; nft; coinbase; binance; hodl; satoshi; sats; web3; dao; airdrop; wallet; cold storage; hot wallet; dogecoin; shitcoin; memecoin; solana; sol; xrp; staking; gas fee.

Advice/help phrases.

help; advice; any advice; looking for advice; seeking advice; any feedback; looking for feedback; any suggestions; any recommendations; what do you think; what are your thoughts; should i buy; should i sell; should i hold; should i invest; what should i do; where should i start; am i missing something; does this make sense; is this a good idea; roast my portfolio; sanity check; am I doing this right; is this normal; wwyd.

Question and length.

Question is an indicator equal to one if a document contains at least one `?`. Post length is $\log(1 + \text{alphabetic word count})$.

Dictionary audit.

Before the full analysis, we drew a fixed-seed one-percent Bernoulli sample of first posts and inspected 20 positive matches for each dictionary. The matches were overwhelmingly on-concept. The dictionaries use context-specific phrases where a standalone term would be ambiguous (for example, *margin call* rather than *margin*). The reproducible audit excerpts are retained with the analysis output.

G Ticker Mention Extraction

This appendix describes how we identify mentions of individual securities in stock-market discussion.

G.1 Source Text and Matching Rule

We process every submission and comment posted in the 320 stock-market subreddits between January 2015 and July 2026. For each post we concatenate the title, the self-text, and the comment body into a single string. We then apply the following rule.

1. We find cashtags matching `$[A-Z]{1,5}`, bounded so that the symbol is not part of a longer alphanumeric token. We retain a cashtag only when its symbol appears in the ticker inventory.
2. If a post contains at least one valid cashtag, we retain those symbols and do not search that post for bare tickers.
3. Otherwise we find bare uppercase tokens matching `[A-Z]{1,5}`. We retain a token only when it appears in the ticker inventory and is absent from the list of the 10,000 most common English words.
4. We deduplicate symbols within a post.

The cashtag priority in step two matters. Users who write $TSLA in a post are signaling the security explicitly, and searching the same post for bare tokens would add noise without adding information. The common-word exclusion in step three removes the largest source of false positives, since many English words are also valid ticker symbols.

The procedure yields 44.7 million post-ticker mentions. Of these, 3.8 million come from cashtags and 40.8 million from bare uppercase tokens. We attach to each mention the author and the posting date, which allows us to merge mentions to the pre-entry user types defined in Section 3. We exclude mentions from accounts flagged by the screening procedure in Appendix H.

G.2 Screening Non-Securities

Bare uppercase tokens can match acronyms that are not securities. This is a serious concern in our setting. Financial discussion is dense with abbreviations, and many of them are also valid ticker symbols. The token `ETF` is a ticker, as are `ATH`, `EOD`, `DCA`, `RSI` and `MACD`. So are `CDC`, `OPEC` and `ESG`. The problem is not merely that these add noise. Different user types use different vocabulary, so uncorrected collisions could produce apparent differences in the securities that types discuss when the underlying difference is only in how they write.

We therefore screen symbols on evidence rather than on judgment about the string. We rank symbols by the number of bare-token mentions they receive and take the 200 largest, which together account for 64 percent of all classified mentions. For each symbol we draw usage snippets from the corpus, retaining a snippet only when our matching rule would have recorded that mention. We then read the snippets and record whether the token is used as a security. We repeat the exercise for every symbol that appears in the enrichment tables, so that each reported cell is validated directly.

The screen removes 96 symbols and 22.7 percent of classified mentions. The largest are `DRS` (1.29 million mentions, direct registration), `ETF` (0.84 million), `WSB` (0.79 million, the subreddit), `ATH` (0.31 million, all-time high) and `BTC` (0.30 million, which is an asset but not an equity). The remainder are trading jargon, broker and exchange names, and political abbreviations.

Two checks indicate that the screen removes noise rather than signal. First, the removed symbols are close to proportionally distributed across types, with type shares between 0.87 and 1.29 times their corpus shares. Second, the results in Section 3.5 are almost unchanged by the screen. Normalized mutual information between type and security falls from 32.4 times chance on the unscreened panel to 27.5 times on the screened panel, even though the screen removes more than a fifth of the data.

G.3 Limitations

Residual collisions. The screen validates the 200 highest-volume symbols and every symbol appearing in our tables, with one exception. PK is too infrequent for our sampling procedure to return usage snippets, so we retain it on the basis that it is a listed company with no common non-financial reading. Symbols outside these groups are not individually validated. Any remaining collisions are small in volume and, by the proportionality check above, unlikely to be concentrated in particular types.

Inventory coverage. We match against a contemporaneous ticker dictionary rather than a date-aware inventory that records which symbols were live in each month. A symbol that was delisted early in the sample and reassigned later is therefore matched throughout. This inflates mention counts, and it inflates them unevenly across symbols. For this reason we base our ticker-level results on standardized enrichment rather than on mention levels. Enrichment compares a type's share of mentions of a given security with that security's share of all mentions, so a per-symbol over-match scales the numerator and the denominator together and largely cancels.

Cashtags are not a cleaner alternative. A natural robustness check restricts attention to cashtag mentions, which cannot collide with ordinary words. We do not use it as our main specification. Cashtag usage is concentrated in speculative communities and carries its own false positives in the form of joke symbols, so the restriction changes which users are represented rather than isolating a cleaner measurement of the same population.

H Author and Archive Screening

Reddit data carry three risks that could generate spurious structure. Automated accounts post at machine scale and could dominate mention counts. Duplicate accounts operated by one person, or coordinated posting rings, could make a handful of actors look like many users. Gaps in the public archive could mis-date entry and deflate mention counts on affected days. This appendix documents the screens we apply for each.

H.1 Automated and Duplicate Accounts

We run the screen on the full first-post ledger of 6,871,602 accounts, of which 6,804,621 have a first stock-market contribution in the January 2015 to July 2026 window the paper analyzes. The remaining 66,981 accounts entered before 2015 and are screened but not analyzed. Percentages below are shares of the 6,871,602 screened accounts.

Name-based. We flag accounts whose names follow common bot conventions, together with a list of widely deployed Reddit bots such as *AutoModerator*, *VisualMod* and *RemindMeBot*. This flags 9,705 accounts, 0.14 percent of the ledger.

Duplicate text. We hash the normalized text of each account's first contribution and flag texts of at least twenty characters shared by five or more distinct accounts. Identical first posts across many accounts indicate copy-paste farms, karma rings or a single operator. This flags 89,593 accounts, 1.30 percent.

Hyperactivity. We flag accounts posting more than 11,000 times in the twelve months before entry, a volume far beyond plausible human activity. This flags 1,359 accounts, 0.02 percent.

In total 100,539 accounts are flagged, 1.46 percent of the ledger. We exclude their contributions from every mention-based measure in the paper. The screen is deliberately blunt. It is designed to remove the accounts that could mechanically drive results, not to identify every automated account.

Duplicate text is the binding screen. This is what we would expect if the main risk is coordinated posting rather than conventional bots, since bots rarely make a first contribution to a stock-market community in the way our entry definition requires.

H.2 Archive Coverage

We check the daily mention series rebuilt from the archive for gaps that would distort either entry timing or spike detection.

There are no days with zero mentions anywhere in the January 2015 to July 2026 window.

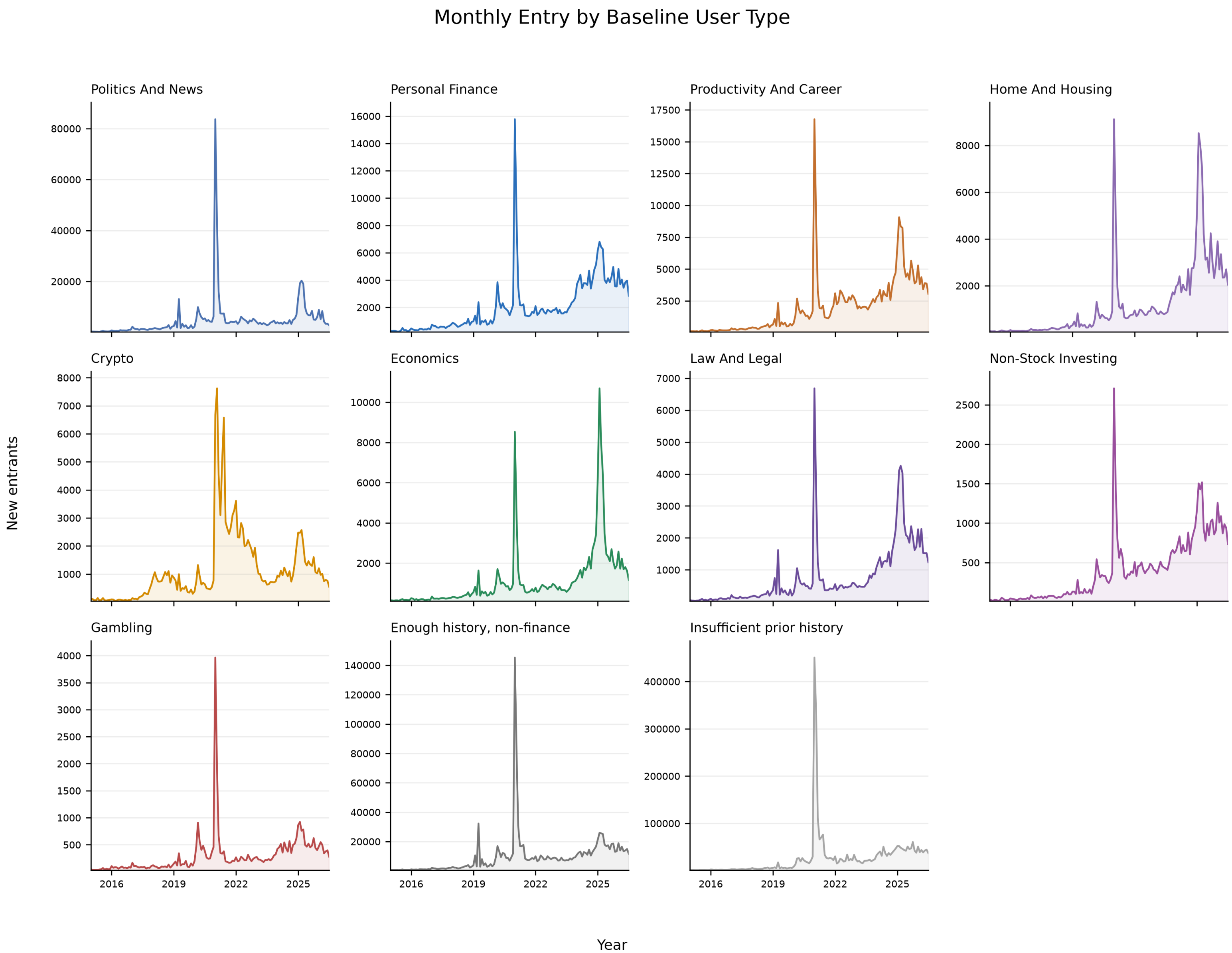
The series shows one anomaly, a depression in activity across March and April 2018. This coincides with a known period of incomplete Pushshift collection and affects both entry counts and mention counts in those two months. It is short relative to the sample and does not overlap the episodes that drive our time-series results.

We take two precautions. First, we re-estimate the uncertainty regressions excluding March, April and May 2018 outright. The aggregate estimate moves from 17.1 percent to 16.7 percent and remains significant at $p = 0.024$, and the test of equal type-specific responses remains significant at $p = 0.006$. The uncertainty results are therefore not driven by the archive discontinuity. Second, our event-study measures are constructed from rolling windows, so a two-month depression affects the estimation window and the event window symmetrically.

I Additional Figures

Figure 11 extends Figure 6 to every user type. The figure uses raw monthly entrant counts and gives each panel its own vertical scale.

Figure 11: Monthly Entry by Baseline User Type



Notes: Each panel plots monthly counts of first-time stock-market entrants assigned to the indicated baseline group from January 2015 through July 2026. The nine substantive types are assigned using pre-entry finance-adjacent activity; the two gray panels contain entrants who do not satisfy the prior-history or finance-concentration requirements. Vertical scales differ across panels. The entry month is excluded from user-type construction.