Investor Gambles and Political Signals

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Abstract

Examining two decades of market behavior, we show investors ‘gamble’ more when the quality of political signals declines. As political information becomes more ambiguous, investors trade more lottery-type (low-priced, high-volatility, high-skewness) stocks in the hope of hitting the investment ‘jackpot’. In parallel, they trade fewer non-lottery-type stocks. This trading volume differential between top and bottom deciles of gambling-prone investors is statistically and economically significant in number and dollar volume. Our findings are robust after controlling for economic policy uncertainty, VIX, and macroeconomic variables, and after including other measures of lottery stocks, political signal quality, and controls for federal lottery jackpots.

JEL Codes: G12, G14, G18

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1. Introduction

Study of gambling behavior has fascinated psychologists, sociologists and economists for several decades (see, *inter alia*, Bloch, 1951, for an early sociological review, Nicoll, 2019, for a more recent one; Williams and Siegel, 2013, for a modern economic review; and Xu and Harvey, 2017, for a behavioral economic perspective). Interestingly, gambling behavior and casino attitude spill over into financial markets particularly with equity investors. It is widely agreed that investors substitute between playing the traditional lottery and gambling in financial markets (Dorn, Dorn and Sengmueller, 2014) and that their gambling preferences varying geographically influence stock returns as well as corporate policies (Kumar, Page, and Spalt, 2011). In the past two decades and particularly since the Kumar (2009) seminal paper, a vibrant strand of literature has focused on why investors are drawn to lottery-type stocks (often described as having a low price, high idiosyncratic volatility and high skewness) and what impact these tendencies have for corporate finance and market outcomes. Investors are widely shown to be willing to accept a negative return premium for stocks with positively skewed returns (see, e.g., Shefrin and Statman, 2000; Brunnermeier, Gollier, and Parker, 2007; Mitton and Vorkink, 2007; and Barberis and Huang, 2008). Stocks with lottery-type payoffs are overpriced in the short run (Chen, Kumar and Zhang, 2021) and earn a negative average risk-adjusted return in the long run.

Despite this rich literature, the impact of information environment on investor propensity to gamble in the stock market is largely overlooked. *How does the nature and quality of information signals received by investors influence their lottery-type investing?* This question is important both for theory and practice. In this paper, we examine how quality of political signals influences stock market gambling. Motivated by the behavioral finance and economics literature on gambling, we hypothesize that investors are more drawn to lottery-type stocks when political signals become more ambiguous and thus more challenging to decipher.[1] Conversely, in an environment where information signals are clear and high-quality, investors have an easier time reaching decisions as to which sector/stock to buy, sell or hold. Therefore, in such environments, most investors do not need to take higher risks by absorbing higher skewness, unless they are naturally thrill-seeking or have above-average tolerance for financial risk-taking.[2]

Therefore, we illustrate a (so far overlooked) variation in trading between top and bottom segments of lottery-type investors when the political information environment becomes more ambiguous. This differential is statistically and economically significant both in number of trades and in dollar volume, and remains robust in all alternative specifications. Specifically, it is observed in response to changes in quality of political signals. As political information becomes more ambiguous, investors trade more lottery-type and fewer non-lottery-type stocks. Importantly, these findings remain after controlling for economic policy uncertainty, VIX, and macroeconomic variables, and after including other measures of lottery-type stocks, political signal quality, and controls for federal lottery jackpots. Further, our results are not driven by return differentials in lottery-type and non-lottery-type stocks. Rather, they relate to the investor motivations for gambling in the stock market when the political information environment becomes more opaque.

[1] At the time of writing in October 2024, this is particularly the case with the Trump-Harris Presidential Election in the US which, according to many experts, is too close to call and playing out in a very 'noisy' information environment.

[2] Prior literature from psychology and neuroscience shows that positive emotions, such as excitement generated by successful outcomes, induce individuals to take more risks and become more confident in future investment decisions (Bjork, Knutson, Fong, Caggiano, Bennett, and Hommer (2004), Kuhnen and Knutson (2011)). Kluger and DeNisi (1996) show that affective psychological reactions have "automatic and pervasive" effects on tasks in other settings.

Stock market gambling and political ambiguity share several common theoretical determinants. In brief, low information quality results in ambiguity (see, e.g., Page, 1976), and ambiguity facilitates gambling in the stock market. This aligns well with the theory of Brenner and Izhakian (2018), who show that investor love for ambiguity increases with the expected probability of unfavorable returns (loss). In the context of lottery-like stocks, as the expected probability of unfavorable return is high, investors of lottery-like stocks would prefer ambiguity, and therefore trade more lottery-like stocks during periods of high ambiguity.

In line with the literature on ambiguity, we distinguish between *risk* in equity markets meaning that future returns are realized with known probabilities, and *ambiguity* meaning the probabilities associated with these realizations are unknown or not uniquely assigned. In this sense, ambiguity is a form of uncertainty commonly known as Knightian uncertainty. Importantly, prior literature shows that investors behave differently under conditions of risk vs. uncertainty. For example, experimental evidence from lotteries shows that "enhanced arousal adaptively decreases risk-taking only when the lottery is highly risky but increases risk taking when the probability of winning is ambiguous" (Feldman et al., 2016). Related to this, it has been shown that poorer performance on ambiguous decision-making tasks (as opposed to decision-making under risk) is associated with higher gambling severity (Brevers et al., 2012).

Prior literature has also shown that, in aggregate, political uncertainty (including ambiguity) diminishes investments in the economy and in financial markets, and this is often manifest cyclically in election years (Julio and Yook, 2012).[3] Further, in the presence of ambiguous

[3] In some cases, there might be a bright side to political uncertainty. For example, Atanassov, Julio, and Leng (2015) show that firms increase R&D investments by an average of 4.6% in election years relative to non-election years. This uncertainty effect is stronger in hotly contested elections, in politically

information, expected excess returns decrease when future information quality goes down. In this paper, we show that lottery-type stocks are a peculiar exception to this general pattern. Specifically, when low quality political information is observed, investors in general, or a subset of sensation-seeking investors in particular, prefer to hold lottery-type stocks in the hope of achieving excess returns from their upside potential.

We develop the links between stock market gambling and the information environment in several ways. Primarily, we know from the gambling literature that a range of 1) *individual*, 2) *social*, 3) *environmental*, 4) *psychological* and 5) *biological* factors drive gambling propensity (see, e.g., Williams and Siegel, 2013; Cox, Kamolsareeratana and Kouwenberg, 2018). The *individual* factors include personality traits such as impulsivity, sensation-seeking, and optimism. In general, behavioral biases manifest themselves in more ambiguous information environments where fundamental valuation is more challenging due to low-quality signals. As Kumar (2009) shows, investors display stronger behavioral biases when stocks are harder to value and when market-level uncertainty is higher. Ambiguity and uncertainty at stock level and market level amplify behavioral biases of individual investors. This is particularly true about political information given the all-encompassing nature of political signals and policies and their immediate impact on the economy and the society. Therefore, in low-quality information environments, the tendency to invest in lottery-type stocks increases as our findings indicate later.

The second set of factors driving gambling are *social* factors including peer pressure, family history of gambling, and cultural norms. It is well-documented in behavioral finance literature

sensitive and hard-to-innovate industries, and in firms subject to higher growth options and greater product market competition.

that ambiguity triggers social transmission and results in herding behavior. In such settings, active investment strategies (e.g., high variance and skewness) can dominate unconditionally, and can be accelerated by the social transmission bias which is itself triggered further through ambiguity and uncertainty (Hirshleifer, 2020; Han, Hirshleifer and Walden, 2022). In effect, when information signals are noisy, people tend to communicate more among their social circles and put more effort into dissecting signal from noise, and in doing so, they accentuate social transmission through hearsay, rumours, information cascades and herding. In principle, this applies to all stocks but is particularly true for lottery-type stocks: 1) due to their low price, these stocks are more accessible to average investors; and 2) due to high volatility and skewness, they tend to be more attention-grabbing and subject to rumours and herding. There is an inherent excitement associated with investing in these stocks (as opposed to more stable and less volatile companies) which translates to more social communication and a stronger social transmission bias in relation to lottery-type stocks.[4]

Furthermore, it is well-documented that distrust of government and other regulatory bodies is common in acutely ambiguous political environments.[5] When the political environment is uncertain, individuals are more likely to believe that the government is not working in their best interests.[6] This applies to investors too who closely monitor political developments. As political ambiguity increases, *some* investors are more likely to ‘gamble’ in the stock market

[4] Other drivers of gambling behavior include *environmental* factors such as the availability of gambling opportunities, the marketing of gambling, and the laws and regulations governing gambling; the *psychological* factors including mental health conditions such as depression and anxiety; and, finally, *biological* factors include possible genetic predisposition.

[5] When faced with uncertainty, ambiguity and contradiction, conspiracy theories provide broad, internally consistent explanations allowing people to preserve their beliefs or attain cognitive disclosure (see, e.g., Douglas, Sutton and Cichoka, 2017).

[6] However, it is important to note that not everyone becomes cynical and distrustful of the government in uncertain political environments. Some may become more hopeful and optimistic about the future, believing that the uncertainty is an opportunity for positive change.

in order to 'get ahead' and earn alpha while others may avoid trading. Increase in ambiguity makes discerning signal from noise far more challenging. Therefore, those investors who trade are more likely to rely on noise, false information and rumours, which, in turn, increases the propensity to gamble due to social pressures.

Hence, taking all these drivers in, we argue that theoretically it is plausible for investors to gamble more when the quality of political signals in their information environment declines.[7] In other words, when politics becomes noisier and more ambiguous, investors searching for excess returns trade more lottery-type stocks in the hope of 'hitting the jackpot', and trade fewer non-lottery-type stocks (see Barberis, 2013 and Conrad, Kapadia and Xing, 2014, for an explanation of why investors prefer jackpot payoffs). What is particularly noticeable in our findings is that the impact of political signal quality on lottery-type investing is markedly asymmetric. In low-quality political signal environments, we observe higher trading volume of lottery-type stocks, and the situation is the opposite for non-lottery-type stocks.

In addition to the above asymmetric pattern, the impact of Economic Policy Uncertainty (EPU) on lottery-type investing is also worth underlining. Our monthly results indicate less trading in lottery-type stocks when EPU goes up. This is understandable in the context of prior literature showing that, in aggregate, political uncertainty diminishes investments in the economy and in

[7] There are many factors that can contribute to political uncertainty, including *Economic conditions*: Economic downturns can lead to political instability, as people become more frustrated with the government's handling of the economy. *Social unrest*: Social unrest, such as protests or riots, can also lead to political instability, as it can create a sense of chaos and disorder. *Political instability*: Political instability in neighbouring countries can also spill over into a country, as it can create a sense of insecurity and fear. *Foreign intervention*: Foreign intervention in a country's internal affairs can also lead to political instability, as it can create a sense of resentment and distrust towards the government. *Weak institutions*: Weak institutions, such as a corrupt judiciary or a lack of independent media, can make it difficult to resolve political disputes peacefully, which can lead to instability.

financial markets. This observation is often manifest cyclically in election years (Julio and Yook, 2012). Therefore, while the impact of EPU on lottery-type stocks is similar to other classes of stocks, the real distinction arises from political ambiguity proxied by the quality of political signals. Interestingly, our findings are additionally robust to controls for EPU, VIX, macroeconomic variables, alternative measures of lottery stocks, alternatives measures of political signal quality such as the number of Trump's daily false/misleading claims, and controls for federal lottery jackpot sizes during the sample period.

Our analysis of the quality of political signals is based on Bialkowski, Dang and Wei (2021) *Qindex* measure which is, in turn, guided by the theoretical model of Pástor and Veronesi (2013). Pástor and Veronesi theoretically distinguish "economic policy uncertainty" from the "quality of political signals" and show that in spite of the high economic policy uncertainty, noisy political signals are likely to result in rare updates in investors' beliefs, which leads to lower political risk premia and market volatility. Based on this, Bialkowski et al. develop a new index of the quality of political signals using the methodology proposed by Baker et al. (2016). Specifically, for a given period, *Qindex* reflects the frequency of articles in leading nationwide newspapers that contain the terms related to policy, signals, and quality. In the period post the election of Donald J. Trump as the U.S. president and the Brexit referendum in the UK, *Qindex* increased substantially, indicating a deterioration in the quality of political signals.

Our findings contribute to at least two distinct strands of finance literature. *First*, we contribute to the finance literature on lottery-type investing and gambling (e.g., Kumar, 2009; Doran, Jiang, and Peterson, 2012; Dorn, Dorn, and Sengmueller, 2014; Gao and Lin, 2014; and Liao, 2017). Our results provide new evidence on the potential link between information signals and gambling behavior in equity markets. We show that political signals, in particular, have a unique attribute in influencing investor behavior when it comes to trading highly volatile and skewed stocks.

Second, we contribute to the growing literature on the quality of political signals. When political signals are imprecise, investors are less likely to update their beliefs and hesitate to trade in the financial markets, leading to lower political risk premia and market volatility (Pástor and Veronesi, 2017). Białkowski, Dang, and Wei (2021) show that a low quality of political signals is responsible for weaker correlation between a fear gauge, such as the CBOE VIX, and economic uncertainty, proxied by Baker, Bloom, and Davis (2016) economic policy uncertainty index. Our findings contribute to this line of literature by highlighting the intermediating role of political signal quality in investor gambling behavior.

2. Data and variables

Our analysis encompasses two distinct sample periods. For our monthly assessment, we draw from data spanning January 2000 through June 2022. Meanwhile, the daily tests focus on a timeframe from January 2017 to January 2021. In the subsequent part of this section, we will delve into the definitions of the variables used for our empirical estimation.

2.1. Lottery-type stocks

Kumar (2009) asserts that investors, much like lottery enthusiasts, are drawn to "cheap bets," thus finding low-priced stocks appealing. Among these affordable options, stocks with high idiosyncratic skewness tend to be more attractive. Further, when considering stocks that are both low-priced and have high idiosyncratic skewness, those with greater idiosyncratic volatility are likely perceived as more lottery-like. This perception is influenced by the level of idiosyncratic volatility, which can alter the estimation of idiosyncratic skewness. With high volatility, investors may perceive that extreme return events from the past have a higher likelihood of reoccurring. Conversely, for a low-priced stock with high skewness but low idiosyncratic volatility, past extreme return events may be seen as anomalies, and the chance of such an event happening again is assigned a substantially lower probability.

Following Kumar, Page, and Spalt (2016), we use the lottery-like index (LIDX) to gauge a stock's appeal as an object of speculation. To construct the LIDX for each stock, we assess the price, idiosyncratic volatility, and idiosyncratic skewness of all stocks in the CRSP database. Each year, we calculate the idiosyncratic volatility as the variance of the residuals obtained from fitting a four-factor model to the daily stock return series. Idiosyncratic skewness, on the other hand, is the scaled measure of the third moment of the residuals obtained from fitting a two-factor model to the daily stock return series for a given year, where the two factors are the excess market returns and the squared excess market returns.

We then categorize all CRSP stocks annually into vigintiles (20 bins) based on price, idiosyncratic volatility, and idiosyncratic skewness, respectively. The 20th bin comprises stocks from the lowest price group and those with the highest idiosyncratic volatility and skewness. For each stock, the corresponding bin scores for price, volatility, and skewness are totalled to produce a score ranging from 3 to 60. This score is then normalized between 0 and 1 using the formula $LIDX=(Score-3)/(60-3)$. A higher LIDX value suggests that the stock is more appealing to speculative traders and those who enjoy gambling. For robustness checks, we also utilize the lottery-stock definition provided by Conrad et al. (2014). Specifically, we calculate the one-year cumulative returns for each stock at the end of each year. A stock is designated as lottery-like if its cumulative return exceeds 100%.

2.2. Quality of political signals

We employ the index proposed by Białkowski et al. (2022), namely *Qindex* as our monthly measure of the quality of political signals. Accordingly, *Qindex* is constructed based on a similar approach applied to generate the policy economic uncertainty (EPU) index by Baker, Bloom, and Davis, (2016). *Qindex* reflects the frequency of articles that contain terms related to “policy”, “signals”, and “quality” in ten leading U.S. nationwide newspapers, namely *USA Today, The Washington Post, The Boston Globe, The New York Times, The Wall Street Journal, Tampa Bay Times, New York Post, New York Daily News, Star Tribune,* and *The Atlanta Journal Constitution*. Articles pertaining to three term categories – quality (e.g., “false”, “misleading”, or “ambiguous”), signal (e.g., “signal”, “declarations”, or “claim”), and policy (e.g., “deficit”, “legislation”, or “Federal Reserve”) are counted on a monthly basis. The number of matched articles is then divided by the total number of articles for each newspaper each month to obtain ten sets of monthly series. Next, these series are standardized and then averaged across newspapers to get one multi-newspaper index, which is re-normalized to an average of 100 in the final step.[8] A high *Qindex* level indicates low quality of political signals

To gauge the quality of political signals on a daily basis, we turn to a method suggested by Białkowski et al. (2022), which utilizes the Washington Post Fact Checker (*WPFC*) data for the U.S. market. The Washington Post meticulously tracked the daily number of false or misleading claims made by former President Donald J. Trump from January 2017 to January 2021. Following Białkowski et al., we apply a five-day moving average of these daily claims across all topics, positing that an increase in reported false or misleading claims correlates with more imprecise political signals. The use of the moving average of these reported claims takes into account that the impact of inaccurate political signals compounds over time. This is due to

[8] Data and more details for *Qindex* are available at https://www.qualityofpoliticalsignals.com.

the fact that the veracity of today's political discourse may not be fully understood until a later time. An advantage of this measure is its exogeneity to other independent variables, which allows us to address potential concerns of reverse causality.

2.3. Trading activities

We utilize three metrics to evaluate investors' trading activities. Specifically, for all CRSP-listed stocks, we initially gather data on their share trading volume (*Volume*) and dollar trading volume (*DVolume*). For NASDAQ-listed stocks, we additionally obtain data on the number of individual trades for each stock (*Trades*). In our regression analysis, we employ the logarithm of these three measures as dependent variables. This allows us to determine whether trading patterns differ between lottery-like and non-lottery-like stocks, contingent upon varying quality of political signals.

2.4. Control variables

Considering our proxy for policy signal quality, the *Qindex*, originally proposed as a measure of political signal quality, a potential concern might be that the impact of the *Qindex* on stock trading activities might actually stem from the EPU, which seems to be the underlying source of political signals. To address this concern, we incorporate widely recognized EPU measures as control variables, specifically, the EPU indices developed by Baker, Bloom, and Davis (2016). For our monthly regressions, we utilize the monthly overall EPU index (*EPU*). For daily analysis, we adopt a method similar to that used for the *WPFC*, employing a five-day moving average of the daily EPU index (EPU^{daily}). Both the monthly and daily EPU data are sourced from the authors' website. [9]

[9] See https://www.policyuncertainty.com.

Gao and Lin (2014) posit that the trading of lottery-like stocks may be influenced by the size of the jackpot lottery. They argue that the fun and excitement associated with gambling in the lottery is similar to that of buying and selling stocks, which could create a substitution effect between the two activities. Based on data from Taiwan, the authors present evidence showing a decrease in stock trading by individual investors on days with larger jackpots. To account for this potential effect, we incorporate the jackpot lottery size into our regressions. Given the diverse range of jackpot lotteries across different states, we focus on the two largest multi-state jackpot lotteries: Mega Millions and Powerball. Daily data for these two lotteries is available from June 2005. For each day, we calculate the market-wide jackpot lottery size as the sum of the jackpots from these two lotteries. For our monthly regression analysis, we consider the average daily jackpot size within a given month and use its logarithmic value (*Jackpot*). For daily tests, we use the logarithm of the daily jackpot size ($Jackpot^{daily}$).

To further control for the impacts of macroeconomic conditions on stock trading, we also include the other control variables used by Gao and Lin (2014). These include the change in the unemployment rate (*Unemploy*) and change in the U.S. coincident index (*Coincident*).[10] To account for potential continuity in trading activities, we incorporate lagged terms into our regressions. Lastly, to account for other shocks that may result in fluctuations in stock trading, we incorporate the CBOE Volatility Index (VIX). A comprehensive description of all variables is provided in Appendix A.

Table 1 reports the summary statistics (Panel A) for the main variables and the correlation between them (Panel B) for monthly analysis. As shown in the Panel, *LIDX* exhibits negative

[10] As the data on these two variables are available on a monthly basis, in our daily analysis, all daily observations within a given month share identical values for both *Unemploy* and *Coincident*.

correlations with monthly trading activities measures (i.e., *Volume*, *Dvolume* and *Trades*). These negative coefficients indicate that on average, lottery-like stocks are less traded than non-lottery-like stocks. This finding is consistent with literature as lottery-likely stocks are primarily trades by individual investors rather than institutional investors who do massive trades but mostly with non-lottery-like stocks.

[Insert Table 1 here]

Table 2 reports the summary statistics (Panel A) and correlations (Panel B) using daily data. Similarly, *LIDX* is negatively correlated with daily trading activities measures (i.e., $Volume^{daily}$, $Dvolume^{daily}$ and $Trades^{daily}$), suggesting lower trading volume of lottery-like stocks than non-lottery-like stocks on a daily basic. In Table 1 and 2, none of the pairs of key independent variables are highly correlated, which indicates a lack of potential multicollinearity issues for the multivariate analysis.

[Insert Table 2 here]

We employ the following regression to cross-sectionally evaluate how the trading activities of lottery-like and non-lottery-like stocks are correlated with the quality of political signals:

$$TA_{i,t}^{k} = \alpha + \beta_1 PIQ_t + \beta_2 Z_t + \beta_4 F_i + \varepsilon_{i,t} , \quad (1)$$

where dependent variable is the monthly or daily trading activities of firm *i* that belongs to the k^{th} portfolio (k=1,2,3…10) sorted by the firm's *LIDX* value at time *t*. *PIQ* is the measure of political information quality. Specifically, for the monthly analysis, PIQ_t is the monthly *Qindex* level. For the daily analysis, PIQ_t reflects the daily *WPFC* values. Z_t denotes other state variables on time *t* including the EPU, VIX, change in unemployment rate, change in coincident index and Jackpot size. *Fi* is the firm fixed effect. Throughout the paper, we apply Eq. (1) for both monthly and daily analyses simultaneously.

3. Empirical findings

To investigate how trading activities of lottery-like and non-lottery-like stocks vary with the quality of political information, we categorize stocks into deciles based on their *LIDX* values for a specific year. Specifically, stocks in the highest (10th) *LIDX* decile are considered 'lottery-like', whereas stocks in the lowest (1st) *LIDX* decile are deemed 'non-lottery like'. For monthly analysis, we define periods with a *Qindex* higher (lower) than its sample median as 'high- (low-) *Qindex'* month. For daily analysis, we define days with *WPFC* exceeding (below) its sample median as 'high- (low-) *WPFC'*. The conditional average trading activity for both lottery-like and non-lottery-like stocks is depicted in Figure 1 (monthly) and Figure 2 (daily).

[Insert Figure 1 here]

[Insert Figure 2 here]

During periods of poor political information quality (high-*Qindex* or high-*WPFC*), lottery-like stock trading sees an uptick compared to periods with better information quality. Conversely, there is reduced trading in non-lottery-like stocks during high-*Qindex* or high-*WPFC* periods. These trends are evident in both monthly and daily data, as demonstrated in Figures 1 and 2.

Tables 3 reports the results of monthly panel regressions for, lottery-like (highest *LIDX* decile) and non-lottery-like (lowest *LIDX* decile) stocks, respectively. The quality of political signals is captured by the monthly *Qindex*. We present the results for three proxies of trading activity, namely share volume (*Volume* in Panel A), dollar trading volume (*DVolume* in Panel B) and the number of individual trades (*Trades* in Panel C). In each panel for each group, we first present the results for univariate panel regressions in columns (1) and (6) by only including *Qindex* as the independent variable. To address the potential concern that the impact of policy signal quality on stock trading activities might actually stem from the EPU, which seems to be the underlying source of political signals, we include EPU as control variables in other columns. Additionally, we control for various fixed effects across columns (3) to (5) and (8) to (10).

[Insert Table 3 here]

In Panel A, we notably observe the relationship between the *Qindex* , representing the monthly quality of political signals, and *Volume*. Within the confines of Lottery-like stocks (highest LIDX decile), a positive and statistically significant relationship between *Qindex* and *Volume* is discernible across all model specifications. These results suggest that more lottery-like stocks are traded during the period when the quality of political signals are low (high *Qindex* and high political ambiguity). Such findings are consistent with our hypothesis that political ambiguity leads to more gambling activities. Contrarily, for nonlottery-like stocks (lowest LIDX decile), the relationship between *Qindex* and *Volume* predominantly becomes negative, implying less trading of relatively normal stocks during high ambiguity periods. These results are in line with previous studies suggesting overall lower market participation during high-ambiguity periods. Furthermore, the EPU shows a variable relationship with *Volume*. With all controls, In the domain of, EPU manifests negative correlations with share trading volume for Lottery-like stocks. Conversely, in the non-lottery-like category, the relationship between EPU and *Volume* is majorly positive and significant. The findings for *Qindex* and EPU collectively suggest that both gamblers and normal investors present different decision-making patterns under ambiguity (*Qindex*) and under risk (*EPU*). The effects of *Qindex* on *Volume* are also economically significant. For instance, the coefficients in columns (5) and (10) suggest that a one-standard-deviation increase in *Qindex* is associated with a 4.42% increase in the share trading volume of lottery-like stocks and a 2.06% decrease in that of non-lottery-like stocks.

The results in Panel B and Panel C show consistent patterns. In the spectrum of lottery-like stocks, *Qindex* consistently exhibits a positive and statistically significant correlation with *DVolume* and *Trades* across all configurations. In contrast, for non-lottery-like stocks, the trend leans toward a negative correlation. Meanwhile, *EP*U primarily aligns negatively with *DVolume* and *Trade*s for lottery-like stocks but associates positively with *DVolume* and *Trades* for non-lottery-like stocks. On an economic scale, the coefficients in columns (5) and (10) in Panel B and C indicate the that a one-standard-deviation increase in *Qindex* corresponds to a 5.45% increase in the dollar trading volume and a 3.56% increase in the number of trades for lottery-like stocks. Conversely, it results in a 1.56% decrease in the dollar trading volume and a 2.25% decrease in the number of trades for non-lottery-like stocks.

In Table 4, we re-run our baseline regressions using a daily dataset. We utilize the *Washington Post Fact Checker* (*WPFC*) as an alternative proxy for the quality of political signals. Maintaining a structure similar to Table 3, we present results for daily share trading volume ($Volume^{daily}$), dollar volume ($DVolume^{daily}$), and number of trades ($Trades^{daily}$) in Panels A, B, and C, respectively.

[Insert Table 4 here]

We observe that the *WPFC* coefficients are statistically and economically significant across all specifications in Table 4. Positive coefficients for lottery-like stocks and negative ones for non-lottery-like stocks indicate more trading of the former and less of the latter during times of low-quality political signals (high *WPFC*). These findings align with those in Table 3, reinforcing our expectations. For the key control variable, daily EPU (EPU^{daily}), its relationship with daily trading activities varies between the two stock groups. For lottery-like stocks, daily EPU positively correlates with share trading volume (Panel A) and number of trades (Panel C) but is inversely related to dollar trading volume (Panel B). In contrast, for non-lottery-like stocks, *EPU*^{daily} positively associates with all three trading measures. Broadly, Tables 3 and 4 reveal that in environments of low-quality political signals, trading activity for lottery-like stocks surges, while non-lottery-like stocks see diminished interest from investors. These outcomes are statistically significant at a 1% level.

To better understand the dynamics of the trading activities of lottery-like and non-lottery-like stocks conditional on the quality of political signals, we examine how the above effect changes across the decile portfolios sorted by LIDX. As shown in Table 5, in specifications for deciles 1 to 7 in all three panels, low quality of political signal decreases the trading activity of non-lottery-like stocks. The trading activities increase with low-quality signals in the case of the highest three deciles defining lottery-like stocks (deciles 8 to 10). Such a positive association is most visible among stocks within the highest LIDX decile portfolio. These results are also consistent across different proxies of market participation and control variables.

[Insert Table 5 here]

The results for daily tests are reported in Table 6. Consistently, *WPFC* is negatively correlated with daily share trading volume (*Volume*^{daily}), dollar volume (*DVolume*^{daily}) and trade numbers (*Trades*^{daily}) across deciles 1 to 9. Furthermore, *WPFC* is found postively correlated with daily trading activity measures for the highest decile. These results further confirm that the selection of the proxy for the quality of political signal and data frequency does not affect the conclusion drawn from the results presented in Table 5.

[Insert Table 6 here]

To further investigate the relationship between quality of political signals and trading activities across stocks, we test whether the impact of political signal quality remains significant when more control variables are considered. Following the study by Gao and Lin (2014), we proposed a model where market participation in stock trading stocks is explained by the lagged trading volumes, change in macroeconomic variables such as the unemployment rate (*Unemploy*), coincident index (*Coincident*), and the logarithm of the average jackpot size. While Gao and Lin (2014) focus on Taiwan market, we calculate the U.S. jackpot size as the sum of two multi-state jackpots, namely Mega Millions and Powerball (*Jackpot*). To control for other market-wide conditions that are not captured by the quality of political signals and EPU, we extended Gao and Lin's (2014) model by including the implied volatility index (*VIX*) as a proxy for the "fear gauge" of market participants. We report the results with those controls in in Table 7 (monthly analysis) and Table 8 (daily analysis). Due to the limited data availability for jackpot size, we modify the sample period of monthly tests to June 2005 to June 2022. As in the layout of Table 5 and 6, we run the panel regression for portfolios constructed based on LIDX deciles.

[Insert Table 7 here]

Robust to the selection of the proxy of trading activity and the frequency of data, we show that in the highest decile of LIDX, the quality of political signal (i.e., *Qindex* in Table 7 and *WPFC* in Table 8) has a statistically significant and positive impact on the trading activities of lottery-like stocks. On the other hand, as the political signal deteriorates, the none-lottery type stocks experience drops in trading activities. The coefficients of *Qindex* in column (10) Table7 indicate that a one-standard-deviation increase in *Qindex* will raise the share trading volume, dollar volume and number of trades of lottery-like stocks by 5.02%, 10.71% and 6.26% on a monthly basis, respectively. On a daily frequency, the results from Table 8 suggest that one-standard-deviation increase in *WPFC* increases the daily share trading volume, dollar volume and number of trades of lottery-like stocks by 0.99 %, 0.53% and 0.58% (i.e., 20.74%, 11.07% and 12.28 on a monthly frequency), respectively. Overall, our results are both statistically and economically significant.

[Insert Table 8 here]

Additionally, EPU shows a positive correlation with the trading activities across all lottery-like and non-lottery-like stock groups in Table 7 on a monthly basis. This suggests both gamblers and conventional investors trade more under heightened policy uncertainty. However, contrasting patterns emerge when examining the relationship between daily EPU and trading activities as detailed in Table 8. Specifically, EPU^{daily} negatively affects the trading of non-lottery-like stocks but is positively linked to the trading activities of lottery-like stocks. These consistent patterns across different daily trading activity proxies ($Volume^{daily}$, $DVolume^{daily}$, and $Trades^{daily}$) raise intriguing questions. Though not the primary focus of our study, the observed discrepancy between the impacts of monthly and daily EPU on non-lottery-like stock trading might arise from potential noise in the daily EPU index's construction, warranting further exploration. Despite this, *EPU* consistently enhances the trading of lottery-like stocks, implying heightened stock gambling during times of high policy uncertainty. This differential behavior underscores the varied decision-making of gambling investors in environments characterized by high ambiguity (low-quality political signals) versus high risk (elevated EPU).

Another interesting finding might be the effects of VIX on trading activities, as presented in Tables 7 and 8. It reveals that VIX is positively associated with the trading of non-lottery-like stocks. In contrast, it negatively correlates with lottery-like stock activities. This suggests that lottery-like stock investors seem to have unique utility benchmarks for gambling. Specifically, in times of low market volatility, stock gamblers trade more lottery-like stocks, chasing the thrill or utility of gambling. However, during high-volatility phases, the entire equity market becomes relatively lottery-like, providing gamblers ample opportunities to derive gambling utility, thereby reducing their engagement with distinctly lottery-like stocks.

In context with jackpot size, while Gao and Lin (2014) highlighted a substitution effect between jackpot size and lottery-like stock trading in Taiwan, our results for the U.S. market diverge.

Both monthly and daily analyses in Tables 7 and 8 show a positive correlation between trading activities and jackpot size across all metrics. Except for specific instances in Panel C of Table 7, these correlations are statistically significant at a 5% level or higher. Therefore, larger jackpots in the U.S. drive investors to trade more stocks, regardless of their lottery-like nature.

To further confirm the robustness of our results, we consider two additional tests. First, we investigate if the above-reported effect of the political signals' quality for portfolios sorted by LIDX is also present in portfolios sorted by classic risk factors such as beta, size, book-to-market ratio, and momentum factors, as someone could argue the impacts of signal quality may not be unique for lottery-like stocks. In addition, we consider a split of a pool of our stocks based on liquidity level since it seems natural to argue stocks with low price, high idiosyncratic volatility and skewness tend to be those illiquid ones. In each case, we construct ten portfolios sorted by each risk factor, respectively.[11] We then test how the top- and bottom-deciles react differently to the quality of political signals for each of the four factors across all stocks. Tables 9 and 10 report the results of panel regressions for three proxies of trading activity, namely share volume, dollar volume, and number of trades on monthly and daily frequency for portfolios sorted by each of the 4 common risk factors rather than a LIDX index.

[Insert Table 9 here]

[Insert Table 10 here]

[11] A stock's size is defined as its market capitalization; a stock's momentum at month *t* is defined as the cumulative return over month *t*-12 to *t*-11; illiquidity is defined as the Amihud's (2002) illiquidity calculated as absolute return divided by dollar trading volume.

None of the examined pairs of portfolios allow us to discover a similar pattern, like in the case of lottery-like stocks. Thus, the link between the level of trading activities for lottery-like stocks and the quality of political signals has a distinctive character. For instance, the coefficients for the *Qindex* and *WPFC* variables reported for a split based on the level of liquidity (see Panel D in Tables 9 and 10) are not consistently statistically significant and have different signs depending on different proxies. It suggests that quality of political signal does not impact the trading activity of liquid and less liquid stocks in the same way as in the case of lottery-like stocks and non-lottery-like stocks. The result addresses the concern that the above reported results found for lottery-like and non-lottery like stocks may be simply driven by low liquidity. Similar results could be found for portfolios sorted by size, book-to-market and momentum.

As a second additional robustness test, we consider an alternative definition of lottery-like stocks and check if our results remain robust. Conrad et al. (2014) defined lottery-like stocks as those characterized by the arithmetic return of over 100% in a 12-month window. In Table 11, we report the results by re-running regressions as those reported in Table 3 and 4. The results confirm our early reported findings. As the quality of political signals decreases (*Qindex* or *WPFC* increases), the trading activities of lottery-like stocks increases. Such a relationship reverses for non-lottery-like stocks.

[Insert Table 11 here]

In our final test, we aim to empirically assess the influence of social transmission channels on the trading volumes of lottery-like stocks. This inquiry is based on the hypothesis that increased ambiguity in financial markets intensifies discussions about these stocks, leading to higher trading activity. To test this hypothesis, we explore the correlation between the *Qindex* and two constructed proxies representing the discourse surrounding lottery-like stocks.

The first proxy is derived from Internet search volumes, specifically using Google Trends. Our method involves systematically tracking and analyzing the monthly search volumes for terms representative of lottery-like stocks, such as 'lottery stock', 'gamble stock', and 'penny stock'. We systematically collect and analyze the monthly search volumes for these terms from Google Trends.[12] To refine our analysis and eliminate seasonal biases inherent in raw search data, we employ a deseasonalization technique. This involves regressing each time series against a set of month dummies, allowing us to extract the residuals that provide a more accurate depiction of the deseasonalized search volumes.

In the subsequent stage, we standardize these deseasonalized search volumes to ensure a consistent scale of measurement. The culmination of this methodological process is the formulation of an *Attention Index* for lottery-like stocks. This index is calculated as the mean of the three deseasonalized and standardized time series, offering a robust measure of the public's attention towards lottery-like stocks. Our methodology not only provides a novel lens to view the impact of social discourse on stock trading but also contributes to the broader understanding of behavioral finance dynamics in the context of lottery-like stock trading.

[Insert Table 12 here]

The empirical findings, as delineated in Table 12, reveal a compelling pattern. Specifically, the *Qindex* exhibits statistically significant and positive coefficients across all four columns of the table. This pattern is indicative of a direct relationship between political ambiguity and heightened attention towards lottery-type stocks. Such a correlation substantiates our theoretical premise that increased ambiguity amplifies social transmission concerning lottery-like stocks, thereby stimulating their trading activity. Further underpinning the relevance of our findings is their economic significance. An illustrative example can be found in column (4) of

[12] The Google Trends data is available since January 2004.

Table 12, where the coefficient of *Qindex* implies that a one-standard-deviation increase in the *Qindex* corresponds to a 0.18 rise in the attention metric for lottery-like stocks. This increment is approximately double the standard deviation of the attention index itself, highlighting the substantial impact of political ambiguity on market behavior.

In constructing the second proxy to gauge discourse about lottery-like stocks, we focus on Twitter post frequency. Specifically, we analyze the monthly count of tweets from U.S. users containing pairs of terms: ‘lottery’ and ‘stock’, ‘gamble’ and ‘stock’, or ‘penny’ and ‘stock’. Over the period from September 2006 to June 2022, this approach yielded a total of 4,720 tweets that met our criteria.[13] Subsequently, we apply a process to deseasonalize and standardize each time series derived from these tweet counts. Finally, we calculate the second proxy, *Tweets*, by taking the mean of the three time-series. The results of this analysis are presented in Table 13. Notably, these findings show a robust consistency with those reported in Table 12, reinforcing our initial observations and conclusions regarding the impact of social media discourse on lottery-like stock trading.

[Insert Table 13 here]

In sum, these results not only reinforce the hypothesized link between political ambiguity and the trading of lottery-like stocks but also align with our prior findings. The consistency observed in the Internet search and Twitter data for lottery-like stocks further validates our conclusions, offering robust evidence in support of the proposed relationship.

[13] This period is subject to the data availability of Twitter posts.

4. Conclusion

There are considerable similarities between real-world gambling and gambling in the stock market through lottery-type investing. As to the former, economists have long been intrigued by the popularity of lotteries despite their typically poor return expectations (e.g., Baker et al., 2020, Stetzka and Winter, 2021). One possible explanation is that buying a lottery ticket is akin to buying a dream (Forrest et al., 2002).[14] And in financial markets, an asset with features akin to those of a gamble can be equally lucrative and can trigger the same kind of gambling attitude by investors. Lottery-like features in financial assets are often translated to positively skewed return distributions, suggesting that the asset has the potential to generate very high returns, albeit with small probabilities (Kumar, 2009). Investors who are attracted to such features are therefore formally known as those who have a preference for skewness or skewness-seeking and are shown to be the same type of individuals who exhibit a strong propensity to gamble in nonfinancial settings.

Although the parallels go far, there are also important differences however between buying lottery tickets and buying lottery-type stocks. The former may offer the possibility of winning a very large jackpot through a single ticket – albeit with extremely small odds – while the latter does not usually provide such skewed returns. That said, what most investors are happy with is the possibility of obtaining above average returns on an investment in line with the risks taken. The other notable difference between the two settings is that the odds of winning a lottery are quite transparent and simple to estimate based on the announced size of the jackpot and the

[14] If that explanation is correct, lottery players would be expected not to spend additional money on other gambling activities that do not offer life-changing wins. In fact, national US surveys show that respondents' dissatisfaction with their current income predicted participation in lotteries but not in other gambling activities that do not offer extreme wins (Brunk, 1981). Escaping from poverty might indeed be one major motive for participating in lotteries, as sales of lotto tickets and poverty rates are significantly positively correlated (see Blalock et al., 2007).

historical average of lotto ticket buyers. On the other hand, the probability of making a return on a risky, skewed investment is much harder to estimate ex ante, and is a function of various risk factors, macroeconomic variables and other externalities.

In this context, our study illustrates a trading volume differential between top and bottom deciles of lottery-type investors, which is statistically and economically significant both in number and dollar volume, and one that remains robust in all alternative specifications. This trading volume differential * in response to changes in quality of political signals. As political information becomes more ambiguous, investors trade more lottery-type (low-priced, high idiosyncratic volatility, high idiosyncratic skewness) stocks, and trade fewer non-lottery-type stocks. Importantly, these findings remain after controlling for economic policy uncertainty, VIX, and macroeconomic variables, and after including other measures of lottery stocks, political signal quality, and controls for federal lottery jackpots. Further, our results are not driven by return differentials in lottery-type and non-lottery-type stocks. Rather, they relate to the investor motivations for gambling in the stock market when the political information environment becomes more ambiguous.

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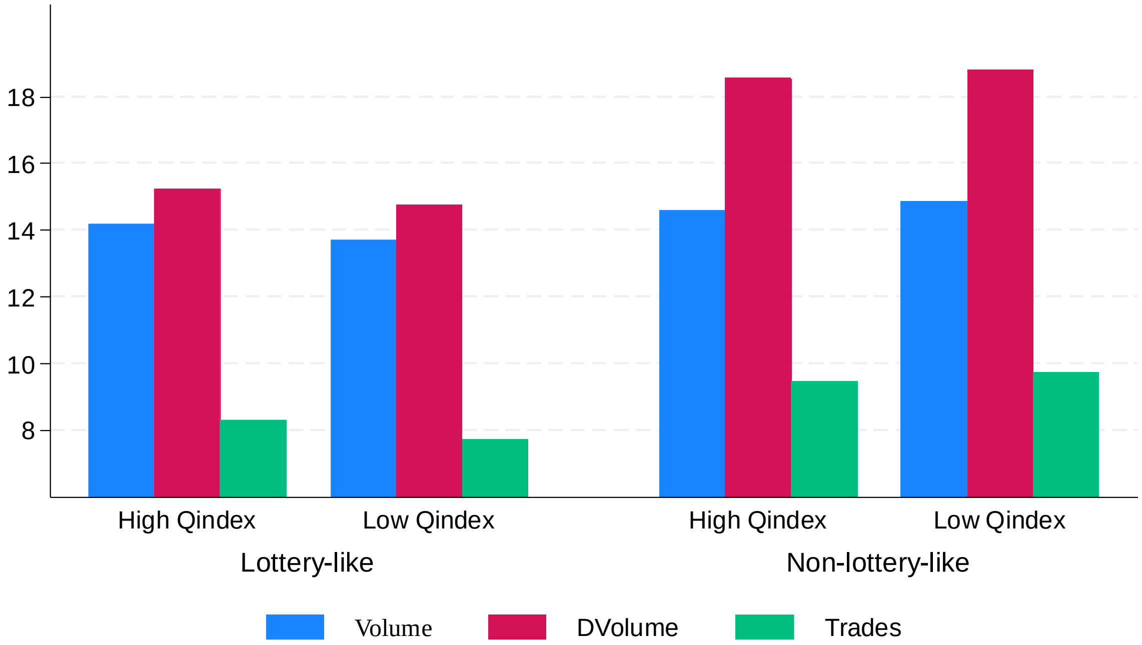
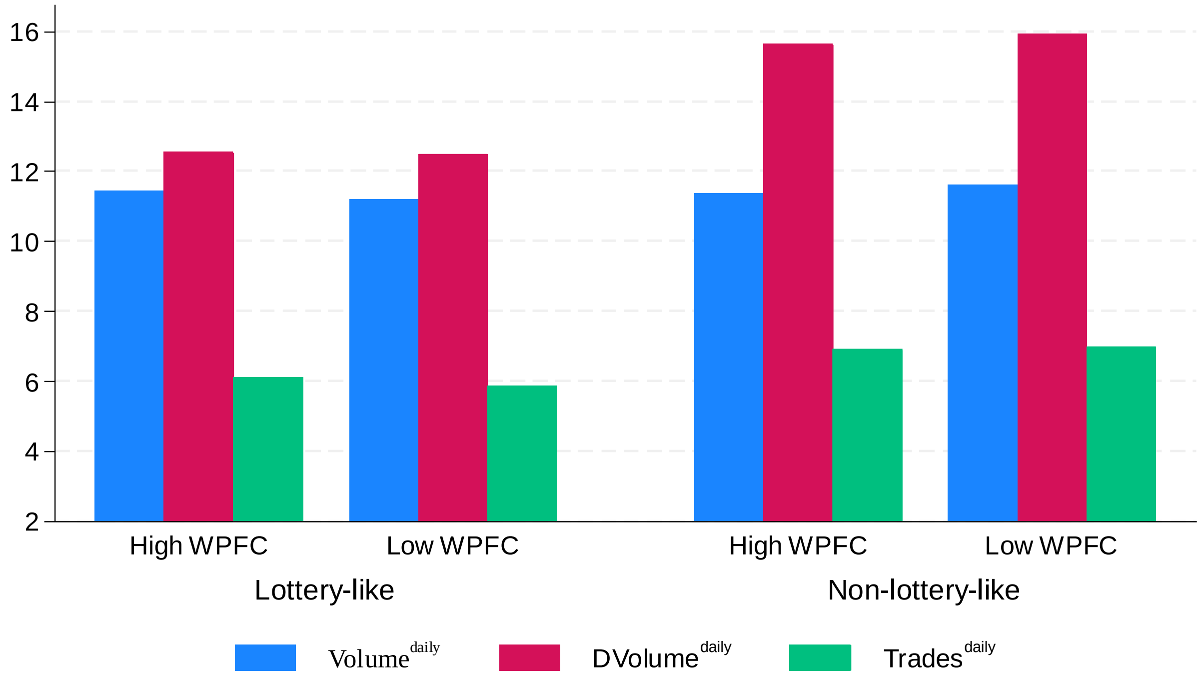
Figure 1. Monthly trading activities and *Qindex*



This figure presents the average monthly trading activities for lottery-like and non-lottery-like stocks conditional on the *Qindex* level. *Qindex* is the monthly measure of quality of political signals index. A high *Qindex* indicates low quality of political signals. A month is defined as a high-*Qindex* (low-*Qindex*) month if the *Qindex* in that month is greater (smaller) than its sample median. *Volume* is the logarithm of monthly share volume of U.S. stocks. *Dvolume* is the logarithm of monthly dollar volume of U.S. stocks. *Trades* is the logarithm of monthly number of trades of stocks listed on NASDAQ. *LIDX* is the firm-level lottery-like index constructed following Han and Kumar (2013) and Kumar et al. (2016). The sample spans January 2000 through June 2022.

Figure 2. Daily trading activities and WPFC



This figure presents the daily trading activities for lottery-like and non-lottery-like stocks conditional on the *WPFC* level. *WPFC* is the five-day moving average of daily count on former president Donald Trump's false or misleading claims reported in *Washington Post.* A day is defined as a high-*WPFC* (low-*WPFC*) day if the *WPFC* on that daily is greater (smaller) than its sample median. *Volume* is the logarithm of monthly share volume of U.S. stocks. $Volume^{daily}$ is the logarithm of daily share volume of U.S. stocks. $Dvolume^{daily}$ is the logarithm of daily dollar volume of U.S. stocks. $Trades^{daily}$ is the logarithm of daily number of trades of stocks listed on NASDAQ. The sample spans January 2017 to January 2021.

Table 1. Summary statistics: Monthly

Sample January 2000 – June 2022

	Obs.	Mean	SD	Min	Max	Median	p5	p95
Volume	1,929,913	14.360	2.485	0.000	23.990	14.519	10.134	18.125
Dvolume	1,929,859	17.164	2.827	2.200	28.071	17.198	12.478	21.679
Trades	860,253	8.694	2.480	0.000	17.246	8.871	4.489	12.504
LIDX	1,740,373	0.495	0.223	0.000	1.000	0.474	0.175	0.895
Qindex	1,930,898	1.049	0.204	0.752	2.112	0.979	0.822	1.398
EPU	1,930,898	1.241	0.455	0.572	3.505	1.152	0.705	2.046
VIX	1,930,898	20.296	8.117	9.510	59.890	18.240	11.400	34.540
Unemploy	1,930,898	-0.004	0.704	-2.200	10.300	0.000	-0.300	0.300
Coincident	1,930,898	0.098	0.866	-10.900	4.200	0.100	-0.500	0.600
Jackpot	1,465,039	19.061	0.545	17.810	20.476	19.035	18.278	20.040

	Volume	Dvolume	Trades	LIDX	*Qindex*	EPU	VIX	Unemploy	Coincident
Dvolume	0.885								
Trades	0.892	0.931							
LIDX	-0.107	-0.412	-0.205						
Qindex	0.121	0.153	0.185	-0.016					
EPU	0.073	0.040	0.110	0.024	0.406				
VIX	0.016	-0.047	0.011	0.016	-0.001	0.565			
Unemploy	-0.009	-0.023	-0.015	0.000	-0.082	0.079	0.151		
Coincident	0.012	0.030	0.019	0.000	0.108	-0.064	-0.226	-0.910	
Jackpot	0.075	0.112	0.133	-0.011	0.514	0.116	-0.186	-0.030	0.042

This table reports the summary statistics in Panel A and correlation matrix in Panel B for monthly data. *Volume* is the logarithm of monthly share volume of U.S. stocks. *Dvolume* is the logarithm of monthly dollar volume of U.S. stocks. *Trades* is the logarithm of monthly number of trades of stocks listed on NASDAQ. *LIDX* is the firm-level lottery-like index constructed following Han and Kumar (2013) and Kumar et al. (2016). *Qindex* is the monthly quality of political signals index constructed by Bialkowski et al (2022). *EPU* is the monthly economic policy uncertainty index developed by BBD. *VIX* is the CBOE VIX value at the end of a given month. *Unemploy* is the change in unemployment rate following Gao and Lin (2014). *Coincident* is the change in U.S. coincident index following Gao and Lin (2014). *Jackpot* is the logarithm of average daily jackpot size calculated as the sum of two multi-state jackpots, namely Mega Millions and Powerball (data available since June 2005) in a given month. The sample spans January 2000 through June 2022.

Table 2. Summary statistics: Daily

Sample: January 2017- January 2021

	Obs.	Mean	SD	Min	Max	Median	p5	p95
$Volume^{daily}$	7,345,893	11.402	2.662	0.000	21.442	11.715	6.625	15.190
$Dvolume^{daily}$	7,345,893	14.484	2.960	-0.139	25.768	14.593	9.523	19.001
$Trades^{daily}$	3,019,214	6.564	2.280	0.000	14.904	6.846	2.398	9.859
LIDX	7,036,688	0.497	0.224	0.000	1.000	0.456	0.175	0.912
WPFC	7,501,431	0.214	0.288	0.000	3.118	0.136	0.026	0.644
EPU^{daily}	7,501,431	1.551	1.185	0.266	6.519	1.071	0.638	4.214
VIX^{daily}	7,501,431	18.370	9.654	9.140	82.690	15.070	9.910	35.550
Unemployed	7,501,431	0.036	1.592	-2.200	10.300	0.000	-1.500	0.200
Coincident	7,501,431	0.102	1.841	-10.900	4.200	0.200	-0.300	1.800
$Jackpot^{daily}$	7,501,431	19.358	0.644	17.504	21.190	19.365	18.270	20.367

	$Volume^{daily}$	$Dvolume^{daily}$	$Trades^{daily}$	LIDX	WPFC	EPU^{daily}	VIX^{daily}	Unemploy	Coincident
$Dvolume^{daily}$	0.885								
$Trades^{daily}$	0.892	0.931							
LIDX	-0.107	-0.412	-0.205						
WPFC	0.121	0.153	0.185	-0.016					
EPU^{daily}	0.073	0.040	0.110	0.024	0.406				
VIX^{daily}	0.016	-0.047	0.011	0.016	-0.001	0.565			
Unemployed	-0.009	-0.023	-0.015	0.000	-0.082	0.079	0.151		
Coincident	0.012	0.030	0.019	0.000	0.108	-0.064	-0.226	-0.910	
$Jackpot^{daily}$	0.075	0.112	0.133	-0.011	0.514	0.116	-0.186	-0.030	0.042

This table reports the summary statistics in Panel A and correlation matrix in Panel B for daily data. $Volume^{daily}$ is the logarithm of daily share volume of U.S. stocks. $Dvolume^{daily}$ is the logarithm of daily dollar volume of U.S. stocks. $Trades^{daily}$ is the logarithm of daily number of trades of stocks listed on NASDAQ. LIDX is the firm-level lottery-like index constructed following Han and Kumar (2013) and Kumar et al. (2016). *WPFC* is the five-day moving average of daily count on former president Donald Trump's false or misleading claims reported in *Washington Post* following Bialkowski et al (2022). EPU^{daily} is the five-day moving average of daily economic policy uncertainty index developed by BBD. VIX^{daily} is the daily CBOE VIX value. *Unemploy* is the change in unemployment rate following Gao and Lin (2014) (daily observations in a given month is filled by the same monthly value). *Coincident* is the change in U.S. coincident index following Gao and Lin (2014) (daily observations in a given month is filled by the same monthly value). $Jackpot^{daily}$ is the logarithm of daily jackpot size calculated as the sum of two multi-state jackpots, namely Mega Millions and Powerball (data available since June 2005). The sample spans January 2017 to January 2021.

Table 3. Baseline regression: Monthly (January 2000 – June 2022)

Panel A Volume	Lottery-like (highest LIDX decile)					Nonlottery-like (lowest LIDX decile)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Qindex	1.653***	1.365***	0.218***	1.280***	0.217***	-0.798***	-0.802***	-0.100	-0.0500***	-0.101***
	(0.0264)	(0.0270)	(0.0577)	(0.0211)	(0.0306)	(0.0278)	(0.0286)	(0.0643)	(0.0111)	(0.0197)
EPU		0.537***	-0.0224	0.147***	-0.0224**		0.00873	0.241***	0.372***	0.242***
		(0.0120)	(0.0211)	(0.00820)	(0.0112)		(0.0126)	(0.0235)	(0.00476)	(0.00720)
Constant	12.21***	11.85***	13.73***	12.42***	13.74***	15.57***	15.56***	14.55***	14.33***	14.55***
	(0.0281)	(0.0291)	(0.0633)	(0.0225)	(0.0335)	(0.0295)	(0.0308)	(0.0705)	(0.0120)	(0.0216)
Year fixed effects	No	No	YES	No	YES	No	No	YES	No	YES
Firm fixed effects	No	No	No	YES	YES	No	No	No	YES	YES
Observations	162,023	162,023	162,023	162,023	162,023	193,873	193,873	193,873	193,873	193,873
Adjusted R-squared	0.024	0.036	0.141	0.708	0.759	0.004	0.004	0.015	0.896	0.907

Panel B DVolume	Lottery-like (highest LIDX decile)					Nonlottery-like (lowest LIDX decile)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Qindex	1.711***	1.503***	0.268***	1.256***	0.267***	-0.693***	-0.767***	-0.0753	0.293***	-0.0763***
	(0.0293)	(0.0301)	(0.0621)	(0.0246)	(0.0363)	(0.0296)	(0.0304)	(0.0676)	(0.0126)	(0.0203)
EPU		0.387***	-0.336***	-0.289***	-0.336***		0.142***	0.145***	0.379***	0.145***
		(0.0133)	(0.0227)	(0.00957)	(0.0133)		(0.0134)	(0.0247)	(0.00541)	(0.00743)
Constant	13.20***	12.94***	15.12***	14.04***	15.12***	19.40***	19.30***	18.58***	17.91***	18.58***
	(0.0311)	(0.0323)	(0.0681)	(0.0263)	(0.0398)	(0.0314)	(0.0327)	(0.0740)	(0.0136)	(0.0223)
Year fixed effects	No	No	YES	No	YES	No	No	YES	No	YES
Firm fixed effects	No	No	No	YES	YES	No	No	No	YES	YES
Observations	162,032	162,032	162,032	162,032	162,032	193,870	193,870	193,870	193,870	193,870
Adjusted R-squared	0.021	0.026	0.190	0.675	0.723	0.003	0.003	0.037	0.881	0.913

Panel C Trades	Lottery-like (highest LIDX decile)					Nonlottery-like (lowest LIDX decile)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Qindex	1.849***	1.424***	0.181***	1.040***	0.176***	-0.836***	-1.342***	-0.106	0.164***	-0.105***
	(0.0320)	(0.0324)	(0.0622)	(0.0251)	(0.0346)	(0.0708)	(0.0733)	(0.154)	(0.0286)	(0.0377)
EPU		0.815***	-0.132***	0.0324***	-0.130***		0.767***	0.169***	0.362***	0.174***
		(0.0145)	(0.0233)	(0.00986)	(0.0130)		(0.0324)	(0.0561)	(0.0118)	(0.0137)
Constant	6.070***	5.506***	7.986***	6.879***	7.990***	10.48***	10.06***	9.487***	8.954***	9.480***
	(0.0343)	(0.0352)	(0.0687)	(0.0270)	(0.0382)	(0.0776)	(0.0789)	(0.174)	(0.0311)	(0.0425)
Year fixed effects	No	No	YES	No	YES	No	No	YES	No	YES
Firm fixed effects	No	No	No	YES	YES	No	No	No	YES	YES
Observations	113,498	113,498	113,498	113,494	113,494	29,001	29,001	29,001	28,998	28,998
Adjusted R-squared	0.029	0.055	0.301	0.722	0.784	0.005	0.024	0.138	0.913	0.948

This table reports the results of monthly panel regressions for lottery-like (highest LIDX decile) and non-lottery-like (lowest LIDX decile) stocks, respectively. We present the results for three proxies of trading activity, namely share volume (*Volume* in Panel A), dollar trading volume (*DVolume* in Panel B) and the number of individual trades (*Trades* in Panel C). *Volume* is the logarithm of monthly share volume of U.S. stocks. *Dvolume* is the logarithm of monthly dollar volume of U.S. stocks. Trades is the logarithm of monthly number of trades of stocks listed on NASDAQ. *LIDX* is the firm-level lottery-like index constructed following Han and Kumar (2013) and Kumar et al. (2016). *Qindex* is the monthly quality of political signals index constructed by Bialkowski et al (2022). *EPU* is the monthly economic policy uncertainty index developed by BBD. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample spans January 2000 through June 2022.

Table 4. Baseline regression: Daily (Jan 2017- Jan 2021)

Panel A $Volume^{daily}$	Lottery-like (highest LIDX decile)					Nonlottery-like (lowest LIDX decile)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
WPFC	0.697***	0.441***	0.148***	0.532***	0.153***	-0.506***	-0.383***	-0.0931***	0.0413***	-0.0968***
	(0.00980)	(0.00999)	(0.0108)	(0.00645)	(0.00655)	(0.0109)	(0.0111)	(0.0121)	(0.00390)	(0.00410)
EPU^{daily}		0.265***	0.0370***	0.315***	0.0385***		-0.130***	0.0748***	0.143***	0.0769***
		(0.00241)	(0.00362)	(0.00175)	(0.00220)		(0.00269)	(0.00404)	(0.00104)	(0.00137)
Constant	11.18***	10.81***	11.24***	10.72***	11.24***	11.59***	11.77***	11.38***	11.25***	11.38***
	(0.00357)	(0.00484)	(0.00701)	(0.00347)	(0.00426)	(0.00399)	(0.00545)	(0.00792)	(0.00209)	(0.00269)
Year fixed effects	No	No	YES	No	YES	No	No	YES	No	YES
Firm fixed effects	No	No	No	YES	YES	No	No	No	YES	YES
Observations	651,381	651,381	651,381	651,381	651,381	735,460	735,460	735,460	735,457	735,457
Adjusted R-squared	0.008	0.026	0.041	0.617	0.646	0.003	0.006	0.013	0.884	0.886

Panel B $DVolume^{daily}$	Lottery-like (highest LIDX decile)					Nonlottery-like (lowest LIDX decile)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
WPFC	0.433***	0.307***	0.112***	0.361***	0.115***	-0.602***	-0.411***	-0.0745***	0.110***	-0.0779***
	(0.0102)	(0.0105)	(0.0113)	(0.00678)	(0.00698)	(0.0119)	(0.0121)	(0.0131)	(0.00391)	(0.00408)
EPU^{daily}		0.131***	-0.0508***	0.158***	-0.0498***		-0.201***	0.0420***	0.139***	0.0443***
		(0.00252)	(0.00379)	(0.00184)	(0.00234)		(0.00293)	(0.00441)	(0.00105)	(0.00137)
Constant	12.43***	12.25***	12.58***	12.19***	12.58***	15.92***	16.20***	15.74***	15.54***	15.73***
	(0.00370)	(0.00506)	(0.00735)	(0.00365)	(0.00454)	(0.00435)	(0.00594)	(0.00862)	(0.00210)	(0.00268)
Year fixed effects	No	No	YES	No	YES	No	No	YES	No	YES
Firm fixed effects	No	No	No	YES	YES	No	No	No	YES	YES
Observations	651,381	651,381	651,381	651,381	651,381	735,460	735,460	735,460	735,457	735,457
Adjusted R-squared	0.003	0.007	0.020	0.606	0.626	0.003	0.010	0.017	0.902	0.905

Panel C Trades^{daily}	Lottery-like (highest LIDX decile)					Nonlottery-like (lowest LIDX decile)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
WPFC	0.691***	0.455***	0.141***	0.476***	0.145***	-0.226***	-0.162***	-0.0145	0.168***	-0.0214***
	(0.00986)	(0.0100)	(0.0108)	(0.00648)	(0.00656)	(0.0211)	(0.0217)	(0.0235)	(0.00555)	(0.00568)
EPU^{daily}		0.247***	0.0224***	0.258***	0.0234***		-0.0657***	0.0413***	0.145***	0.0442***
		(0.00242)	(0.00362)	(0.00175)	(0.00220)		(0.00522)	(0.00789)	(0.00149)	(0.00191)
Constant	5.838***	5.498***	5.922***	5.476***	5.920***	7.000***	7.088***	6.891***	6.691***	6.888***
	(0.00360)	(0.00488)	(0.00704)	(0.00349)	(0.00429)	(0.00752)	(0.0103)	(0.0150)	(0.00288)	(0.00362)
Year fixed effects	No	No	YES	No	YES	No	No	YES	No	YES
Firm fixed effects	No	No	No	YES	YES	No	No	No	YES	YES
Observations	465,353	465,353	465,353	465,353	465,353	160,548	160,548	160,548	160,548	160,548
Adjusted R-squared	0.010	0.032	0.054	0.618	0.650	0.001	0.002	0.006	0.938	0.942

This table reports the results of daily panel regressions for lottery-like (highest LIDX decile) and non-lottery-like (lowest LIDX decile) stocks, respectively. We present the results for three proxies of trading activity, namely share volume ($Volume^{daily}$ in Panel A), dollar trading volume ($DVolume^{daily}$ in Panel B) and the number of individual trades ($Trades^{daily}$ in Panel C). $Volume^{daily}$ is the logarithm of daily share volume of U.S. stocks. $Dvolume^{daily}$ is the logarithm of daily dollar volume of U.S. stocks. Trades is the logarithm of daily number of trades of stocks listed on NASDAQ. *LIDX* is the firm-level lottery-like index constructed following Han and Kumar (2013) and Kumar et al. (2016). *WPFC* is the daily quality of political signals measure, calculated as the five-day moving average of daily count on former president Donald Trump's false or misleading claims reported in *Washington Post*. EPU^{daily} is the five-day moving average of daily economic policy uncertainty index developed by BBD. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample spans January 2017 to January 2021

Table 5. Portfolios sorted by LIDX without controls: Monthly (January 2000 – June 2022)

Panel A Volume	(1) Nonlottery-like	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) Lottery-like
Qindex	-0.101***	-0.0832***	-0.0904***	-0.0526***	-0.0650***	-0.0918***	-0.0317	0.0123	0.0732***	0.217***
	(0.0197)	(0.0179)	(0.0185)	(0.0185)	(0.0178)	(0.0188)	(0.0208)	(0.0240)	(0.0240)	(0.0306)
EPU	0.242***	0.195***	0.167***	0.130***	0.109***	0.0817***	0.0412***	0.0152*	-0.0443***	-0.0224**
	(0.00720)	(0.00671)	(0.00668)	(0.00688)	(0.00653)	(0.00680)	(0.00768)	(0.00885)	(0.00881)	(0.0112)
Constant	14.55***	14.31***	14.38***	14.41***	14.51***	14.57***	14.40***	14.19***	14.08***	13.74***
	(0.0216)	(0.0199)	(0.0200)	(0.0203)	(0.0195)	(0.0206)	(0.0231)	(0.0263)	(0.0263)	(0.0335)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	193,873	179,328	178,577	165,936	175,140	177,775	168,481	169,890	168,845	162,023
Adjusted R-squared	0.907	0.923	0.929	0.930	0.930	0.924	0.911	0.879	0.860	0.759

Panel B DVolume	(1) Nonlottery-like	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) Lottery-like
Qindex	-0.0763***	-0.0589***	-0.0803***	-0.0431**	-0.0723***	-0.0744***	-0.0200	0.0242	0.0885***	0.267***
	(0.0203)	(0.0189)	(0.0195)	(0.0200)	(0.0200)	(0.0218)	(0.0239)	(0.0274)	(0.0296)	(0.0363)
EPU	0.145***	0.0753***	0.0162**	-0.0240***	-0.0648***	-0.112***	-0.184***	-0.233***	-0.325***	-0.336***
	(0.00743)	(0.00707)	(0.00707)	(0.00744)	(0.00738)	(0.00787)	(0.00881)	(0.0101)	(0.0109)	(0.0133)
Constant	18.58***	17.99***	17.90***	17.81***	17.81***	17.72***	17.37***	16.83***	16.22***	15.12***
	(0.0223)	(0.0209)	(0.0212)	(0.0219)	(0.0221)	(0.0238)	(0.0264)	(0.0300)	(0.0325)	(0.0398)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	193,870	179,325	178,577	165,936	175,140	177,775	168,484	169,893	168,852	162,032
Adjusted R-squared	0.913	0.927	0.929	0.927	0.921	0.908	0.892	0.856	0.829	0.723

Panel C Trades	(1) Nonlottery-like	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) Lottery-like
Qindex	-0.105***	-0.0722**	-0.0629**	-0.0656**	-0.122***	-0.116***	-0.0687***	0.0107	0.0340	0.176***
	(0.0377)	(0.0290)	(0.0281)	(0.0265)	(0.0249)	(0.0251)	(0.0259)	(0.0280)	(0.0286)	(0.0346)
EPU	0.174***	0.124***	0.0715***	0.0358***	0.0466***	0.00729	-0.0344***	-0.0887***	-0.140***	-0.130***
	(0.0137)	(0.0120)	(0.0113)	(0.0108)	(0.0101)	(0.00962)	(0.00991)	(0.0107)	(0.0109)	(0.0130)
Constant	9.480***	9.182***	9.167***	9.125***	9.036***	9.067***	8.980***	8.679***	8.419***	7.990***
	(0.0425)	(0.0330)	(0.0310)	(0.0294)	(0.0275)	(0.0275)	(0.0286)	(0.0306)	(0.0314)	(0.0382)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	28,998	39,337	48,659	56,406	72,628	89,372	97,025	108,220	114,941	113,494
Adjusted R-squared	0.948	0.953	0.950	0.947	0.938	0.924	0.909	0.877	0.859	0.784

This table reports the results of monthly panel regressions across the portfolio deciles sorted by *LIDX*. We present the results for three proxies of trading activity, namely share volume (*Volume* in Panel A), dollar trading volume (*DVolume* in Panel B) and the number of individual trades (*Trades* in Panel C). *Volume* is the logarithm of monthly share volume of U.S. stocks. *Dvolume* is the logarithm of monthly dollar volume of U.S. stocks. Trades is the logarithm of monthly number of trades of stocks listed on NASDAQ. *LIDX* is the firm-level lottery-like index constructed following Han and Kumar (2013) and Kumar et al. (2016). *Qindex* is the monthly quality of political signals index constructed by Bialkowski et al (2022). *EPU* is the monthly economic policy uncertainty index developed by BBD. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample spans January 2000 through June 2022.

Table 6. Portfolios sorted by LIDX without controls: Daily (Jan 2017- Jan 2021)

Panel A Volume^{daily}	(1) Nonlottery-like	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) Lottery-like
WPFC	-0.0968***	-0.102***	-0.112***	-0.107***	-0.0941***	-0.0905***	-0.0619***	-0.0624***	-0.0512***	0.153***
	(0.00410)	(0.00421)	(0.00457)	(0.00452)	(0.00377)	(0.00358)	(0.00404)	(0.00465)	(0.00501)	(0.00655)
EPU^{daily}	0.0769***	0.0703***	0.0692***	0.0671***	0.0636***	0.0610***	0.0570***	0.0460***	0.0285***	0.0385***
	(0.00137)	(0.00141)	(0.00153)	(0.00152)	(0.00126)	(0.00120)	(0.00136)	(0.00156)	(0.00168)	(0.00220)
Constant	11.38***	11.08***	11.11***	11.18***	11.55***	11.74***	11.72***	11.57***	11.47***	11.24***
	(0.00269)	(0.00265)	(0.00290)	(0.00283)	(0.00244)	(0.00239)	(0.00250)	(0.00298)	(0.00321)	(0.00426)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	735,457	789,446	642,892	647,010	693,690	687,827	727,549	679,011	667,098	651,381
Adjusted R-squared	0.886	0.886	0.887	0.892	0.900	0.894	0.882	0.854	0.817	0.646

Panel B DVolume^{daily}	(1) Nonlottery-like	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) Lottery-like
WPFC	-0.0779***	-0.0914***	-0.109***	-0.118***	-0.111***	-0.124***	-0.105***	-0.119***	-0.0949***	0.115***
	(0.00408)	(0.00423)	(0.00455)	(0.00450)	(0.00378)	(0.00362)	(0.00412)	(0.00466)	(0.00533)	(0.00698)
EPU^{daily}	0.0443***	0.0255***	0.0198***	0.0118***	0.00177	-0.0115***	-0.0206***	-0.0348***	-0.0551***	-0.0498***
	(0.00137)	(0.00142)	(0.00153)	(0.00151)	(0.00126)	(0.00122)	(0.00139)	(0.00156)	(0.00179)	(0.00234)
Constant	15.73***	15.06***	14.84***	14.79***	15.02***	15.07***	14.79***	14.29***	13.66***	12.58***
	(0.00268)	(0.00266)	(0.00289)	(0.00282)	(0.00245)	(0.00241)	(0.00255)	(0.00298)	(0.00341)	(0.00454)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	735,457	789,446	642,892	647,010	693,690	687,827	727,549	679,011	667,098	651,381
Adjusted R-squared	0.905	0.904	0.905	0.910	0.916	0.908	0.891	0.858	0.816	0.626

Panel C $Trades^{daily}$	(1) Nonlottery-like	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) Lottery-like
WPFC	-0.0214***	-0.0175***	-0.0130**	-0.00198	-0.0402***	-0.0285***	-0.0346***	-0.0165***	-0.00525	0.145***
	(0.00568)	(0.00552)	(0.00586)	(0.00548)	(0.00428)	(0.00401)	(0.00452)	(0.00520)	(0.00538)	(0.00656)
EPU^{daily}	0.0442***	0.0436***	0.0473***	0.0416***	0.0539***	0.0431***	0.0373***	0.0267***	0.0120***	0.0234***
	(0.00191)	(0.00186)	(0.00196)	(0.00185)	(0.00143)	(0.00135)	(0.00152)	(0.00175)	(0.00181)	(0.00220)
Constant	6.888***	6.622***	6.744***	6.761***	6.929***	6.956***	6.841***	6.496***	6.328***	5.920***
	(0.00362)	(0.00338)	(0.00369)	(0.00345)	(0.00290)	(0.00282)	(0.00289)	(0.00328)	(0.00344)	(0.00429)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	160,548	196,185	163,183	190,779	230,110	280,539	354,315	379,340	412,273	465,353
Adjusted R-squared	0.942	0.945	0.945	0.944	0.940	0.925	0.898	0.858	0.824	0.650

This table reports the results of monthly panel regressions across the portfolio deciles sorted by LIDX. We present the results for three proxies of trading activity, namely share volume ($Volume^{daily}$ in Panel A), dollar trading volume ($DVolume^{daily}$ in Panel B) and the number of individual trades ($Trades^{daily}$ in Panel C). $Volume^{daily}$ is the logarithm of daily share volume of U.S. stocks. $Dvolume^{daily}$ is the logarithm of daily dollar volume of U.S. stocks. Trades is the logarithm of daily number of trades of stocks listed on NASDAQ. *LIDX* is the firm-level lottery-like index constructed following Han and Kumar (2013) and Kumar et al. (2016). *WPFC* is the daily quality of political signals measure, calculated as the five-day moving average of daily count on former president Donald Trump's false or misleading claims reported in *Washington Post*. EPU^{daily} is the five-day moving average of daily economic policy uncertainty index developed by BBD. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample spans January 2017 to January 2021.

Table 7. Portfolios sorted by LIDX with controls: Monthly (June 2005 – June 2022)

Panel A Volume	(1) Nonlottery-like	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) Lottery-like
Qindex	-0.0940***	-0.0491**	-0.0625***	-0.0447**	-0.129***	-0.115***	-0.125***	-0.0881***	0.0288	0.246***
	(0.0215)	(0.0216)	(0.0226)	(0.0212)	(0.0211)	(0.0209)	(0.0223)	(0.0264)	(0.0276)	(0.0381)
EPU	0.0571***	0.0521***	0.0686***	0.0556***	0.0559***	0.0428***	0.0601***	0.0494***	0.0657***	0.153***
	(0.00610)	(0.00632)	(0.00634)	(0.00640)	(0.00575)	(0.00586)	(0.00658)	(0.00745)	(0.00797)	(0.0108)
VIX	0.832***	0.812***	0.703***	0.658***	0.517***	0.458***	0.248***	0.110***	-0.0909**	-0.601***
	(0.0273)	(0.0295)	(0.0280)	(0.0290)	(0.0261)	(0.0267)	(0.0298)	(0.0333)	(0.0360)	(0.0489)
L.Volume	0.720***	0.622***	0.595***	0.596***	0.617***	0.630***	0.655***	0.694***	0.628***	0.607***
	(0.00178)	(0.00213)	(0.00220)	(0.00228)	(0.00221)	(0.00215)	(0.00217)	(0.00205)	(0.00221)	(0.00232)
Jackpot	0.0431***	0.0382***	0.0268***	0.0284***	0.0337***	0.0209***	0.0250***	0.0267***	0.00925**	0.0129**
	(0.00342)	(0.00355)	(0.00349)	(0.00346)	(0.00330)	(0.00333)	(0.00366)	(0.00415)	(0.00445)	(0.00608)
Unemployed	-0.0558***	-0.0383***	-0.0491***	-0.0205***	-0.0382***	-0.0234***	-0.0143***	-0.0135***	0.00961*	0.0357***
	(0.00425)	(0.00444)	(0.00443)	(0.00440)	(0.00412)	(0.00409)	(0.00458)	(0.00521)	(0.00553)	(0.00752)
Coincident	-0.0256***	-0.0162***	-0.0307***	-0.00828**	-0.0175***	-0.00411	0.00403	0.00626	0.0265***	0.0539***
	(0.00358)	(0.00374)	(0.00370)	(0.00367)	(0.00347)	(0.00345)	(0.00384)	(0.00439)	(0.00464)	(0.00634)
Constant	3.196***	4.606***	5.244***	5.225***	4.992***	5.072***	4.601***	3.933***	5.083***	5.013***
	(0.0734)	(0.0772)	(0.0773)	(0.0764)	(0.0742)	(0.0740)	(0.0798)	(0.0885)	(0.0945)	(0.126)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	145,743	134,619	133,998	126,393	130,116	133,926	126,616	128,268	126,188	122,367
Adjusted R-squared	0.956	0.954	0.958	0.959	0.962	0.960	0.954	0.942	0.924	0.847

Panel B DVolume	(1) Nonlottery-like	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) Lottery-like
Qindex	-0.0544**	0.0289	-0.0143	0.0353*	-0.0513**	-0.00704	-0.00390	0.0520*	0.227***	0.525***
	(0.0215)	(0.0217)	(0.0226)	(0.0213)	(0.0214)	(0.0213)	(0.0229)	(0.0274)	(0.0297)	(0.0422)
EPU	0.0462***	0.0339***	0.0489***	0.0337***	0.0317***	0.0159***	0.0307***	0.0214***	0.0389***	0.121***
	(0.00611)	(0.00633)	(0.00635)	(0.00643)	(0.00582)	(0.00598)	(0.00674)	(0.00773)	(0.00856)	(0.0119)
VIX	0.410***	0.310***	0.107***	0.0898***	-0.0993***	-0.185***	-0.393***	-0.582***	-0.794***	-1.397***
	(0.0273)	(0.0295)	(0.0280)	(0.0291)	(0.0263)	(0.0273)	(0.0305)	(0.0346)	(0.0387)	(0.0543)
L.DVolume	0.737***	0.653***	0.623***	0.630***	0.665***	0.689***	0.701***	0.718***	0.716***	0.650***
	(0.00175)	(0.00207)	(0.00215)	(0.00221)	(0.00210)	(0.00201)	(0.00205)	(0.00198)	(0.00200)	(0.00223)
Jackpot	0.0412***	0.0373***	0.0265***	0.0297***	0.0363***	0.0242***	0.0309***	0.0320***	0.0150***	0.0238***
	(0.00343)	(0.00356)	(0.00350)	(0.00348)	(0.00334)	(0.00340)	(0.00375)	(0.00431)	(0.00478)	(0.00674)
Unemployed	-0.0608***	-0.0452***	-0.0578***	-0.0288***	-0.0463***	-0.0283***	-0.0204***	-0.0152***	0.00524	0.0376***
	(0.00426)	(0.00445)	(0.00443)	(0.00442)	(0.00416)	(0.00417)	(0.00469)	(0.00542)	(0.00594)	(0.00834)
Coincident	-0.0284***	-0.0187***	-0.0343***	-0.0116***	-0.0197***	-0.00337	0.00449	0.00913**	0.0259***	0.0596***
	(0.00358)	(0.00375)	(0.00371)	(0.00369)	(0.00351)	(0.00353)	(0.00393)	(0.00456)	(0.00499)	(0.00703)
Constant	4.124***	5.489***	6.243***	5.994***	5.371***	5.130***	4.695***	4.211***	4.240***	4.529***
	(0.0763)	(0.0805)	(0.0806)	(0.0800)	(0.0776)	(0.0773)	(0.0833)	(0.0930)	(0.101)	(0.139)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	145,740	134,615	133,997	126,392	130,115	133,926	126,618	128,274	126,200	122,379
Adjusted R-squared	0.960	0.960	0.962	0.963	0.964	0.960	0.953	0.939	0.925	0.838

Panel C Trades	(1) Nonlottery-like	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) Lottery-like
Qindex	-0.0777**	-0.0456	-0.0661*	-0.0368	-0.206***	-0.181***	-0.165***	-0.0785**	0.0290	0.307***
	(0.0340)	(0.0317)	(0.0346)	(0.0301)	(0.0300)	(0.0270)	(0.0269)	(0.0308)	(0.0311)	(0.0431)
EPU	0.00277	0.0227**	0.0429***	0.0333***	0.0508***	0.0379***	0.0617***	0.0532***	0.0648***	0.130***
	(0.00978)	(0.00963)	(0.00982)	(0.00914)	(0.00811)	(0.00749)	(0.00783)	(0.00875)	(0.00899)	(0.0123)
VIX	0.811***	0.625***	0.365***	0.365***	0.276***	0.175***	0.0394	-0.172***	-0.336***	-0.763***
	(0.0463)	(0.0463)	(0.0430)	(0.0403)	(0.0355)	(0.0330)	(0.0345)	(0.0381)	(0.0397)	(0.0566)
L.Trades	0.769***	0.703***	0.663***	0.689***	0.678***	0.711***	0.712***	0.716***	0.713***	0.630***
	(0.00402)	(0.00427)	(0.00420)	(0.00375)	(0.00339)	(0.00285)	(0.00272)	(0.00253)	(0.00244)	(0.00275)
Jackpot	0.0336***	0.0283***	0.00862	0.0128***	0.0177***	0.00941**	0.0250***	0.0203***	0.00708	0.00846
	(0.00564)	(0.00532)	(0.00530)	(0.00484)	(0.00457)	(0.00423)	(0.00434)	(0.00478)	(0.00496)	(0.00698)
Unemployed	-0.0583***	-0.0374***	-0.0495***	-0.0182***	-0.0273***	-0.0198***	-0.0102*	-0.00862	0.00646	0.0382***
	(0.00686)	(0.00671)	(0.00684)	(0.00618)	(0.00574)	(0.00519)	(0.00543)	(0.00611)	(0.00622)	(0.00856)
Coincident	-0.0248***	-0.0142**	-0.0282***	-5.89e-05	-0.00494	0.00402	0.0113**	0.0118**	0.0266***	0.0547***
	(0.00585)	(0.00569)	(0.00573)	(0.00515)	(0.00485)	(0.00439)	(0.00455)	(0.00511)	(0.00520)	(0.00724)
Constant	1.606***	2.291***	3.111***	2.733***	2.890***	2.709***	2.344***	2.251***	2.357***	2.669***
	(0.119)	(0.114)	(0.115)	(0.103)	(0.0981)	(0.0892)	(0.0906)	(0.0985)	(0.101)	(0.141)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	22,736	27,799	32,383	37,892	48,008	61,581	68,667	78,092	82,452	83,363
Adjusted R-squared	0.979	0.977	0.973	0.972	0.969	0.964	0.957	0.941	0.934	0.858

This table reports the results of monthly panel regressions across the portfolio deciles sorted by LIDX. We present the results for three proxies of trading activity, namely share volume (*Volume* in Panel A), dollar trading volume (*DVolume* in Panel B) and the number of individual trades (*Trades* in Panel C). *Volume* is the logarithm of monthly share volume of U.S. stocks. *Dvolume* is the logarithm of monthly dollar volume of U.S. stocks. Trades is the logarithm of monthly number of trades of stocks listed on NASDAQ. *LIDX* is the firm-level lottery-like index constructed following Han and Kumar (2013) and Kumar et al. (2016). *Qindex* is the monthly quality of political signals index constructed by Bialkowski et al (2022). *EPU* is the monthly economic policy uncertainty index developed by BBD. *VIX* is the CBOE VIX value at the end of a given month. *Unemploy* is the change in unemployment rate following Gao and Lin (2014). *Coincident* is the change in U.S. coincident index following Gao and Lin (2014). *Jackpot* is the logarithm of average daily jackpot size calculated as the sum of two multi-state jackpots, namely Mega Millions and Powerball in a given month. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample spans June 2005 through June 2022. Lagged dependent variables (volume measures) are controlled following Gao and Lin (2014).

Table 8. Portfolio sorted by LIDX with controls: Daily (Jan 2017- Jan 2021)

Panel A Volume^{daily}	(1) Nonlottery-like	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) Lottery-like
WPFC	-0.0595***	-0.0694***	-0.0733***	-0.0684***	-0.0616***	-0.0558***	-0.0382***	-0.0271***	-0.0273***	0.0343***
	(0.00374)	(0.00394)	(0.00427)	(0.00423)	(0.00353)	(0.00329)	(0.00362)	(0.00394)	(0.00427)	(0.00494)
EPU^{daily}	-0.0362***	-0.0293***	-0.0246***	-0.0223***	-0.0146***	-0.00917***	0.00253*	0.00329**	0.0119***	0.0495***
	(0.00154)	(0.00161)	(0.00175)	(0.00173)	(0.00145)	(0.00136)	(0.00148)	(0.00162)	(0.00176)	(0.00204)
VIX^{daily}	0.0168***	0.0157***	0.0145***	0.0139***	0.0122***	0.0103***	0.00741***	0.00480***	0.00269***	-0.00289***
	(0.000166)	(0.000172)	(0.000187)	(0.000184)	(0.000156)	(0.000145)	(0.000156)	(0.000172)	(0.000186)	(0.000216)
L.Volume^{daily}	0.406***	0.354***	0.349***	0.349***	0.361***	0.407***	0.457***	0.556***	0.554***	0.676***
	(0.00107)	(0.00106)	(0.00118)	(0.00118)	(0.00113)	(0.00111)	(0.00105)	(0.00101)	(0.00103)	(0.000917)
Jackpot^{daily}	0.0237***	0.0221***	0.0224***	0.0213***	0.0199***	0.0168***	0.0124***	0.0166***	0.0179***	0.0174***
	(0.00160)	(0.00161)	(0.00177)	(0.00172)	(0.00149)	(0.00143)	(0.00145)	(0.00164)	(0.00178)	(0.00209)
Unemployed	0.00816***	0.00689***	0.00290	0.00937***	0.00276	0.00804***	0.00337	0.00625**	-0.00416	-0.0247***
	(0.00239)	(0.00249)	(0.00271)	(0.00267)	(0.00224)	(0.00211)	(0.00228)	(0.00251)	(0.00271)	(0.00315)
Coincident	0.00509**	0.00427**	-0.000305	0.00622***	0.00334*	0.0103***	0.00885***	0.0125***	0.00966***	0.00135
	(0.00202)	(0.00211)	(0.00229)	(0.00226)	(0.00190)	(0.00179)	(0.00192)	(0.00213)	(0.00230)	(0.00267)
Constant	6.115***	6.573***	6.668***	6.746***	6.884***	6.542***	6.072***	4.785***	4.742***	3.297***
	(0.0334)	(0.0336)	(0.0369)	(0.0362)	(0.0318)	(0.0307)	(0.0310)	(0.0342)	(0.0367)	(0.0423)
Day of the week effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	728,768	779,461	633,572	638,128	687,041	682,195	721,940	674,185	662,172	647,847
Adjusted R-squared	0.909	0.904	0.904	0.908	0.915	0.914	0.908	0.900	0.873	0.809

Panel B $DVolume^{daily}$	(1) Nonlottery-like	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) Lottery-like
WPFC	-0.0481***	-0.0609***	-0.0711***	-0.0749***	-0.0684***	-0.0695***	-0.0566***	-0.0515***	-0.0402***	0.0183***
	(0.00374)	(0.00395)	(0.00427)	(0.00423)	(0.00354)	(0.00331)	(0.00366)	(0.00395)	(0.00435)	(0.00505)
EPU^{daily}	-0.0406***	-0.0383***	-0.0359***	-0.0373***	-0.0335***	-0.0304***	-0.0164***	-0.0106***	-0.00113	0.0412***
	(0.00154)	(0.00162)	(0.00175)	(0.00173)	(0.00146)	(0.00137)	(0.00149)	(0.00163)	(0.00179)	(0.00208)
VIX^{daily}	0.0139***	0.0117***	0.0104***	0.00963***	0.00796***	0.00571***	0.00279***	0.000609***	-0.00156***	-0.00621***
	(0.000166)	(0.000172)	(0.000186)	(0.000183)	(0.000156)	(0.000146)	(0.000157)	(0.000172)	(0.000190)	(0.000221)
$L.DVolume^{daily}$	0.408***	0.366***	0.349***	0.349***	0.372***	0.425***	0.482***	0.556***	0.603***	0.706***
	(0.00107)	(0.00106)	(0.00118)	(0.00118)	(0.00112)	(0.00110)	(0.00103)	(0.00101)	(0.000983)	(0.000881)
$Jackpot^{daily}$	0.0232***	0.0232***	0.0233***	0.0223***	0.0236***	0.0207***	0.0163***	0.0201***	0.0219***	0.0208***
	(0.00160)	(0.00162)	(0.00177)	(0.00172)	(0.00150)	(0.00144)	(0.00147)	(0.00165)	(0.00181)	(0.00214)
Unemployed	-0.000230	-0.00410	-0.0107***	-0.00353	-0.00716***	-0.000807	-0.00888***	-0.00833***	-0.0153***	-0.0358***
	(0.00239)	(0.00250)	(0.00271)	(0.00268)	(0.00225)	(0.00213)	(0.00230)	(0.00252)	(0.00277)	(0.00322)
Coincident	-0.00151	-0.00454**	-0.0115***	-0.00502**	-0.00569***	0.00164	-0.00198	0.000133	-0.000300	-0.00783***
	(0.00202)	(0.00211)	(0.00229)	(0.00226)	(0.00191)	(0.00180)	(0.00194)	(0.00213)	(0.00234)	(0.00273)
Constant	8.713***	8.993***	9.122***	9.115***	8.919***	8.221***	7.337***	5.959***	5.018***	3.325***
	(0.0353)	(0.0353)	(0.0386)	(0.0378)	(0.0336)	(0.0324)	(0.0324)	(0.0353)	(0.0379)	(0.0434)
Day of the week effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	728,768	779,461	633,572	638,128	687,041	682,195	721,940	674,185	662,172	647,847
Adjusted R-squared	0.924	0.918	0.919	0.923	0.929	0.926	0.917	0.902	0.883	0.815

Panel C Trades^{daily}	(1) Nonlottery-like	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) Lottery-like
WPFC	-0.0149***	-0.0105**	-0.00704	-0.00211	-0.0204***	-0.0171***	-0.0172***	-0.00755*	-0.00708*	0.0203***
	(0.00479)	(0.00479)	(0.00519)	(0.00490)	(0.00379)	(0.00343)	(0.00367)	(0.00407)	(0.00406)	(0.00447)
EPU^{daily}	-0.0257***	-0.0164***	-0.0123***	-0.00971***	-0.00528***	-0.00264*	0.000253	0.00621***	0.00979***	0.0374***
	(0.00196)	(0.00195)	(0.00212)	(0.00201)	(0.00157)	(0.00143)	(0.00151)	(0.00168)	(0.00167)	(0.00185)
VIX^{daily}	0.00926***	0.00841***	0.00790***	0.00716***	0.00750***	0.00563***	0.00411***	0.00202***	0.000794***	-0.00273***
	(0.000210)	(0.000205)	(0.000227)	(0.000213)	(0.000171)	(0.000155)	(0.000160)	(0.000177)	(0.000177)	(0.000196)
L.Trades^{daily}	0.546***	0.511***	0.490***	0.479***	0.490***	0.548***	0.602***	0.645***	0.675***	0.745***
	(0.00209)	(0.00194)	(0.00217)	(0.00202)	(0.00182)	(0.00159)	(0.00135)	(0.00125)	(0.00115)	(0.000982)
Jackpot^{daily}	0.00960***	0.0118***	0.0109***	0.00875***	0.00928***	0.00663***	0.00632***	0.0127***	0.0125***	0.0109***
	(0.00198)	(0.00190)	(0.00213)	(0.00200)	(0.00167)	(0.00156)	(0.00153)	(0.00167)	(0.00169)	(0.00190)
Unemployed	0.00201	0.00317	0.00909***	0.0101***	0.0145***	0.0104***	0.00778***	0.00404	-0.00110	-0.0193***
	(0.00304)	(0.00301)	(0.00328)	(0.00310)	(0.00243)	(0.00223)	(0.00233)	(0.00259)	(0.00258)	(0.00286)
Coincident	0.00209	0.00555**	0.0111***	0.0129***	0.0175***	0.0163***	0.0139***	0.0120***	0.0113***	0.00130
	(0.00257)	(0.00255)	(0.00278)	(0.00263)	(0.00206)	(0.00189)	(0.00197)	(0.00219)	(0.00219)	(0.00242)
Constant	2.814***	2.893***	3.137***	3.272***	3.267***	2.947***	2.548***	2.020***	1.778***	1.282***
	(0.0413)	(0.0394)	(0.0441)	(0.0415)	(0.0351)	(0.0326)	(0.0314)	(0.0336)	(0.0339)	(0.0379)
Day of the week effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	159,907	195,098	161,986	189,133	228,660	278,661	352,040	376,734	409,863	462,890
Adjusted R-squared	0.961	0.960	0.959	0.957	0.955	0.947	0.935	0.916	0.904	0.845

This table reports the results of daily panel regressions across the portfolio deciles sorted by *LIDX*. We present the results for three proxies of trading activity, namely share volume (*Volume^{daily}* in Panel A), dollar trading volume (*DVolume^{daily}* in Panel B) and the number of individual trades (*Trades^{daily}* in Panel C). *Volume^{daily}* is the logarithm of daily share volume of U.S. stocks. *Dvolume^{daily}* is the logarithm of daily dollar volume of U.S. stocks. Trades is the logarithm of daily number of trades of stocks listed on NASDAQ. *LIDX* is the firm-level lottery-like index constructed following Han and Kumar (2013) and Kumar et al. (2016). *WPFC* is the daily quality of political signals measure, calculated as the five-day moving average of daily count on former president Donald Trump's false or misleading claims reported in *Washington Post*. EPU^{daily} is the five-day moving average of daily economic policy uncertainty index developed by BBD. *VIX^{daily}* is the daily CBOE VIX value. *Unemploy* is the change in unemployment rate following Gao and Lin (2014). *Coincident* is the change in U.S. coincident index following Gao and Lin (2014). *Jackpot^{daily}* is the logarithm of daily jackpot size calculated as the sum of two multi-state jackpots, namely Mega Millions and Powerball. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample spans January 2017 to January 2021. Lagged dependent variables (volume measures) are controlled following Gao and Lin (2014).

Table 9. Portfolio sorted by other factors: Monthly (June 2005 – June 2022)

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Beta portfolios	Volume		DVolume		Trades	
	Low-beta	High-beta	Low-beta	High-beta	Low-beta	High-beta
Qindex	-0.216***	0.00513	-0.183***	0.313***	0.00664	0.110***
	(0.0340)	(0.0214)	(0.0347)	(0.0230)	(0.0586)	(0.0279)
Controls	YES	YES	YES	YES	YES	YES
Year, firm fixed effects	YES	YES	YES	YES	YES	YES

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Size portfolios	Volume		DVolume		Trades	
	Small	Big	Small	Big	Small	Big
Qindex	-0.0762*	-0.0480***	0.0116	0.0260**	-0.0448	-0.144***
	(0.0429)	(0.0123)	(0.0438)	(0.0122)	(0.0602)	(0.0220)
Controls	YES	YES	YES	YES	YES	YES
Year, firm fixed effects	YES	YES	YES	YES	YES	YES

Panel C	(1)	(2)	(3)	(4)	(5)	(6)
BM portfolios	Volume		DVolume		Trades	
	Low	High	Low	High	Low	High
Qindex	-0.0560	-0.113**	0.0991**	0.00370	-0.0217	-0.133**
	(0.0384)	(0.0456)	(0.0407)	(0.0485)	(0.0436)	(0.0599)
Controls	YES	YES	YES	YES	YES	YES
Year, firm fixed effects	YES	YES	YES	YES	YES	YES

Panel D	(1)	(2)	(3)	(4)	(5)	(6)
Momentum portfolios	Volume		DVolume		Trades	
	Loser	Winner	Loser	Winner	Loser	Winner
Qindex	-0.0384*	0.0312	0.136***	0.219***	-0.0526**	0.0292
	(0.0215)	(0.0317)	(0.0230)	(0.0340)	(0.0256)	(0.0383)
Controls	YES	YES	YES	YES	YES	YES
Year, firm fixed effects	YES	YES	YES	YES	YES	YES

Panel E	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity portfolios	Volume		DVolume		Trades	
	Liquid	Illiquid	Liquid	Illiquid	Liquid	Illiquid
Qindex	-0.00819	-0.190***	0.0444***	-0.0791*	-0.0807***	-0.0555
	(0.0128)	(0.0420)	(0.0126)	(0.0428)	(0.0239)	(0.0445)
Controls	YES	YES	YES	YES	YES	YES
Year, firm fixed effects	YES	YES	YES	YES	YES	YES

This table reports the results of monthly panel regressions across the portfolio deciles sorted by beta, size, book-to-market ratio, momentum, and liquidity in Panel A, B, C D and E, respectively. In each panel, we present the results for three proxies of trading activity, namely share volume (*Volume* in columns 1 and 2), dollar trading volume (*DVolume* in columns 3 and 4) and the number of individual trades (*Trades* in columns 5 and 6). *Volume* is the logarithm of monthly share volume of U.S. stocks. *Dvolume* is the logarithm of monthly dollar volume of U.S. stocks. Trades is the logarithm of monthly number of trades of stocks listed on NASDAQ. *LIDX* is the firm-level lottery-like index constructed following Han and Kumar (2013) and Kumar et al. (2016). *Qindex* is the monthly quality of political signals index constructed by Bialkowski et al (2022). Controls include *EPU*, the monthly economic policy uncertainty index developed by BBD; *VIX*, the CBOE VIX value at the end of a given month; *Unemploy*, the change in unemployment rate following Gao and Lin (2014); *Coincident*, the change in U.S. coincident index following Gao and Lin (2014); *Jackpot*, the logarithm of average daily jackpot size calculated as the sum of two multi-state jackpots, namely Mega Millions and Powerball in a given month. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample spans June 2005 through June 2022.

Table 10. Portfolio sorted by other factors: Daily (Jan 2017- Jan 2021)

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Beta portfolios	Volume		DVolume		Trades	
	Low-beta	High-beta	Low-beta	High-beta	Low-beta	High-beta
WPFC	-0.00124	-0.0122***	-0.0152**	-0.0300***	0.0198***	0.000979
	(0.00602)	(0.00280)	(0.00603)	(0.00286)	(0.00767)	(0.00368)
Controls	YES	YES	YES	YES	YES	YES
Year, firm fixed effects	YES	YES	YES	YES	YES	YES

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Size portfolios	$Volume^{daily}$		$DVolume^{daily}$		$Trades^{daily}$	
	Small	Big	Small	Big	Small	Big
WPFC	0.0644***	-0.0249***	0.0518***	-0.0200***	0.0337***	0.00566**
	(0.00831)	(0.00178)	(0.00828)	(0.00178)	(0.00761)	(0.00271)
Controls	YES	YES	YES	YES	YES	YES
Year, firm fixed effects	YES	YES	YES	YES	YES	YES

Panel C	(1)	(2)	(3)	(4)	(5)	(6)
BM portfolios	$Volume^{daily}$		$DVolume^{daily}$		$Trades^{daily}$	
	Low	High	Low	High	Low	High
WPFC	-0.000725	0.00869	0.00562	-0.00228	0.0116**	-0.00548
	(0.00516)	(0.00712)	(0.00523)	(0.00722)	(0.00542)	(0.00735)
Controls	YES	YES	YES	YES	YES	YES
Year, firm fixed effects	YES	YES	YES	YES	YES	YES

Panel D	(1)	(2)	(3)	(4)	(5)	(6)
Momentum portfolios	$Volume^{daily}$		$DVolume^{daily}$		$Trades^{daily}$	
	Loser	Winner	Loser	Winner	Loser	Winner
WPFC	-0.0282***	0.0245***	-0.0178***	-0.00106	0.000838	0.00552
	(0.00302)	(0.00431)	(0.00309)	(0.00434)	(0.00297)	(0.00424)
Controls	YES	YES	YES	YES	YES	YES
Year, firm fixed effects	YES	YES	YES	YES	YES	YES

Panel E	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity portfolios	$Volume^{daily}$		$DVolume^{daily}$		$Trades^{daily}$	
	Liquid	Illiquid	Liquid	Illiquid	Liquid	Illiquid
WPFC	-0.0232***	0.0229***	-0.0180***	0.00355	0.0290***	0.0427***
	(0.00614)	(0.00808)	(0.00616)	(0.00810)	(0.00602)	(0.00797)
Controls	YES	YES	YES	YES	YES	YES
Year, firm fixed effects	YES	YES	YES	YES	YES	YES

This table reports the results of daily panel regressions across the portfolio deciles sorted by beta, size, book-to-market ratio, momentum, and liquidity in Panel A, B, C, D and E, respectively. In each panel, we present the results for three proxies of trading activity, namely share volume ($Volume^{daily}$ in columns 1 and 2), dollar trading volume ($DVolume^{daily}$ in columns 3 and 4) and the number of individual trades ($Trades^{daily}$ in columns 5 and 6). *WPFC* is the daily quality of political signals measure, calculated as the five-day moving average of daily count on former president Donald Trump's false or misleading claims reported in *Washington Post*. Controls include EPU^{daily}, the five-day moving average of daily economic policy uncertainty index developed by BBD; VIX^{daily}, the daily CBOE VIX value; *Unemploy*, the change in unemployment rate following Gao and Lin (2014); *Coincident*, the change in U.S. coincident index following Gao and Lin (2014); $Jackpot^{daily}$, the logarithm of daily jackpot size calculated as the sum of two multi-state jackpots, namely Mega Millions and Powerball. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample spans January 2017 to January 2021.

Table 11. Alternative definitions for lottery-like stocks (Conrad et al., 2014)

Panel A Monthly	(1)	(2)	(3)	(4)	(5)	(6)
	Nonlottery-like			Lottery-like		
	Volume	DVolume	Trades	Volume	DVolume	Trades
Qindex	-0.0860***	-0.0839***	-0.106***	0.315***	0.387***	0.303***
	(0.00835)	(0.00943)	(0.0118)	(0.0320)	(0.0433)	(0.0419)
EPU	0.110***	-0.0673***	-0.00152	-0.250***	-0.533***	-0.345***
	(0.00308)	(0.00348)	(0.00465)	(0.0130)	(0.0176)	(0.0168)
Constant	14.29***	17.34***	8.790***	14.76***	17.26***	9.071***
	(0.00927)	(0.0105)	(0.0132)	(0.0381)	(0.0515)	(0.0504)
Year fixed effects	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES
Observations	1,843,118	1,843,065	804,130	86,638	86,636	56,017
Adjusted R-squared	0.844	0.845	0.850	0.828	0.778	0.806

Panel B Daily	(1)	(2)	(3)	(4)	(5)	(6)
	Nonlottery-like			Lottery-like		
	$Volume^{daily}$	$DVolume^{daily}$	$Trades^{daily}$	$Volume^{daily}$	$DVolume^{daily}$	$Trades^{daily}$
WPFC	-0.0864***	-0.120***	-0.0344***	0.130***	0.343***	0.212***
	(0.00160)	(0.00161)	(0.00203)	(0.00606)	(0.00740)	(0.00685)
EPU^{daily}	0.0605***	-0.00357***	0.0373***	-0.00983***	-0.0810***	-0.0125***
	(0.000543)	(0.000544)	(0.000693)	(0.00205)	(0.00251)	(0.00231)
Constant	11.28***	14.50***	6.450***	12.54***	15.10***	7.476***
	(0.00102)	(0.00102)	(0.00130)	(0.00505)	(0.00616)	(0.00573)
Year fixed effects	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES
Observations	7,065,438	7,065,438	2,826,384	280,449	280,449	192,830
Adjusted R-squared	0.835	0.866	0.855	0.749	0.777	0.737

This table reports the results with alternative definition of lottery-like stocks. The results for monthly and daily analysis are presented in Panel A and B, respectively. Following Conrad et al. (2014), a stock is defined as lottery-like if they are characterized by the arithmetic return of over 100% in a 12-month window, otherwise it is categorized as non-lottery-like. In Panel A, *Qindex* is the monthly quality of political signals index constructed by Bialkowski et al (2022). In Panel B, *WPFC* is the daily quality of political signals measure, calculated as the five-day moving average of daily count on former president Donald Trump's false or misleading claims reported in *Washington Post*. Controls for monthly and daily regressions are the same as those reported in previous tables. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample in Panel A spans January 2000 through June 2022, and the sample in Panel B spans January 2017 to January 2021.

Table 12. Google Trends and lottery-like stocks

	(1)	(2)	(3)	(4)
Qindex	3.014***		2.541***	0.881***
	(0.368)		(0.319)	(0.244)
EPU		0.887***	0.534***	0.103
		(0.164)	(0.127)	(0.087)
VIX				0.960*
				(0.536)
L. Attention				0.661***
				(0.088)
Jackpot				0.123**
				(0.056)
Unemployed				-0.234
				(0.168)
Coincident				-0.180
				(0.157)
Adj.R-squared	0.5053	0.2768	0.5930	0.8149
N	222	222	222	205

This table reports the results for the tests of the correlation between political ambiguity and attention based on Internet search to lottery-like stocks. The dependent variable *(Attention)* is the average of the monthly deseasonalized and standardized Internet searching volume (proxied Google Trend) for terms including "lottery stock", "gamble stock" and "penny stock". *Qindex* is the monthly quality of political signals index constructed by Bialkowski et al (2022 *Qindex* is the monthly quality of political signals index constructed by Bialkowski et al (2022). *EPU* is the monthly economic policy uncertainty index developed by BBD. *VIX* is the CBOE VIX value at the end of a given month. *Unemploy* is the change in unemployment rate following Gao and Lin (2014). *Coincident* is the change in U.S. coincident index following Gao and Lin (2014). *Jackpot* is the logarithm of average daily jackpot size calculated as the sum of two multi-state jackpots, namely Mega Millions and Powerball in a given month. Additionally. we also controlled for the lagged dependent (*L.Attention*). Newey-West standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample for columns (1)-(3) spans January 2004 through June 2022, and the sample for columns (4) spans June 2005 through June 2022.

Table 13. Twitter attention and lottery-like stocks

	(1)	(2)	(3)	(4)
Qindex	2.834***		2.880***	1.688***
	(0.286)		(0.266)	(0.330)
EPU		0.375**	-0.055	0.007
		(0.164)	(0.126)	(0.073)
VIX				-0.304
				(0.546)
L. Tweets				0.376***
				(0.073)
Jackpot				0.120
				(0.084)
Unemployed				-0.125
				(0.115)
Coincident				-0.153
				(0.109)
Adj.R-squared	0.4912	0.0438	0.4894	0.5815
N	190	190	190	189

This table reports the results for the tests of the correlation between political ambiguity and attention based on Titter posts to lottery-like stocks. The dependent variable (*Tweets*) is the average of the deseasonalized and standardized count of tweets from U.S. users containing pairs of terms: 'lottery' and 'stock', 'gamble' and 'stock', or 'penny' and 'stock'. *Qindex* is the monthly quality of political signals index constructed by Bialkowski et al (2022 Qindex is the monthly quality of political signals index constructed by Bialkowski et al (2022). EPU is the monthly economic policy uncertainty index developed by BBD. VIX is the CBOE VIX value at the end of a given month. Unemploy is the change in unemployment rate following Gao and Lin (2014). Coincident is the change in U.S. coincident index following Gao and Lin (2014). Jackpot is the logarithm of average daily jackpot size calculated as the sum of two multi-state jackpots, namely Mega Millions and Powerball in a given month. Additionally. we also controlled for the lagged dependent (*L.Tweets*). Newey-West standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample spans September 2006 through June 2022.

Table 13. Lottery-like investing premium

		Port1	Port2	Port3	Port4	Port5	Port6	Port7	Port8	Port9	Port10	High-Low
h=0	Qindex	0.002	0.001	0.001	-0.003	-0.003	-0.004	-0.004	-0.007	0.002	0.028	0.025
		(0.69)	(0.44)	(0.28)	(-0.72)	(-0.65)	(-0.93)	(-0.78)	(-0.92)	(0.14)	(1.20)	(1.04)
h=1	Qindex	0.017	0.022	0.025	0.025	0.027	0.029	0.032	0.032	0.051	0.083**	0.068**
		(1.42)	(1.52)	(1.58)	(1.45)	(1.39)	(1.29)	(1.25)	(1.14)	(1.54)	(2.04)	(1.97)
h=2	Qindex	0.012	0.013	0.015	0.013	0.012	0.013	0.015	0.016	0.037	0.063	0.052
		(1.01)	(0.92)	(0.90)	(0.75)	(0.61)	(0.53)	(0.56)	(0.52)	(0.92)	(1.23)	(1.14)
h=3	Qindex	0.011	0.010	0.009	0.006	0.004	-0.000	-0.004	-0.006	0.002	0.013	0.002
		(0.95)	(0.67)	(0.55)	(0.34)	(0.20)	(-0.01)	(-0.15)	(-0.19)	(0.05)	(0.25)	(0.04)
h=4	Qindex	0.011	0.011	0.014	0.013	0.013	0.012	0.010	0.009	0.020	0.037	0.023
		(0.86)	(0.74)	(0.84)	(0.72)	(0.69)	(0.54)	(0.41)	(0.34)	(0.62)	(0.84)	(0.62)

This table represents the coefficient estimation of the following regressions:

$$R_{j,t+h} = \alpha + \beta_j Qindex_t + \gamma_j MKT_t + \delta_j SMB_t + \varepsilon_j HML_t + \mu_j RMW_t + \rho_j CMA_t + \sigma_j MOM_t + \varepsilon_{t+h}$$

, where the dependent variable is the return of portfolios sorted by LIDX or the return difference between the top- and bottom-decile portfolios at time $t+h$ (*h*=0,1,2,3,4). *Qindex* is the monthly quality of political signals index constructed by Bialkowski et al (2022). In addition, Fama-French six factors (*MKT*, *SMB*, *HML*, *RMW*, *CMA*, *MOM*) are included. Newey-West standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample spans January 2000 through June 2022.

Appendix: List of Variables and Definitions

Variable	Description
LIDX	The lottery-like index developed by Kumar, Page, and Spalt (2016) to gauge a stock's appeal as an object of speculation
Qindex	Monthly measure of the quality of political signals proposed by Białkowski, Dang and Wei (2022). It reflects the frequency of articles that contain terms related to "policy", "signals", and "quality" in ten leading U.S. nationwide newspapers
WPFC	Daily measure of the quality of political signals. It measures the daily number of false or misleading claims made by former President Donald J. Trump from January 2017 to January 2021 reported by the Washington Post Fact Checker
Volume	Logarithm of monthly share trading volume for all CRSP-listed stocks
DVolume	Logarithm of monthly dollar trading volume for all CRSP-listed stocks
Trades	Logarithm of monthly number of individual trades for each stock for NASDAQ-listed stocks
$Volume^{daily}$	Logarithm of daily share trading volume for all CRSP-listed stocks
$DVolume^{daily}$	Logarithm of daily dollar trading volume for all CRSP-listed stocks
$Trades^{daily}$	Logarithm of daily number of individual trades for each stock for NASDAQ-listed stocks
EPU	Monthly economic policy uncertainty index developed by Baker, Bloom, and Davis (2016)
VIX	CBOE VIX value at the end of a given month
Unemploy	The change in unemployment rate following Gao and Lin (2014)
Coincident	The change in U.S. coincident index following Gao and Lin (2014)
Jackpot	The logarithm of average daily jackpot size calculated as the sum of two multi-state jackpots, namely Mega Millions and Powerball (data available since June 2005) in a given month
EPU^{daily}	The five-day moving average of daily economic policy uncertainty index developed by BBD
VIX^{daily}	Daily CBOE VIX value
$Jackpot^{daily}$	Logarithm of daily jackpot size calculated as the sum of two multi-state jackpots, namely Mega Millions and Powerball (data available since June 2005)
Attention	The average of the monthly deseasonalized and standardized Internet searching volume (proxied Google Trend) for terms including "lottery stock", "gamble stock" and "penny stock"
Tweets	The average of the deseasonalized and standardized count of tweets from U.S. users containing pairs of terms: 'lottery' and 'stock', 'gamble' and 'stock', or 'penny' and 'stock'