Trading Under Scrutiny: Social Media Attention and Congressional Trading

Xian Gu
Durham University
xian.gu@durham.ac.uk

Yiming Qian
University of Connecticut
yiming.qian@uconn.edu

Hao Zhao
Durham University
hao.zhao@durham.ac.uk

This version: September 2026

Trading Under Scrutiny:
Social Media Attention and Congressional Trading

Abstract

We examine how targeted public scrutiny on social media relates to congressional trading. Using optical character recognition (OCR), large language models (LLMs), and manual collection, we build a dataset of congressional trades from 2014 to 2022 that covers both electronic and scanned Periodic Transaction Reports (PTRs) for senators and representatives. We find that congressional trades earn little abnormal return on average, but high abnormal returns are concentrated in the right tail. Heightened politician-specific Twitter attention is associated with less trading and fewer high-return trades. These effects are stronger among leaders of powerful committees and around presidential elections, consistent with politicians responding more when reputational costs are higher. Scanned-only and mixed filers also report larger stock trades than electronic-only filers. Our findings highlight the role of public scrutiny in disciplining congressional trading and suggest that it may complement formal regulation.

Keywords: informed trading; social media; congressional trading; STOCK Act
JEL Classification: G12, G14, G18, G41

1 Introduction

Congressional trading continues to attract scrutiny because elected officials may have access to non-public information and face potential conflicts between public responsibilities and private financial interests. The STOCK Act, signed into law in 2012, explicitly prohibits members of Congress from trading on non-public information and requires timely disclosure of securities transactions. Nevertheless, the March 2020 congressional trading scandal, prominently involving Senators Richard Burr, Kelly Loeffler, and others, renewed public concern about potential misconduct.[1] Prior studies provide mixed evidence on whether politicians systematically earn excess returns (e.g., Ziobrowski et al. 2011, Eggers and Hainmueller 2013, Karadas 2018, Belmont et al. 2022, Blonien et al. 2025). Yet limited average outperformance does not eliminate concerns about congressional trading, as occasional unusually successful trades may still attract scrutiny over conflicts of interest and the use of privileged information.

Social media has become an important channel through which concerns about congressional trading are expressed and amplified. While the STOCK Act makes politicians' transactions publicly available, disclosure alone does not ensure that individual trades receive public attention. Twitter discussions can make particular politicians and their trading activity more visible, rapidly disseminate concerns about potential conflicts of interest, and increase the reputational costs of controversial trades. This distinction between disclosure and public scrutiny is important because politicians may respond not simply to what they are required to disclose, but to how visible their trading becomes to voters and the broader public. Against this backdrop, we first examine the performance of congressional trades, asking whether favorable

[1] Recent legislative efforts, including the proposed PELOSI Act (introduced in 2025) and the HONEST Act, seek to further restrict stock trading by lawmakers and their spouses. While the PELOSI Act specifically aims to ban the purchase and sale of individual stocks, the HONEST Act aims to increase penalties for non-compliance with disclosure requirements.

abnormal returns are systematic or concentrated in a subset of unusually successful trades. We then examine whether heightened scrutiny is associated with changes in politicians' trading behavior, and whether these responses are stronger when reputational costs are likely to be higher.

We construct a comprehensive dataset of congressional trades from Periodic Transaction Reports (PTRs) filed by both senators and representatives under the STOCK Act. The filings include both electronic and scanned records. We use a fine-tuned optical character recognition (OCR) pipeline to process structured scanned PTRs and manually collect transactions from unstructured scanned PTRs, yielding more than 115,000 transactions from 2014 to 2022. We further use Google Search and a suite of large language models (LLMs) to identify tickers and asset types. Our final sample includes 112,327 transactions with asset type information and 77,304 stock purchase and sales transactions matched with CRSP identifiers. By recovering transactions from filing formats that are difficult to process electronically, our approach substantially expands coverage relative to existing studies and reduces potential measurement differences arising from filing format.[2]

We combine these trading records with Twitter data measuring politician-specific public scrutiny. For each member of Congress, we identify original tweets that mention the politician by full name together with trading-related keywords, such as "insider trading" and "stock trading." We construct three measures capturing the production, diffusion, and broader engagement of these discussions: original posts; posts including retweets and quote tweets; and total engagement including replies and likes. We validate the underlying tweets to remove false positives and ensure that the measures capture genuine scrutiny of politicians' trading activity.

[2] For example, Belmont et al. (2022) covers 42,324 transactions for the period of 2012 to 2020, Blonien et al. (2025) covers 64,127 transactions for the period of 2012 to mid-May 2025; and Dong and Xu (2025) covers 31,543 transactions (only for the House) for the period of 2014 to 2022.

We also construct corresponding measures of broader congressional-trading attention that do not mention the focal politician and use them to control for general public discussion.

We then aggregate trading and attention measures to the politician-month level, and merge them with politician characteristics including tenure and committee leadership roles. The resulting panel spans from January 2014 to December 2022, and contains 28,206 politician-month observations, covering 78 senators and 302 representatives.

We first document that congressional trades do not earn economically meaningful abnormal returns on average. Mean abnormal returns are close to zero across return horizons, both at the politician-month and transaction levels, and politicians in powerful committee positions do not systematically outperform other members of Congress. Average performance, however, masks substantial dispersion in trade outcomes. At the transaction level, the 80th percentile of abnormal returns rises from 4.91% over one month to 17.66% over twelve months, while the corresponding 95th percentile rises from 12.26% to 41.42%. Thus, unusually favorable outcomes are concentrated in the right tail of the return distribution, motivating our focus on high-return trades rather than average returns.

We then examine whether targeted Twitter scrutiny is associated with subsequent trading behavior. We find that politicians receiving greater politician-specific attention trade less in the following months, both in the number and dollar value of trades. A one-standard-deviation increase in total Twitter engagement mentioning a politician's name and trading keywords (around 12,135 engagements) is associated with an average decrease of 1.61 trades and $161,151 in trade value per month. General discussion of congressional trading that does not name the politician is not significantly related to subsequent trading outcomes. In other words, this negative relationship is concentrated only in attention that names the politician.

We next focus on high-return trades, defined as trades in the top quintile of the full-sample CAR distribution at each return horizon. Using these measures as outcomes in our baseline specification, we find that a one-standard-deviation increase in total Twitter engagement is associated with a 4.77 percentage point decrease in the share of stock trade amount from high-return trades for 1-month CARs, and a 14.22 percentage point lower probability of making any high-return trade during the month.

The results are consistent with reputational concerns playing an important role. If public scrutiny constrains trading by raising reputational costs, the response should be stronger for politicians for whom controversy is more visible and costly. We therefore examine chairs and ranking members of the five most powerful committees in each chamber, following Stewart III (2012). These positions combine substantial policy influence with greater public visibility. We find that committee leaders respond significantly more strongly to Twitter attention: a one-standard-deviation increase in total engagement is associated with an additional decline of 1.88 trades and $180,070 in monthly trade value relative to other politicians. We also find larger reductions in high-return trading among these politicians.

We further examine variation in reputational exposure across chambers and over the electoral cycle. Senators represent statewide constituencies, serve longer terms, and typically receive greater national attention than representatives. Although senators do not respond significantly more strongly on average, the response among powerful committee leaders is significantly greater for senators, both for trading volume and the high-return trade value share. Reputational stakes may also rise around elections. Consistent with this view, the negative relation between Twitter attention and both trading volume and high-return trading is stronger in the months leading up to presidential elections, particularly among powerful committee leaders. Together, these results indicate that politicians respond more strongly to public scrutiny when controversial trading is likely to carry greater reputational costs.

Beyond politicians' responses to public scrutiny, the visibility of congressional trading also depends on how transactions are disclosed. Electronic PTRs are readily machine-readable, whereas scanned reports are more difficult for outside observers to process at scale. Although electronic filing is more common, 38% of politicians use scanned or mixed PTRs. We find that scanned-only and mixed filers report larger stock trades on average than electronic-only filers. Among politicians who use both formats, transactions disclosed through scanned filings are also substantially larger than those disclosed electronically. These differences in trading scale, however, do not extend systematically to trading performance: neither average abnormal returns nor the incidence of high-return trades shows a robust advantage for scanned filings. Thus, less readily processed disclosures contain economically larger transactions, even though they do not appear to contain systematically more profitable trades.

This paper makes several key contributions to the literature. First, we contribute to the literature on congressional trading by constructing a substantially broader dataset that covers both electronic and scanned PTRs filed by senators and representatives. Using OCR, LLMs, and manual collection, we recover more than 115,000 transactions from 2014 to 2022, nearly doubling the number of transactions available from electronically retrievable records alone and providing broader coverage than several recent studies (e.g., Ziobrowski et al. 2011, Eggers and Hainmueller 2013, Belmont et al. 2022, Dong and Xu 2025). This expanded coverage allows us to revisit the mixed evidence on congressional trading performance.

Early studies document substantial abnormal returns among members of Congress (Ziobrowski et al. 2004, 2011), whereas more recent work finds mediocre overall performance (Eggers and Hainmueller 2013), a sharp decline in abnormal returns after the STOCK Act (Karadas 2019), or no significant post-2012 outperformance (Belmont et al. 2022). Blonien et al. (2025) further show that abnormal profits occur only occasionally and are concentrated in particular periods. Consistent with the more recent evidence, we find little abnormal return on average. However, we show that economically large abnormal returns remain concentrated in the right tail of the return distribution. We therefore shift attention from average performance to unusually successful trades and show that targeted public scrutiny is associated with a significant reduction in these high-return trades.

Second, we contribute to the literature on social media and reputational discipline by showing that targeted public scrutiny is associated with meaningful changes in politicians' financial behavior. Prior studies show that social media can improve information dissemination, shape investor beliefs, and influence corporate decisions (e.g., Blankespoor et al. 2014; Chen et al. 2014; Ang et al. 2021; Cookson, Lu, et al. 2024; Cookson, Niessner, et al. 2024). We extend this literature to the political setting by documenting that politicians trade less and make fewer high-return trades following greater Twitter attention directed specifically at their trading activity. Moreover, these responses are stronger among leaders of powerful committees and around presidential elections, when controversial trading is likely to carry greater reputational costs. These findings highlight how targeted social-media scrutiny can generate reputational pressure and shape the behavior of elected officials.

Third, we contribute to the literature on disclosure and transparency by showing that the accessibility of mandated disclosures is systematically related to the underlying trading activity. Existing evidence suggests that informational concerns surrounding congressional trading can persist despite formal restrictions (Hanousek et al. 2023), while congressional trade disclosures themselves convey information relevant to investors and future policy outcomes (Dong and Xu 2025). We show that electronic and scanned PTRs differ not only in how easily they can be processed, but also in the size of the transactions they contain. Scanned-only and mixed filers report larger stock trades than electronic-only filers, and, among politicians who use both formats, transactions disclosed through scanned filings are substantially larger than those disclosed electronically. These differences in trading scale are not accompanied by consistent differences in average abnormal returns or high-return trading. More broadly, the findings suggest that the economic content of mandatory disclosures may vary with how readily those disclosures can be accessed and monitored.

The remainder of the paper proceeds as follows. Section 2 describes the congressional trading data and the distribution of abnormal returns. Section 3 describes the measures of public scrutiny and the final sample. Section 4 presents the empirical strategy. Section 5 presents our main empirical findings. Section 6 concludes.

2 Congressional trading: Data and stylized facts

2.1 Congressional transaction records

The congressional transaction records come from Periodic Transaction Reports (PTRs) filed by members of Congress under the STOCK Act. We retrieve PTRs from the official Senate and House disclosure portals to cover transactions from January 2014 through December 2022.[3,4] The PTR filings have three formats. First, electronic PTRs can be parsed from HTML or machine-readable PDFs. Second, structured scanned PTRs preserve the standard form but are stored as images. We recover these records with a fine-tuned optical character recognition (OCR) pipeline. Third, unstructured scanned PTRs contain handwritten entries, free-form text, or nonstandard grids that cannot be reliably processed through automated methods. We therefore employ a dedicated team of research assistants to manually collect these records.

---

[3] Senator filings are from https://efdsearch.senate.gov/, and representative filings are from https://disclosures-clerk.house.gov/.

[4] The STOCK Act, enacted in April 2012 during the 112th Congress, created for the first time a requirement that members of Congress disclose securities transactions at the transaction level through PTRs. Under the STOCK Act, members are legally required to disclose qualifying transactions within 30 days of receiving notice of the transaction and no later than 45 days after the trade execution date. In practice, compliance is uneven. Many filings are submitted after the statutory deadline, and the additional processing and publication steps in the PTR system often delay public availability further. To address these issues and ensure consistent coverage, we first collect all PTRs filed between 2014 and 2023, then restrict the sample to transactions with trading dates on or before December 31, 2022.

Panel A of Table 1 reports the sample construction. Before applying common parsing procedures, the three sources contain 62,614 electronic, 7,530 structured scanned, and 62,233 unstructured scanned transaction records. We exclude filings by former members, outdated versions, and records missing trade type, transaction date, or transaction amount. The resulting source samples contain 51,559 electronic records (*Sample A*), 4,340 OCR-recovered records (*Sample B*), and 59,513 manually collected records (*Sample C*). Pooling these parsed sources yields 115,412 transaction records (*Sample D*), including 12,692 Senate and 102,720 House records.

[Table 1]

Asset types are not reported consistently across PTRs. Some filings identify the asset class within the description, but many omit the disclosure or use unstructured descriptions. Missing and unstructured asset descriptions occur most often in scanned filings but also appear in electronic records. Therefore, a consistent classification procedure is necessary to measure trading across asset classes and to identify publicly traded stocks.

Table 1 summarizes the classification procedure. First, we retain asset types reported directly in the PTRs. For example, an electronic filing may report Apple stocks as "(AAPL) [ST]." Directly reported asset types identify 36,544 records, equal to 32% of *Sample D* and 71% of *Sample A*.

Second, for records without an explicit asset type, we use DeepSeek-V3 to classify the raw asset description.[5] In the first round, the model receives each asset description and

[5] According to the DeepSeek (2025) technical report, as of February 2025, DeepSeek-V3 performs well across a wide set of evaluations relative to leading models such as GPT-4o, LLaMA-3.1, Claude-3.5, and Qwen-2.5. On tests that measure reasoning across multiple subject areas, on tasks that evaluate contextual inference and common-sense understanding, and on benchmarks that combine coding with logical reasoning, DeepSeek-V3 consistently ranks at or near the top. While these evaluations are not built around financial data, they demonstrate an ability to recover structured meaning from irregular or incomplete language, which is essential for parsing PTR entries. Each candidate ticker and asset type returned by the language model is validated against the original asset description in a second pass, and candidates that are inconsistent or uncertain are rejected rather than retained. Internet Appendix B.4 reports the prompts and Internet Appendix B.5 reports the field-level accuracy audit.

proposes a ticker and asset class, which we retain only when the model reports high confidence. To reduce AI hallucinations, in the second round, the model receives the original description again together with the proposed ticker and asset class, and evaluates whether the classification is consistent with the disclosed information. We discard classifications that fail this verification. We also use a separate procedure to standardize transaction dates, including dates with missing years or inconsistent formats. This step raises the number of records with an identified asset type to 98,205, or 85% of *Sample D*.

Third, for records that remain unclassified, we map available tickers to CRSP to obtain the corresponding CRSP classification. We prioritize tickers reported in the PTR, followed by tickers recovered through targeted web searches and tickers identified by the LLM pipeline. This step raises the number of records with an identified asset type to 112,327, or 97% of Sample D. Internet Appendix B.1 explains the collection and validation procedures.

2.2 Sample construction and coverage

We then retain only transactions with successfully identified asset types (*Sample E*) for the trade volume measure. *Sample F* further excludes observations without matched CRSP tickers, yielding 77,861 transactions restricted to publicly traded equities. *Sample G* narrows the sample to stock purchase and sale transactions, resulting in 77,304 transactions.

Panel B of Table 1 reports the distribution of asset types separately for the CRSP-matched transactions (labeled as "*Public stock plus*"; *Sample F*) and the remaining non-CRSP assets (labeled as "*Other investment*"; *Sample D* minus *F*). Trading in the CRSP-matched sample is concentrated in common stocks, which account for 96% of records, with funds (e.g., ETFs and closed-end mutual funds) at 3% and ownership interests at 1%. The non-CRSP sample is more diversified: unidentified stocks still represent the largest category at 56%, and a sizable fraction consists of government and agency debt (15%), corporate bonds and notes

(8%), and options (5%), with the remaining categories individually small and other/missing assets accounting for 9%.[6]

PTRs disclose transaction values in ranges rather than exact amounts. The eleven ranges begin with $1,001–$15,000 and extend to values above $50 million. We assign each record the midpoint of its disclosed range. For example, the $15,001 through $50,000 range is assigned a value of $32,500. The top range is open-ended, so we assign those records the lower bound of $50 million. These constructed values are then used both to calculate total trade amounts and as weights in the calculation of value-weighted abnormal returns.

Overall, the dataset contains 115,412 parsed transaction records (12,692 Senate and 102,720 House), of which 112,327 carry an identified asset type (12,565 Senate and 99,762 House) and 77,304 are CRSP-matched equity purchases and sales (9,777 Senate and 67,527 House). Among these CRSP-matched equities, 37,174 come from electronic filings, 2,598 from OCR recovery, and 37,532 from hand collection. For comparison with the literature using the same sample period, Moe and Ma (2024) report 7,421 Senate stock trades and 20,985 House stock trades for 2014 to 2022 using data from a commercial provider; our total CRSP-matched equity sample is about 172% larger, and the subset drawn from electronic filings alone is roughly 31% larger. Dong and Xu (2025) report 31,543 House transactions over 2014 to 2022; our House sample over the same period is about 114% larger. Other studies with overlapping but not identical periods include Belmont et al. (2022), who report 10,995 Senate and 31,329 House transactions between 2012 and 2020; Hanousek et al. (2021), who analyze 7,474 Senate stock trades from 2012 to 2019 using only electronic PTRs; and Blonien et al. (2025), who extend Belmont et al. (2022) through mid-May 2025 and report 64,127 records. Table 2

[6] Note for "*Other & Missing*" asset type: the "*Other*" category includes politicians' self-reported asset classification (127 transaction records). "*Missing*" indicates that the asset type is not reported in the PTR filing and cannot be recovered either (3,085 records). *Sample E* therefore excludes only these missing-asset-type records from *Sample D* (i.e., 112,327 = 115,412 - 3,085).

organizes the full comparisons with prior studies by sample period, chamber, asset scope, and filing source.

[Table 2]

2.3 Measuring trading performance

For each stock trade in *Sample G*, we first construct cumulative abnormal returns (CARs) based on the Fama-French five-factor model (Fama and French, 2015) with the momentum factor of Carhart (1997), over horizons of 1, 2, 3, 6, and 12 months, corresponding to 21, 42, 63, 126, and 252 trading days, respectively. We obtain the daily U.S. factor returns and risk-free rate from Kenneth R. French's Data Library. The factors include the market excess return, size, value, profitability, investment, and momentum. For each security, we estimate factor loadings using up to 250 trading days ending on day *t-1* and require at least 100 observations. Daily abnormal return equals the stock's realized excess return minus the return implied by the estimated factor loadings. The trade-level CAR is the simple sum of daily abnormal returns over the horizon. We multiply the CAR by -1 for sales at the transaction level so that positive values indicate favorable outcomes for both purchases and sales, and then aggregate all trades to politician-month value-weighted CARs using trade amounts as weights.

In addition, a mean CAR computed across a politician's entire trades might not reveal whether a subset of those trades is unusually profitable, because favorable and unfavorable outcomes offset one another. Thus, we further construct outcomes that isolate the right tail of the return distribution in two steps. First, at the transaction level, we define a trade as "high-return" if its CAR exceeds the horizon-specific 80th percentile of the full-sample transaction-level distribution. The CAR cutoffs are 4.91%, 6.96%, 8.62%, 12.41%, and 17.66% for the 1-, 2-, 3-, 6-, and 12-month horizons, respectively. The corresponding 90th-percentile cutoffs are 8.36%, 11.85%, 14.38%, 20.34%, and 28.95%, and are used to define alternative measures for robustness tests.

Then at the politician-month level, we construct *%($high-return)*, which equals the dollar value of high-return stock trades divided by the dollar value of stock trades with a usable CAR at that horizon, measured from 0 to 100. The measure equals zero in months without observed high-return activity and therefore reflects both the extensive and intensive margins of high-return trading activity. We also construct *1{high-return}*, which equals one if the politician has at least one stock trade classified as high-return and zero otherwise. This outcome isolates the extensive margin of high-return trading activity.

2.4 Average abnormal returns and the right tail

Table 3 reports the distribution of abnormal returns at the politician-month level. Panel A shows that the average value-weighted CARs are slightly negative at every return horizon, from -0.23% over one month to -0.84% over twelve months. The medians are also nonpositive and near zero. Furthermore, access to more powerful positions does not alter this average pattern. Panel B compares months in which a politician serves as chair or ranking member of a top-five committee with all other politician-months. The top-five leaders' mean value-weighted CARs are 0.22% at one month and 0.63% at twelve months, compared with -0.26% and -0.94% in other politician-months, with none of the mean differences statistically significant. Powerful positions may provide greater access to information and influence, but the average returns do not indicate that politicians systematically convert that access into superior trading performance.

[Table 3]

Table 4 reports the same distribution at the transaction level, before trades are aggregated to the politician-month. Panel A pools all public equity transactions with a valid CAR at the five return horizons. Again, mean transaction-level CARs are close to zero at every horizon, from -0.06% at one month to -0.04% at twelve months, and the medians are close to zero as well. Despite the lack of average outperformance, abnormal returns exhibit substantial dispersion. The 80th percentile rises from 4.91% at the 1-month horizon to 17.66% at 12 months, while the 95th percentile rises from 12.26% to 41.42%. Thus, returns in the right tail are substantially larger than the average. The 80th and 90th percentiles reported in Panel A define the high-return outcomes' cutoffs used in Section 2.3.

Panel B repeats the statistics for transactions in months in which the politician was chair or ranking member of a top-five committee. Mean CARs in Panel B remain close to zero, ranging from 0.28% to 0.60%, and are only slightly higher than the corresponding means in Panel A, while the 80th, 90th, and 95th percentiles exceed those of the full politicians' distribution by 0.88 to 4.41 percentage points. Overall, powerful positions are associated with very small differences in transaction-level returns, though these differences are larger among the most profitable trades than at the center of the distribution. Unusually profitable trades occur in both groups but remain concentrated in the right tail, motivating our focus on these trades rather than average returns.

[Table 4]

Nancy Pelosi provides an illustrative example of why right-tail performance can differ from average performance. Internet Appendix Table C.1 shows that her value-weighted mean CAR across all trades is 1.23% at one month but -5.37% at twelve months, with her corresponding average-performance ranking falling from the 75.5th to the 22.5th percentile. Yet at the 12-month horizon, the mean CAR of her top 10% most profitable stock trades is 56.31%, placing her at the 79.4th percentile among politicians, while her best trade earns a 66.24% 12-month CAR. By contrast, her top 10% ranking rises with the horizon, from the 46.4th percentile at three months to the 74.8th and 79.4th percentiles at six and twelve months, even as her average-performance ranking continues to fall, indicating that her right-tail performance is concentrated at longer horizons. Overall, this example illustrates how unusually strong performance can be concentrated in a small number of trades even when average performance is unremarkable.

Internet Appendix Table C.2 shows that the absence of average outperformance is robust to alternative definitions of political power. Table C.3 further shows that the regression coefficient on *Top5_leader* is statistically insignificant at every CAR horizon, both in specifications testing overall variation and within-politician variation in leadership status. Overall, these patterns motivate the paper's empirical design: average CARs provide little evidence of broad outperformance, while potentially informative variation is concentrated in the right tail.

3 Measuring public scrutiny

3.1 Twitter attention measures

We use Twitter activity to measure public scrutiny directed at each politician. For each month, we identify original tweets that contain a politician's full name and trading-related terms such as "insider trading," "financial investment," and "stock trading". Table A.2 lists all search terms. We construct three measures: *Attention_post* counts original tweets. *Attention_share* adds retweets and quote tweets of those posts. *Attention_total* further adds replies and likes. Thus, the measures capture, in sequence, the production, diffusion, and broader engagement of politician-specific scrutiny.

To ensure that the measure captures genuine public scrutiny, we manually review and validate the tweet sample. Tweets that are irrelevant, unrelated to trading, or framed positively are excluded. In ambiguous cases where sentiment shifts over time, we further review and retain only the portion of discussion that follows the onset of trading-related scrutiny. This procedure removes false matches from common names, advocacy messages, and unrelated investment references, ensuring that the final set reflects negative attention to individual trading activity.

To capture broader public scrutiny of congressional trading beyond individual politicians, we construct a parallel set of "*other*" attention variables. These variables are designed to reflect general Twitter discussion on congressional trading that does not directly name the focal politician. Specifically, we include two types of tweets: (1) original tweets that mention congressional terms such as "senator" or "congress" alongside trading-related keywords (see full list in Table A.2), excluding those that reference the focal politician by name; and (2) original tweets that mention other politicians' full names with trading-related keywords, again excluding the focal politician. We exclude the discussion related to the focal politician from these measures to avoid mechanical correlation. The corresponding other share and other activity measures are constructed analogously by adding retweets, quote tweets, replies, and likes. All three variables are included as controls in the regression analysis to account for broader public attention and peer-related pressure that are not directed at the focal politician.

3.2 Political characteristics and final sample

We obtain committee assignments for each Congress from OpenSecrets and congressional tenure from GovTrack.us. To measure institutional power, we construct an indicator variable, *Top5_leader*, which equals one when a politician is the chair or ranking member of one of the five highest-ranked committees in the relevant chamber and Congress. The ranking follows Stewart III (2012), which estimates committee values from preferences in observed voluntary transfers. The five Senate committees are Finance, Appropriations, Rules & Administration, Armed Services, and Commerce. The five House committees are Ways & Means, Energy & Commerce, Appropriations, Rules, and Foreign Affairs.

We aggregate both congressional transaction and Twitter attention data at the politician-month level. First, we construct the number and total disclosed dollar value of transactions using *Sample D*, which includes all parsed transaction records. Second, we construct analogous trade volume measures for only public equity transactions using *Sample G*. The baseline attention measures sum activity during the preceding three months to allow for response lags and reduce simultaneity concerns.

The panel includes every member of Congress who reports at least one transaction in any asset class in PTRs during the sample period. The final sample contains 28,206 politician-month observations from January 2014 through December 2022 and covers 78 senators and 302 representatives.

3.3 Summary statistics

Table 5 reports summary statistics for the politician-month panel dataset. Members of Congress engage in an average of 3.6 trades per month, with a mean monthly transaction value of about $186,000. Stock trades account for a substantial portion of this activity, averaging 2.5 transactions and roughly $93,000 per month. The distribution is highly skewed, with maximum trade values exceeding $125 million. Social media attention directed at individual politicians remains limited in absolute terms. To align with the main analysis, for each politician-month the table reports the summary of total attention accumulated over the prior three months. Under this definition, the average politician receives 6.2 original tweets that mention them in the context of insider trading, rising to 753 total interactions once quotes, retweets, replies, and likes are included. In contrast, congressional trading in general attracts far greater public discussion, with 1,099 original tweets and more than 114,000 total engagements over the same window. Across horizons, 9.14% to 9.43% of politician-months contain at least one high-return trade, and the average share of stock trade amount from high-return trades ranges from 3.32% to 3.46%. Top-five committee leaders account for 4.69% of politician-month observations.

[Table 5]

4 Empirical strategy

We begin by examining whether higher politician-specific Twitter attention is followed by a reduction in congressional trading. Trading volume provides the most direct measure of whether politicians trade less when public scrutiny increases. We then examine whether greater attention is also followed by fewer trades with high ex post abnormal returns. This second analysis matters because politicians may reduce their overall trading without changing the portion of trades that may contain private information. As discussed earlier, CARs are not well suited to this test, because politicians do not earn positive abnormal returns on average. In other words, there is no reason to expect heightened attention to reduce returns across all trades when only a subset may be informed.

To examine the relationship between politician-specific attention and trading volume, we estimate the following regression using the politician-month panel:

$$\begin{aligned} \text{Trading}_{i,t} = \alpha_0 \quad & +\beta_1 \text{ Attention}_{i,t-3:t-1} + \beta_2 \text{ Attention}^{\text{other}}_{i,t-3:t-1} \\ & +\gamma' \text{ (Politician control)}_{i,\tau} + \theta_i + \lambda_\tau + \varepsilon_{i,t}. \end{aligned} \tag{1}$$

The dependent variable is the natural logarithm of the number or dollar value of trades by politician i in year-month t. The main explanatory variables are *Ln(Attention_post)*, *Ln(Attention_share)*, and *Ln(Attention_total)*, capturing politician-specific Twitter attention aggregated over the prior three months. The model also includes the corresponding general attention measures that account for background pressure not directed at the focal politician. Politician control includes *Ln(Tenure)* to capture variation in seniority and changes in chamber roles across years, which may influence both trading activity and exposure to public attention. Politician fixed effects (θ_i) control for time-invariant differences across individuals, and year fixed (λ_τ) account for macroeconomic and institutional changes over time. Standard errors are clustered by politician. The coefficient β_1 captures whether politicians respond to attention specifically targeting their own trading behavior, while β_2 controls for other public attention on congressional trading.

Next, we use the specification in equation (1) to examine high-return trades. For each return horizon, we estimate the model separately with either *%($high-return)* or *1{high-return}* as the dependent variable. The first measure is the share of stock-trade dollars from high-return trades. Because this share equals zero in months without observed high-return activity, it reflects both whether a high-return trade occurs and the share of stock-trade dollars attributable to such trades. The second measure indicates whether a politician makes at least one high-return trade during the month, therefore captures the decision to engage in any such trading.

We then examine heterogeneity in the response to scrutiny across settings in which reputational costs are plausibly higher. We first interact *Attention* with *Top5_leader* to test whether powerful committee leaders respond more strongly to public scrutiny. We further examine whether the response differs between senators and representatives and over the presidential election cycle, when the reputational stakes of controversial trading may vary across politicians and over time.

5 Empirical results and discussions

5.1 Politician-specific Twitter attention and trading volume

Table 6 examines how politician-specific Twitter attention relates to subsequent congressional trading volume. Panel A of Table 6 reports estimates of equation (1) for trading in all asset types at the politician-month level. Across specifications, the coefficient on *Ln(Attention_post)* is negative and significant at the 10% level, while the two broader measures that capture diffusion and total engagement are negative and significant at the 5% level. For instance, in columns (3) and (6), a one-standard-deviation increase in *Attention_total* (12,135 engagements) is associated with an average decrease of 1.61 trades per month and an average decrease of $161,151 in monthly trade value, respectively.[7]

[Table 6]

In contrast, general attention to congressional trading, measured by tweets that mention congressional and trading-related terms without naming the focal politician, is positively but statistically insignificantly associated with trading volume. This divergence highlights that reductions in activity are driven by targeted scrutiny of individual members rather than by general attention.

Panel B reports negative coefficients on politician-specific attention for both stock trade number and amount, with slightly smaller magnitudes than in Panel A. For instance, a one-standard-deviation increase in total Twitter engagements is associated with an average decrease of 1.12 stock trades per month in column (3), and an average decrease of $77,704 in monthly stock trade value in column (6). Overall, higher politician-specific attention is followed by lower overall trading and lower stock trading, highlighting a personal response to targeted scrutiny rather than a reaction to general discussion on congressional trading.

5.2 Attention and high-return trades

A reduction in trading volume does not necessarily imply that politicians avoid trades that subsequently earn unusually high returns. As Section 2 shows, politicians do not earn positive abnormal returns on average: mean CARs do not isolate the part of the return distribution that may contain private information. Therefore, we examine whether higher attention is followed by fewer high-return trades, focusing only on the right tail of the CAR

---

[7] Calculation of economic significance: the standard deviation of *Attention_total* is 12,135 (denoted as s_A). For each politician-month i, set $d_i = \ln(1 + A_i + s_A) - \ln(1 + A_i)$. For our log-log baseline models, $\Delta Y_i = (1 + Y_i)[\exp(\beta d_i) - 1]$; for the level-log models, $\Delta Y_i = \beta d_i$.

distribution. Table 7 reports the relationship between politician-specific Twitter attention and the two high-return outcomes across the five CAR horizons.

[Table 7]

Panel A reports results for *%($high-return)*, the share of stock-trade dollars from high-return trades. The coefficient on the total Twitter engagement measure is significantly negative at every horizon, ranges from -0.445 to -0.535. For instance, in column (1), a one-standard-deviation increase in total Twitter engagements is associated with a 4.77 percentage point decrease in the share of high-return trade value. Because the share equals zero in months without an observed high-return trade, this reduction reflects both whether a high-return trade occurs (extensive margins) and the share of high-return public equity trade amount out of total trades (intensive margins).

Panel B reports results for *1{high-return}*, which equals one when a politician makes at least one high-return trade during the month, focusing only on the extensive margins of whether any such trade occurs. The coefficient on total Twitter engagements is significantly negative at every horizon and ranges from -0.0138 to -0.0159. In column (1), a one-standard-deviation increase in total engagements is associated with a 14.22 percentage point lower probability of any high-return trade.

We do not interpret high-return trades as direct evidence of informed trading. Whether a particular trade reflects private information depends on the information available to the politician at the time and is difficult to establish outside specific cases. Instead, our measures provide a transparent way to examine whether high-abnormal-return trades become less common following greater public scrutiny.

5.3 Reputational exposure and the response to scrutiny

5.3.1 Powerful committee leaders

One interpretation of the baseline results is reputational concerns, which predict a larger decline among politicians whose positions make controversy over personal trading especially costly. To test this interpretation, we focus on top-five committee leaders, defined as chairs and ranking members of the five highest-ranked committees in each chamber under Stewart III (2012). Stewart's ranking infers the value of committee assignments from members' voluntary transfers across committees. For example, Karadas (2018) uses the same ranking to measure political power in the congressional trading setting. Serving as chair or ranking member of these highly valued committees brings greater public visibility and policy influence, potentially increasing the reputational costs of controversial personal trading.

Table 8 shows that top-five committee leaders reduce their trading more than other politicians when attention rises. The larger decline for top-five committee leaders is significant at the 1% level for all four trade-volume outcomes. In columns (1) and (2), a one-standard-deviation increase in total Twitter engagement measure is associated with additional average decreases of 1.88 trades and $180,070 in trade value per month for top-five committee leaders relative to other politicians. Columns (3) and (4) imply additional average decreases of 1.42 stock trades and $89,539 in stock trade value per month.

[Table 8]

The main effect of committee power alone is positive and non-significant. Since the model includes politician fixed effects, this estimate implies that, for a given politician, moving into the top committee-power chairman or ranking member positions does not by itself lead to a detectable change in trading activity in periods without attention. The stronger response appears only when reputational pressure is activated through public scrutiny.

Table 3 and Internet Appendix Tables C.2 and C.3 show that powerful committee positions are not associated with reliably higher average CARs. Accordingly, the analysis does not assume that committee leaders generally trade at an informational advantage. It asks instead whether high-return trades respond more strongly to scrutiny among politicians for whom unusually profitable trading may create greater reputational costs.

Table 9 shows that high-return trading declines further among top-five committee leaders when attention rises. Panel A reports a significant negative standalone attention effect at every horizon, together with an additional decline for top-five committee leaders that is significant at the 1% level. At the 1-month horizon, a one-standard-deviation increase in total Twitter engagement is associated with an additional 9.54 percentage point decrease in the high-return dollar share for top-five committee leaders relative to other politicians. Panel B shows the same pattern for the probability of any high-return trade. At the 1-month horizon, the additional decrease for top-five committee leaders is 20.46 percentage points.

[Table 9]

5.3.2 Senators and the presidential election cycle

If the response to attention is reputational, that response should be stronger where reputation is more valuable. Senators serve statewide constituencies, hold six-year terms, and receive more national coverage than representatives, so a controversial trade plausibly costs a senator more. Internet Appendix Table C.4 compares the attention-trading relationship between senators and representatives. The interaction between attention and the Senate indicator is not significant for either stock trading outcome or for the high-return trade value share. However, once top-five committee leadership is considered, the triple interaction among attention, Senate membership, and committee leadership is negative and significant at the 1% level for both trading outcomes. The findings suggest that the stronger response among powerful politicians is concentrated among senators.

Reputational stakes also vary over the electoral cycle. Internet Appendix Table C.5 interacts attention with an indicator for the three months up to a presidential election month, using months 4 through 24 before the election as the comparison period. Within the pre-election window, attention is more negatively related to both stock trading volume and high-return trade value share. Furthermore, the triple interaction among attention, the election window, and committee leadership is negative and significant for both trading outcomes. Similar to the chamber test results, the response to attention is strongest when reputational stakes are highest among powerful committee leaders.

5.4 Filing format, trading scale, and trading performance

We next examine whether trading activity differs across PTR filing formats. Electronic PTRs are machine-readable and readily processed at scale, whereas scanned filings require substantially more effort to collect and process. Table 10 compares filing patterns, trading scale, average abnormal returns, and high-return trades across electronic and scanned formats.

[Table 10]

Panel A shows that 236 politicians (62%) file exclusively electronically, 75 (20%) file exclusively scanned reports, and 69 (18%) use both formats. Electronic filing is particularly common among senators, 87% of whom file exclusively electronically, while scanned and mixed formats are concentrated among representatives. Partisan differences are small: 64% of Republicans and 59% of Democrats file only electronically. Among the 26 politicians who are ever a top-five committee leader, 14 (54%) file only electronically, 7 (27%) file only scanned reports, and 5 (19%) use both. The scanned-only percentage among these leaders exceeds the percentage among senators and is close to that among representatives.

Panel B presents univariate comparisons of trade size, FF5 plus momentum CARs, and high-return trades across three groups of politicians: (i) electronic-only filers, (ii) scanned-only filers, and (iii) mixed filers, at both the transaction and politician levels. At the transaction level, electronic-only and scanned-only filers have almost identical average trade sizes, differing by only $26, whereas mixed filers report trades that are about $53,000 larger on average. Median trade size is $8,000 in all three groups. For stock trades, however, mean transaction size is significantly larger for both scanned-only and mixed filers than for electronic-only filers. The differences are more pronounced at the politician level and are concentrated in stock trading: scanned-only and mixed filers report average stock trading amounts that are approximately $61,000 and $138,000 higher, respectively, than those of electronic-only filers.

Trading performance shows a different pattern. At the transaction level, equal-weighted CARs of electronic-only filers exceed those of mixed filers at the 1-, 6-, and 12-month horizons reported in Panel B, with the electronic-only minus mixed-filer difference increasing from 0.34 percentage points at one month to 1.58 percentage points at twelve months. Once trades are aggregated to the politician level and weighted by transaction amount, however, the CAR differences are statistically insignificant at all three horizons, providing no evidence of systematically higher performance for electronic-only filers when larger transactions receive greater weight. The high-return-trade comparisons are similarly limited. At the 1-month horizon, the percentage of high-return trades is 0.75 percentage points higher for electronic-only than scanned-only filers and 1.12 percentage points higher than for mixed filers, but the corresponding differences at the 6- and 12-month horizons are insignificant. At the politician level, neither the percentage of trades nor the percentage of trade dollars in the right tail differs consistently across filing formats. Internet Appendix Table C.6 reports the full 1-, 2-, 3-, 6-, and 12-month results and shows similarly mixed patterns across filing formats.

Panel C addresses the possibility that the differences in Panel B reflect persistent differences across politicians by focusing on the 23 politicians who use both electronic and scanned filings, with scanned PTRs appearing after prior electronic use. For politicians who begin with electronic filings and later submit scanned PTRs, we compare transactions across both formats over the full sample period. For those who begin with scanned filings, switch to electronic, and subsequently return to scanned submissions, we restrict the comparison to the period following the return to scanned filing. We report results at both the transaction level and after aggregating outcomes within politician.

The differences in trading scale are substantially larger in this within-politician sample than in the cross-politician comparisons in Panel B. At the transaction level, trades reported through scanned filings are approximately $1.0 million larger on average for all assets and $1.3 million larger for stocks than the same politicians' electronically reported trades. Median differences are smaller but remain economically meaningful, at $24,500 for both measures. After aggregating transactions within politician, scanned filings continue to be associated with substantially larger trading volumes, although the estimates are less statistically precise.

Trading performance, by contrast, does not exhibit a similarly consistent difference across filing formats. At the transaction level, scanned records have CARs that are 1.04 to 2.85 percentage points higher than the same politicians' electronic records across the reported horizons, with median differences of 2.15 and 4.58 percentage points at six and twelve months, respectively, both statistically significant. After aggregation to the politician level, however, the signs of the value-weighted CAR differences vary across horizons and none is statistically significant. The high-return measures show a similarly mixed pattern. Transaction-level differences are insignificant, while at the politician level electronic records exceed scanned records at the one-month horizon by 11.82 percentage points in the share of high-return trades and 13.53 percentage points in the share of trade dollars accounted for by high-return trades. These differences are no longer significant at six or twelve months. Taken together, the within-politician evidence reinforces the finding that filing format is strongly related to trading scale, but not to a stable difference in trading performance across horizons or levels of aggregation.

5.5 Alternative tests and robustness

We first check the robustness of the main definition of high-return trades, using the top 10% of the full-sample CAR distribution instead of the baseline top 20% cutoff. The negative relation between attention and high-return trading remains robust under this more stringent definition. Internet Appendix Table C.7 further reports the filing-format results using the top 10% definition under the same setting as Table 10. In Panel A, electronic-only filers continue to have a higher transaction-level frequency of high-return trades than scanned-only filers across all five CAR horizons, while the other differences among the three groups are small and inconsistent. In Panel B, the politician-level differences between electronic and scanned trades within the filing switchers are positive and weakly significant at the 1-month horizon, but the differences are insignificant and have inconsistent signs at the other horizons.

Next, we examine whether the finding of mediocre average returns depends on how political power is defined. Internet Appendix Table C.2 repeats the univariate tests under four alternative definitions of political power: top-three committee leadership, membership on a top-three committee, membership on a top-five committee, and core congressional party leadership as defined in Wei and Zhou (2025). The mean CAR differences remain statistically insignificant at every horizon, consistent with the baseline conclusion that politically powerful positions are not associated with reliably higher average abnormal returns.

Finally, we examine whether politician-specific Twitter attention captures broader public interest in the politician rather than scrutiny of trading. Internet Appendix Table C.8 controls for Google Trends search interest and Wikipedia pageviews for each politician over the preceding three months. The Twitter attention estimates change little and remain negative and significant for all four trading outcomes, suggesting that the baseline results are not explained by broader public interest targeting the politician.

6 Conclusion

We examine congressional trading and how it relates to targeted public scrutiny on social media. Using a suite of fine-tuned optical character recognition (OCR) tools and large language models (LLMs), together with manual collection, we construct a comprehensive dataset of congressional trades from 2014 to 2022 that recovers both electronic and scanned Periodic Transaction Reports (PTRs) for senators and representatives.

We first document that congressional trades earn little abnormal return on average, while unusually high abnormal returns remain concentrated in the right tail of the return distribution. We then show that politicians trade less following heightened politician-specific Twitter attention and are also less likely to make these high-return trades. These responses are stronger among leaders of powerful committees and around presidential elections, when controversial trading is likely to carry greater reputational costs. The patterns suggest that politicians respond more strongly to public scrutiny when their trading activity is more reputationally consequential.

We also show that the accessibility of mandated disclosures is systematically related to the scale of reported trading. Scanned-only and mixed filers report larger stock trades than electronic-only filers, and politicians who use both formats disclose substantially larger transactions through scanned filings. These differences in trading scale, however, are not accompanied by consistent differences in trading performance: neither average abnormal returns nor the incidence of high-return trades shows a stable pattern across filing formats. These findings highlight that less readily processed disclosures contain economically larger transactions, even though they do not appear to contain systematically more profitable trades.

Overall, our findings point to an important role for public visibility in congressional trading. Formal disclosure makes politicians' transactions publicly available, but social media can amplify attention to those transactions and increase the reputational costs associated with controversial trading. Our evidence suggests that such public scrutiny can provide an additional source of discipline and may reinforce formal disclosure requirements such as those established by the STOCK Act.

References

Ang JS, Hsu C, Tang D, Wu C (2021) The role of social media in corporate governance. *The Accounting Review* 96(2):1–32.

Belmont W, Sacerdote B, Sehgal R, Van Hoek I (2022) Do senators and house members beat the stock market? Evidence from the STOCK Act. *Journal of Public Economics* 207:104602.

Blankespoor E, Miller GS, White HD (2014) The role of dissemination in market liquidity: Evidence from firms' use of Twitter. *The Accounting Review* 89(1):79–112.

Blonien P, Crane AD, Crotty K (2025) Should the Public be Concerned about Congressional Stock Trading? *SSRN 5524863*.

Carhart MM (1997) On Persistence in Mutual Fund Performance. *The Journal of Finance* 52(1):57–82.

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

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

Cookson JA, Niessner M, Schiller C (2024) Can social media inform corporate decisions? Evidence from merger withdrawals. *Journal of Finance, Forthcoming*.

DeepSeek-AI, Liu A, Feng B, Xue B, Wang B, Wu B, Lu C, et al. (2025) DeepSeek-V3 Technical Report. (February 18) http://arxiv.org/abs/2412.19437.

Dong Z, Xu NR (2025) Legislative Trades. *SSRN 5514978*.

Dong Z, Xu NR, Yu X (2026) Unreadable Political Trades. *Working Paper*.

Eggers A, Hainmueller J (2013) Capitol losses: The mediocre performance of Congressional stock portfolios. *The Journal of Politics* 75(2):535–551.

Fama EF, French KR (2015) A five-factor asset pricing model. *Journal of Financial Economics* 116(1):1–22.

Hanousek J, Jo H, Pantzalis C, Park JC (2023) A Dilemma of Self-interest vs. Ethical Responsibilities in Political Insider Trading. *J Bus Ethics* 187(1):137–167.

Hanousek Jr J, Park JC, Pantzalis C (2021) Political Insider Trading: A narrow versus comprehensive approach. *Available at SSRN 3808702*.

Karadas S (2018) Family ties and informed trading: Evidence from Capitol Hill. *Journal of Economics and Finance* 42:211–248.

Karadas S (2019) Trading on Private Information: Evidence from Members of Congress. *The Financial Review* 54(1):85–131.

Moe YB, Ma Y (2024) Congressional Stock Trades and Economic Policy Uncertainty. *FEB-RN Research Paper* (13).

Stewart III C (2012) The Value of Committee Assignments in Congress Since 1994. (April 6) https://papers.ssrn.com/abstract=2035632.

Wei SJ, Zhou Y (2025) "Captain Gains" on Capitol Hill. *NBER Working Paper*.

Ziobrowski AJ, Boyd JW, Cheng P, Ziobrowski BJ (2011) Abnormal returns from the common stock investments of members of the US House of Representatives. *Business and Politics* 13(1):1–22.

Ziobrowski AJ, Cheng P, Boyd JW, Ziobrowski BJ (2004) Abnormal returns from the common stock investments of the US Senate. *Journal of Financial and Quantitative Analysis* 39(4):661–676.

Table 1. Sample construction and asset type distribution

This table summarizes the construction of the transaction sample used to create monthly trading activity measures for the analysis, and presents the distribution of asset types. Panel A describes the stepwise procedure, including electronic PTR records, structured scanned PTRs processed via OCR, and unstructured scanned PTRs collected manually. "*After data parsing*" means the exclusion of filings from former members, outdated versions, and transactions missing trade type, trading date, or transaction amount. "*minus*" indicates an exclusion condition, and "*plus*" indicates an inclusion condition. *Sample A* combines parsed electronic records, *Sample B* parsed structured scanned records, and *Sample C* parsed unstructured scanned records. *Sample D* aggregates all three. *Sample E* retains only trades with a specified or successfully identified asset type. *Sample F* excludes trades without a matched CRSP ticker. *Sample G* further restricts to stock purchases and sales. Panel B reports the distribution of asset types across two groups: (1) *Public stock plus*, defined as the CRSP-matched transactions (*Sample F*), and (2) *Other investment*, defined as the remaining parsed transaction records that have no matched CRSP ticker (*Sample D minus F*).

Panel A. Transaction sample construction

Number of transactions	*Senators*	*Representatives*	*Total*	*Sample*
Electronic PTR records	17,756	44,858	62,614	
After data parsing	11,410	40,149	51,559	(Sample A)
Structured scanned records (via OCRs)	1,497	6,033	7,530	
After data parsing	963	3,377	4,340	(Sample B)
Unstructured scanned records (via manual)	524	61,709	62,233	
After data parsing	319	59,194	59,513	(Sample C)
Sample A, B and C	12,692	102,720	115,412	(Sample D)
minus records without specified asset types	9,781	26,763	36,544	
plus LLM identified asset types	10,680	87,525	98,205	
plus CRSP asset types (stock/ETF) via CRSP ticker	12,565	99,762	112,327	(Sample E)
minus trades without matched CRSP ticker	9,841	68,020	77,861	(Sample F)
minus "exchange" trade type	9,777	67,527	77,304	(Sample G)

Panel B. Asset type distribution

	(1) Public stock plus		*(2) Other investment*	
Asset type	*# records*	*%*	*# records*	*%*
Stock	74,537	96%	21,160	56%
Fund (e.g., ETF, Closed-End Mutual Funds)	2,206	3%	1,264	3%
Ownership Interest	1,118	1%	549	1%
Government Securities and Agency Debt			5,765	15%
Corporate Securities (Bonds and Notes)			2,946	8%
Options			1,705	5%
Non-Public Stock			289	1%
Commodities/Futures Contract			148	0.4%
Hedge Funds & Private Equity Funds (non-EIF)			148	0.4%
Cryptocurrency			137	0.4%
Asset-Backed Securities			101	0.3%
Variable Annuity			88	0.2%
Exchange Traded Notes			36	0.1%
Stock Appreciation Right			3	0.01%
Other & Missing			3,212	9%
Total	77,861	(Sample F)	37,551	(Sample D *minus* F)

Table 2. Sample coverage relative to related congressional trading studies

This table compares reported transaction coverage across studies. "Rep." denotes House representatives; "Sen." denotes senators. Empty cells are values the cited paper does not disclose. Percentages divide each reported count by this paper's count in the same category column. They are descriptive rather than like-for-like coverage estimates, because sample periods, chambers, asset scopes, and filing sources differ across studies. Total transaction records use all our parsed transaction records (*Sample D*), 115,412 records with 102,720 House and 12,692 Senate. Public equity uses our *Sample G* of CRSP-matched stock purchases and sales, 77,304 records with 67,527 House and 9,777 Senate.

		Total records of any assets			Public equity trades				
Study	**Period**	**All**	**Rep.**	**Sen.**	**All**	**Rep.**	**Sen.**	**Source and collection**	**Description**
This paper	2014-2022	115,412 (100.0%)	102,720 (100.0%)	12,692 (100.0%)	77,304 (100.0%)	67,527 (100.0%)	9,777 (100.0%)	All PTR; electronic, OCR, and manual	Benchmark: both chambers and all filing formats.
Belmont et al. (2022)	2012-2020				42,324 (54.8%)	31,329 (46.4%)	10,995 (112.5%)	All PTR and annual FD; electronic and manual	Closest broad public-stock benchmark.
Hanousek et al. (2023)	2012-2019			8,509 (67.0%)			7,474 (76.4%)	Senate; electronic	Senate electronic-only; excludes the House and scans.
Dong and Xu (2025)	2014-2022		37,226 (36.2%)			31,543 (46.7%)		House; electronic	Electronic House sample; excludes the scanned trades.
Dong, Xu, and Yu (2026)	2013-2022		92,713 (90.3%)			39,013 (57.8%)		House; electronic and manual	Unreadable House filings are large; the public equity count is from the CAR observations.
Moe and Ma (2024)	2014-2023	30,252 (26.2%)			28,406 (36.7%)	20,985 (31.1%)	7,421 (75.9%)	Quiver, a third-party provider	Commercial provider benchmark.
Wei and Zhou (2025)	1995-2021 (subsample)				4,351 (5.6%)			Selected core leaders; annual and PTR	Matched leaders vs. control design; subsample only.

Table 3. Abnormal return summary and univariate tests by committee power
This table reports summary statistics and univariate comparisons of value-weighted FF5 plus momentum cumulative abnormal returns (VW CARs) at the politician-month level. The sample includes all politician-months with at least one CRSP-matched public equity trade with a valid abnormal return. Panel A reports the distribution of VW CARs measured over horizons of one to twelve months. Panel B compares VW CARs between months in which the politician chaired or was the ranking member of a top-five committee and all other months. For each group, means and medians are reported together with tests against zero; the difference columns report mean and median differences with tests of equality. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Distribution of monthly VW CARs of all politicians

Variable	*Obs.*	*Mean*	*STD*	*Min*	*p25*	*Median*	*p75*	*Max*
CAR (1-month)	5,206	-0.0023	0.0725	-1.2649	-0.0226	-0.0001	0.0212	0.7422
CAR (2-month)	5,206	-0.0024	0.0942	-1.7465	-0.0324	-0.0006	0.0305	0.7217
CAR (3-month)	5,206	-0.0025	0.1167	-1.6012	-0.0395	-0.0007	0.0365	2.1729
CAR (6-month)	5,206	-0.0045	0.1669	-2.5821	-0.0543	-0.0009	0.0514	3.1248
CAR (12-month)	5,206	-0.0084	0.2377	-3.8846	-0.0798	-0.0022	0.0776	3.1660

Panel B. Top-5 chair & ranking members vs others

	Top-5 chair & rank months		*Other politician-months*		*Difference: (1) − (2)*	
	(1)		(2)		(3)	
	Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*
CAR (1-month)	0.0022	0.0007	-0.0026**	-0.0002	0.0048	0.0009
CAR (2-month)	0.0036	-0.0001	-0.0028**	-0.0006	0.0064	0.0005
CAR (3-month)	0.0030	0.0053	-0.0029*	-0.0009	0.0059	0.0062
CAR (6-month)	0.0040	0.0053	-0.0051**	-0.0013	0.0090	0.0066
CAR (12-month)	0.0063	0.0068*	-0.0094***	-0.0031	0.0157	0.0099*

Table 4. Transaction-level distribution of abnormal returns

This table reports the transaction-level distribution of FF5 plus momentum cumulative abnormal returns (CARs) for CRSP-matched public equity trades over the sample period, January 2014 to December 2022. Panel A pools all 76,048 transactions with a valid CAR at the indicated horizon; Panel B restricts to 7,229 transactions in politician-months in which the politician was the chair or the ranking member of a top-five committee. For each horizon, the table reports the mean and the 20th, median, 80th, 90th, and 95th percentiles of the CAR distribution within the panel.

Panel A. All transactions

Horizon	*Mean*	*p20*	*Median*	*p80*	*p90*	*p95*
CAR (1-month)	-0.0006	-0.0498	0.0002	0.0491	0.0836	0.1226
CAR (2-month)	-0.0007	-0.0716	-0.0002	0.0696	0.1185	0.1723
CAR (3-month)	-0.0008	-0.0866	-0.0001	0.0862	0.1438	0.2078
CAR (6-month)	-0.0007	-0.1243	0.0006	0.1241	0.2034	0.2920
CAR (12-month)	-0.0004	-0.1778	0.0017	0.1766	0.2895	0.4142

Panel B. Transactions by top-5 chair & ranking members

Horizon	*Mean*	*p20*	*Median*	*p80*	*p90*	*p95*
CAR (1-month)	0.0033	-0.0512	0.0015	0.0583	0.0932	0.1354
CAR (2-month)	0.0033	-0.0756	0.0011	0.0784	0.1365	0.2002
CAR (3-month)	0.0043	-0.0911	0.0039	0.0975	0.1661	0.2389
CAR (6-month)	0.0060	-0.1308	0.0071	0.1450	0.2313	0.3361
CAR (12-month)	0.0028	-0.1868	0.0085	0.2095	0.3243	0.4439

Table 5. Summary statistics

This table reports summary statistics for the politician-month panel used in the regression analysis. The sample includes all politicians who ever submitted PTRs during the sample period. The definition of variables is detailed in Appendix Table A.1.

Variable	Obs.	Mean	STD	Min	Median	Max
Trade volume						
#trade_all	28,206	3.56	24.49	0.00	0.00	1,124.00
$trade_all	28,206	185,724	2,029,288	0.00	0.00	125,100,000
$trade_all (in traded months)	6,681	784,097	4,113,181	8,000	80,000	125,100,000
Ln(#trade_all)	28,206	0.42	0.93	0.00	0.00	7.03
Ln($trade_all)	28,206	2.72	4.97	0.00	0.00	18.64
#trade_stock	28,206	2.46	16.49	0.00	0.00	832.00
$trade_stock	28,206	93,187	1,322,727	0.00	0.00	113,000,000
$trade_stock (in traded months)	5,107	514,673	3,073,707	8,000	64,500	113,000,000
Ln(#trade_stock)	28,206	0.32	0.83	0.00	0.00	6.73
Ln($trade_stock)	28,206	2.03	4.37	0.00	0.00	18.54
Individual social media attention						
Attention_post	28,206	6.19	161.12	0.00	0.00	12,326.00
Attention_share	28,206	210.91	3,433.60	0.00	0.00	189,191.00
Attention_total	28,206	753.03	12,135.07	0.00	0.00	636,522.00
Ln(Attention_post)	28,206	0.11	0.62	0.00	0.00	9.42
Ln(Attention_share)	28,206	0.21	1.12	0.00	0.00	12.15
Ln(Attention_total)	28,206	0.25	1.31	0.00	0.00	13.36
Other social media attention						
Attention_post_other	28,206	1,098.97	2,911.40	0.00	0.00	17,120.00
Attention_share_other	28,206	28,297.97	84,512.45	0.00	0.00	733,564.00
Attention_total_other	28,206	114,183.01	342,172.96	0.00	0.00	2,701,739.00
Ln(Attention_post_other)	28,206	2.38	3.51	0.00	0.00	9.75
Ln(Attention_share_other)	28,206	3.17	4.76	0.00	0.00	13.51
Ln(Attention_total_other)	28,206	3.49	5.26	0.00	0.00	14.81
Politician characteristics						
Top5_leader	28,206	0.047	0.211	0.000	0.000	1.000
Tenure	28,206	10.85	8.64	1.00	8.00	61.00
Ln(Tenure)	28,206	2.21	0.74	0.69	2.20	4.13
Senate	28,206	0.23	0.42	0.00	0.00	1.00
High-return trading						
%($high-return), 1-month	28,206	3.34	13.57	0.00	0.00	100.00
%($high-return), 2-month	28,206	3.46	14.04	0.00	0.00	100.00
%($high-return), 3-month	28,206	3.46	13.98	0.00	0.00	100.00
%($high-return), 6-month	28,206	3.36	13.80	0.00	0.00	100.00
%($high-return), 12-month	28,206	3.32	13.64	0.00	0.00	100.00
1{high-return}, 1-month	28,206	0.09	0.29	0.00	0.00	1.00
1{high-return}, 2-month	28,206	0.09	0.29	0.00	0.00	1.00
1{high-return}, 3-month	28,206	0.09	0.29	0.00	0.00	1.00
1{high-return}, 6-month	28,206	0.09	0.29	0.00	0.00	1.00
1{high-return}, 12-month	28,206	0.09	0.29	0.00	0.00	1.00

Table 6. Social media attention and trade volume

This table reports estimates examining how politician-specific Twitter attention relates to congressional trading volume. In Panel A, the dependent variable is *Ln(#trade_all)* in columns (1) to (3) and *Ln($trade_all)* in columns (4) to (6), defined as the logarithm of one plus the total number and total value of politicians' trades in *Sample D*, which includes all parsed transaction records. In Panel B, the dependent variable is *Ln(#trade_stock)* in columns (1) to (3) and *Ln($trade_stock)* in columns (4) to (6), constructed using "*Public stock plus*" trades in *Sample G* only. *Ln(Attention_post)* is the log number of original tweets that mention and discuss a given politician in the three months prior. *Ln(Attention_share)* includes original tweets, retweets, and quote tweets. *Ln(Attention_total)* aggregates all forms of engagement, including original tweets, retweets, quote tweets, likes, and replies. The "*(other)*" suffix indicates attention variables that capture the same measures for general discussions of congressional trading, excluding references to the focal politician. All regressions include politician and year fixed effects. *Ln(Tenure)* controls for the total number of years a politician has served in Congress. Definitions for all variables are provided in Appendix Table A.1. Standard errors are clustered at the politician level and reported in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Panel A. Trading of all asset types

Dependent variable:	*Ln(#trade_all)*			*Ln($trade_all)*		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Attention_post)	-0.0819*			-0.395*		
	(0.0420)			(0.203)		
Ln(Attention_share)		-0.0555**			-0.288**	
		(0.0241)			(0.116)	
Ln(Attention_total)			-0.0483**			-0.250**
			(0.0204)			(0.0982)
Ln(Attention_post_other)	0.00710			0.0712		
	(0.0143)			(0.0755)		
Ln(Attention_share_other)		0.0117			0.0958	
		(0.0133)			(0.0681)	
Ln(Attention_total_other)			0.0108			0.0875
			(0.0117)			(0.0602)
Ln(Tenure)	-0.106	-0.107	-0.107	-0.487	-0.491	-0.492
	(0.0778)	(0.0774)	(0.0774)	(0.425)	(0.420)	(0.420)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,206	28,206	28,206	28,206	28,206	28,206
Adjusted R-squared	0.551	0.552	0.552	0.441	0.442	0.442

Panel B. Stock trading

Dependent variable:	*Ln(#trade_stock)*			*Ln($trade_stock)*		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Attention_post)	-0.0708*			-0.333*		
	(0.0407)			(0.185)		
Ln(Attention_share)		-0.0502**			-0.261**	
		(0.0237)			(0.112)	
Ln(Attention_total)			-0.0433**			-0.224**
			(0.0200)			(0.0952)
Ln(Attention_post_other)	0.00110			0.00747		
	(0.0127)			(0.0682)		
Ln(Attention_share_other)		0.00489			0.0386	
		(0.0118)			(0.0627)	
Ln(Attention_total_other)			0.00431			0.0332
			(0.0104)			(0.0556)
Ln(Tenure)	-0.0963	-0.0977	-0.0979	-0.419	-0.426	-0.426
	(0.0711)	(0.0708)	(0.0709)	(0.387)	(0.384)	(0.384)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,206	28,206	28,206	28,206	28,206	28,206
Adjusted R-squared	0.540	0.541	0.541	0.434	0.435	0.435

Table 7. Social media attention and high-return trades

This table reports estimates examining how politician-specific Twitter attention relates to high-return trades at the politician-month level. A transaction is a high-return trade when its FF5 plus momentum cumulative abnormal return (CAR) exceeds the pooled 80th percentile of the full sample transactions for the relevant return horizon. In Panel A, the dependent variable is *%($high-return)*, which equals high-return stock trade amount divided by total stock trade amount in the traded months, and zero otherwise. In Panel B, the dependent variable is *1{high-return}*, an indicator equal to one when at least one high-return trade is observed in the politician-month, and zero otherwise. Columns (1) to (5) vary the horizon over which the CAR is measured. *Ln(Attention_total)* is the log of all forms of engagement with original tweets that mention and discuss a given politician in the three months prior, including retweets, quote tweets, likes, and replies. All regressions include politician and year fixed effects. Definitions for all variables are provided in Appendix Table A.1. Standard errors are clustered at the politician level and reported in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Panel A. Share of high-return trades

Dependent variable:	*%($high-return)*				
CAR horizon:	1 month	2 months	3 months	6 months	12 months
	(1)	(2)	(3)	(4)	(5)
Ln(Attention_total)	-0.520***	-0.445**	-0.535**	-0.510**	-0.519**
	(0.163)	(0.211)	(0.222)	(0.212)	(0.204)
Constant	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Politician Control	Yes	Yes	Yes	Yes	Yes
Other Attention Control	Yes	Yes	Yes	Yes	Yes
Observations	28,206	28,206	28,206	28,206	28,206
Adjusted R-squared	0.128	0.125	0.125	0.126	0.123

Panel B. Any high-return trades

Dependent variable:	*1{high-return}*				
CAR horizon:	1 month	2 months	3 months	6 months	12 months
	(1)	(2)	(3)	(4)	(5)
Ln(Attention_total)	-0.0155***	-0.0138**	-0.0155**	-0.0156**	-0.0159***
	(0.00575)	(0.00586)	(0.00604)	(0.00616)	(0.00577)
Constant	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Politician Control	Yes	Yes	Yes	Yes	Yes
Other Attention Control	Yes	Yes	Yes	Yes	Yes
Observations	28,206	28,206	28,206	28,206	28,206
Adjusted R-squared	0.343	0.338	0.345	0.342	0.339

Table 8. Powerful committee leadership and trade volume

This table reports estimates examining whether the relationship of politician-specific Twitter attention with trading volume differs for top-five committee leaders. Columns (1) through (4) use *Ln(#trade_all)*, *Ln($trade_all)*, *Ln(#trade_stock)*, and *Ln($trade_stock)*, respectively. The first two outcomes are constructed from *Sample D*, which includes all parsed transaction records; the last two use "*Public stock plus*" trades in *Sample G*. *Ln(Attention_total)* is the log of all forms of engagement with original tweets that mention and discuss a given politician in the three months prior, including retweets, quote tweets, likes, and replies. *Top5_leader is an indicator equal to one if the politician serves as chair or ranking member of one of the five highest-ranked* powerful committees in the politician's chamber, based on Stewart III (2012). All specifications include politician and year fixed effects. Definitions for all variables are provided in Appendix Table A.1. Standard errors are clustered at the politician level and reported in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	*Trade volume*			
Outcome:	Ln(#trade_all)	Ln($trade_all)	Ln(#trade_stock)	Ln($trade_stock)
	(1)	(2)	(3)	(4)
Ln(Attention_total) ×	-0.0590***	-0.639***	-0.0587***	-0.632***
Top5_leader	(0.0212)	(0.119)	(0.0205)	(0.113)
Ln(Attention_total)	-0.0437**	-0.200**	-0.0387*	-0.174*
	(0.0216)	(0.0939)	(0.0212)	(0.0898)
Top5_leader	0.0970	0.679	0.0636	0.589
	(0.100)	(0.491)	(0.0852)	(0.474)
Constant	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Politician Control	Yes	Yes	Yes	Yes
Other Attention Control	Yes	Yes	Yes	Yes
Observations	28,206	28,206	28,206	28,206
Adjusted R-squared	0.553	0.444	0.541	0.437

Table 9. Powerful committee leadership and high-return trades

This table reports estimates examining whether the relationship of politician-specific Twitter attention with high-return trades differs for top-five committee leaders. A transaction is a high-return trade when its FF5 plus momentum cumulative abnormal return (CAR) exceeds the pooled 80th percentile of the full sample transactions for the relevant return horizon. In Panel A, the dependent variable is *%($high-return)*, which equals high-return stock trade amount divided by total stock trade amount in the traded months, and zero otherwise. In Panel B, the dependent variable is *1{high-return}*, an indicator equal to one when at least one high-return trade is observed in the politician-month, and zero otherwise. Columns (1) to (5) vary the horizon over which the CAR is measured. All regressions include politician and year fixed effects. Definitions for all variables are provided in Appendix Table A.1. Standard errors are clustered at the politician level and reported in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Panel A. Share of high-return trades

Dependent variable:	*%($high-return)*				
CAR horizon:	1 month	2 months	3 months	6 months	12 months
	(1)	(2)	(3)	(4)	(5)
Ln(Attention_total) × Top5_leader	-1.040***	-1.286***	-1.406***	-1.582***	-1.533***
	(0.194)	(0.272)	(0.254)	(0.315)	(0.265)
Ln(Attention_total)	-0.438***	-0.341*	-0.422**	-0.383**	-0.396**
	(0.154)	(0.200)	(0.209)	(0.183)	(0.177)
Top5_leader	0.856	0.464	0.302	0.662	0.483
	(0.955)	(1.041)	(0.911)	(0.878)	(1.057)
Constant	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Politician Control	Yes	Yes	Yes	Yes	Yes
Other Attention Control	Yes	Yes	Yes	Yes	Yes
Observations	28,206	28,206	28,206	28,206	28,206
Adjusted R-squared	0.129	0.126	0.126	0.127	0.124

Panel B. Any high-return trades

Dependent variable:	*1{high-return}*				
CAR horizon:	1 month	2 months	3 months	6 months	12 months
	(1)	(2)	(3)	(4)	(5)
Ln(Attention_total) ×	-0.0223***	-0.0248***	-0.0271***	-0.0278***	-0.0256***
Top5_leader	(0.00648)	(0.00660)	(0.00699)	(0.00729)	(0.00660)
Ln(Attention_total)	-0.0138**	-0.0118**	-0.0134**	-0.0134**	-0.0139**
	(0.00595)	(0.00598)	(0.00610)	(0.00623)	(0.00586)
Top5_leader	0.0391	0.0245	0.0208	0.0298	0.0351
	(0.0285)	(0.0278)	(0.0269)	(0.0238)	(0.0280)
Constant	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Politician Control	Yes	Yes	Yes	Yes	Yes
Other Attention Control	Yes	Yes	Yes	Yes	Yes
Observations	28,206	28,206	28,206	28,206	28,206
Adjusted R-squared	0.343	0.339	0.346	0.343	0.339

Table 10. Filing format of politicians' PTRs: electronic, scanned, or mixed

This table reports politician-level and transaction-level statistics by the filing format of Periodic Transaction Reports (PTRs). Panel A reports the distribution of politician characteristics by filing format: exclusively electronic (236 politicians), exclusively scanned (75), and mixed (69), showing the number and percentage of politicians in each filing group within their respective cohorts.

Panel B compares trade amounts (USD), FF5 plus momentum cumulative abnormal returns (CARs), and high-return trades across the same filing groups at two levels. The main table reports the 1-, 6-, and 12-month CAR horizons. A high-return trade is one whose signed FF5 plus momentum CAR is strictly above the pooled 80th percentile among all transactions with nonmissing CAR at the corresponding horizon. CARs are signed so that positive values indicate favorable ex post outcomes for both purchases and sales. Transaction-level rows summarize individual trading records. Politician-level rows first aggregate within politician, with CARs weighted by trade amount for each record, and report high-return trades as percentages by number and dollar amount. Columns (1) to (3) report means and medians for three filing groups. Column (4) reports mean and median differences between the electronic and scanned groups. Column (5) reports mean and median differences between the electronic and mixed groups. Only CARs are tested against zero in the standalone columns, with statistical significance reported by stars; for trade volume and high-return measures, stars are reported only for differences.

Panel C compares transactions for the 23 politicians who switched from electronic to scanned. For those who began in electronic and later filed scanned, both formats use the full sample period. For those who began in scanned, moved to electronic, and later submitted scanned at some point, the sample is restricted to the period after the return to scanned. Results are reported at the transaction and politician levels. At the transaction level, columns (1) and (2) show means and medians for electronic and scanned submissions. Column (3) reports mean and median differences between electronic and scanned filings. The politician-level panel repeats the three-column layout after aggregating within politician; for CARs, aggregation is value weighted by transaction amount, and high-return trades are reported as percentages by number and dollar amount. Across Panels B and C, differences in means are tested with t-tests and differences in medians with Wilcoxon tests. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Politician distribution: filing format

Group by PTR Format	*1. Electronic*	*2. Scanned*	*3. Both*	*Total*
Number of politicians (percentage in each politician group)				
Number of politicians	236 (62%)	75 (20%)	69 (18%)	380
Number of senators	68 (87%)	4 (5%)	6 (8%)	78
Number of representatives	168 (56%)	71 (24%)	63 (21%)	302
Number of Republicans	140 (64%)	50 (23%)	28 (13%)	218
Number of Democrats	94 (59%)	25 (16%)	40 (25%)	159
Number of top-five committee leaders (ever)	14 (54%)	7 (27%)	5 (19%)	26

Panel B. Trade volume, CARs, and high-return trades across politician groups defined by PTR format

By PTR Format	*1. Electronic*		*2. Scanned*		*3. Both*		*Difference: Group 1 - 2*		*Difference: Group 1 - 3*	
	(1)		(2)		(3)		(4)		(5)	
	Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*
Transaction-level										
Trade volume										
$trade_all	44,578	8,000	44,604	8,000	97,920	8,000	-26	0***	-53,343***	0***
$trade_stock	28,891	8,000	32,585	8,000	75,458	8,000	-3,694***	0***	-46,566***	0***
FF5 plus momentum cumulative abnormal return (CAR)										
CAR (1-month)	-0.0000	0.0002	-0.0003	0.0005	-0.0034***	-0.0009**	0.0002	-0.0002	0.0034***	0.0011***
CAR (6-month)	0.0011	0.0014	-0.0010	0.0007	-0.0044*	-0.0019	0.0022	0.0006	0.0055**	0.0032**
CAR (12-month)	0.0052***	0.0045***	-0.0014	0.0005	-0.0106***	-0.0029*	0.0066***	0.0041**	0.0158***	0.0074***
High-return trade indicator										
1-month	0.2050	0.0000	0.1975	0.0000	0.1938	0.0000	0.0075**	0.0000**	0.0112**	0.0000**
6-month	0.1995	0.0000	0.2005	0.0000	0.1990	0.0000	-0.0010	0.0000	0.0004	0.0000
12-month	0.2009	0.0000	0.2013	0.0000	0.1952	0.0000	-0.0004	0.0000	0.0057	0.0000
Politician-level										
Trade volume										
$trade_all	161,753	20,755	90,484	18,974	101,010	23,152	71,269	1,781	60,744	-2,397
$trade_stock	41,389	12,995	102,179	17,484	179,439	18,321	-60,790*	-4,488	-138,050*	-5,325***
FF5 plus momentum cumulative abnormal return (CAR)										
CAR (1-month)	-0.0026	-0.0001	0.0013	-0.0023	0.0003	-0.0011	-0.0039	0.0021	-0.0029	0.0009
CAR (6-month)	0.0007	-0.0040*	0.0038	0.0022	-0.0241*	-0.0114***	-0.0031	-0.0062	0.0248	0.0073
CAR (12-month)	-0.0071	0.0002	0.0202	0.0056	-0.0294*	-0.0178**	-0.0273	-0.0055	0.0223	0.0180
% of trades that are high return										
1-month	21.95	18.20	18.92	15.96	19.36	18.12	3.03	2.25	2.59	0.08
6-month	20.42	17.05	19.52	18.24	16.47	16.67	0.90	-1.19	3.95	0.38
12-month	19.44	16.72	22.90	19.23	17.37	16.54	-3.46	-2.51	2.07	0.18
% of trade dollars in high-return trades										
1-month	21.18	17.21	17.22	12.02	19.16	15.02	3.96	5.20*	2.02	2.19
6-month	19.22	15.23	18.32	14.44	16.18	13.13	0.90	0.79	3.03	2.10
12-month	17.94	15.09	21.42	17.71	15.94	12.46	-3.48	-2.62	2.00	2.63

Panel C. Trade volume, CARs, and high-return trades following switches to scanned filings

	Electronic records			*Scanned records*			*Difference*	
	(1)			(2)			(3) *Electronic - Scanned*	
	Mean	*Median*	*Obs*	*Mean*	*Median*	*Obs*	*Mean*	*Median*
Transaction-level								
Trade volume								
$trade_all	73,510	8,000	4,480	1,085,201	32,500	216	-1,011,692***	-24,500***
$trade_stock	38,593	8,000	3,555	1,374,685	32,500	138	-1,336,091***	-24,500***
FF5 plus momentum cumulative abnormal return (CAR)								
CAR (1-month)	-0.0041*	-0.0014*	3,577	0.0063	0.0025	138	-0.0104	-0.0039
CAR (6-month)	-0.0067	-0.0042*	3,539	0.0136	0.0173	137	-0.0203	-0.0215*
CAR (12-month)	-0.0152***	-0.0077**	3,496	0.0134	0.0382*	136	-0.0285	-0.0458**
High-return trade indicator								
1-month	0.2158	0.0000	3,577	0.1667	0.0000	138	0.0492	0.0000
6-month	0.2173	0.0000	3,539	0.1971	0.0000	137	0.0202	0.0000
12-month	0.2068	0.0000	3,496	0.1838	0.0000	136	0.0230	0.0000
Politician-level								
Trade volume								
$trade_all	82,610	26,841	23	1,030,514	32,500	23	-994,381	-3,586
$trade_stock	50,895	24,333	19	1,432,670	32,500	19	-1,639,874	-13,167
FF5 plus momentum cumulative abnormal return (CAR)								
CAR (1-month)	-0.0009	-0.0007	19	-0.0273	-0.0065	19	0.0247	0.0058
CAR (6-month)	-0.0228	-0.0097	19	-0.0180	-0.0125	19	-0.0033	0.0027
CAR (12-month)	-0.0213	-0.0176	19	-0.0665	-0.0027	19	0.0719	0.0342
% of trades that are high return								
1-month	22.57	21.31	19	12.31	0.00	19	11.82***	11.72***
6-month	19.96	19.61	19	15.53	0.00	19	2.32	13.37
12-month	19.91	19.95	19	18.13	0.00	19	2.02	12.08
% of trade dollars in high-return trades								
1-month	23.41	19.24	19	9.96	0.00	19	13.53***	15.22***
6-month	19.51	17.46	19	11.94	0.00	19	6.66	12.47
12-month	15.53	13.95	19	14.32	0.00	19	-0.89	6.10

Appendix
Table A.1. Variable definitions

Variable	Definition	Source
Trade volume		
$trade_all	Total dollar value of all asset purchases and sales made by the politician in month *t*, constructed from *Sample D*. The natural logarithm of one plus the variable is used in regressions.	PTR
#trade_all	Count of all asset purchases and sales made by the politician in month *t*, constructed from *Sample D*. The natural logarithm of one plus the variable is used in regressions.	PTR
$trade_stock	Total dollar value of all stock purchases and sales made by the politician in month *t*, constructed from *Sample G*. The natural logarithm of one plus the variable is used in regressions.	PTR
#trade_stock	Count of all stock purchases and sales made by the politician in month *t*, constructed from *Sample G*. The natural logarithm of one plus the variable is used in regressions.	PTR
Individual social media attention		
Attention_post	Number of original tweets discussing the politician's name together with trading-related keywords during months *t-3* to *t-1*. See Table A.2 for the list of trading-related keywords. The natural logarithm of one plus the variable is used in regressions.	Twitter
Attention_share	Number of original tweets from *Attention_post* plus the number of their retweets and quote tweets during months *t-3* to *t-1*. The natural logarithm of one plus the variable is used in regressions.	Twitter
Attention_total	Number of tweets from *Attention_post* plus the number of their retweets, quote tweets, replies, and likes during months *t-3* to *t-1*. The natural logarithm of one plus the variable is used in regressions.	Twitter
Other social media attention		
Attention_post_other	Number of original tweets that mention congressional keywords and trading-related keywords during months *t-3* to *t-1*, excluding tweets that mention the politician's name. See Table A.2 for the lists of congressional and trading-related keywords. The natural logarithm of one plus the variable is used in regressions.	Twitter
Attention_share_other	Number of original tweets from *Attention_post_other* plus the number of their retweets and quote tweets during months *t-3* to *t-1*. The natural logarithm of one plus the variable is used in regressions.	Twitter
Attention_total_other	Number of tweets from *Attention_post_other* plus the number of their retweets, quote tweets, replies, and likes during months *t-3* to *t-1*. The natural logarithm of one plus the variable is used in regressions.	Twitter
Politician characteristics		
Senate	Indicator variable equal to one if the politician is a senator, and zero if a representative.	Senate.gov, House.gov
Tenure	Number of years the politician has served in Congress. Log value is used in regressions.	GovTrack.us
Top5_leader	Indicator variable equal to one if the politician is chairperson or ranking member of a top five committee by power (Stewart III 2012), and zero otherwise.	Stewart III (2012), OpenSecrets
President_elect	Indicator variable equal to one for observations in the three months up to and including the presidential election month,	USA.gov

	and zero for observations in months 4 to 24 before that election. Observations outside this range are excluded.	
<u>Returns and high-return outcomes</u>		
CAR	Cumulative abnormal return based on the transaction in the "*Public stock plus*" category with "exchange" trade type excluded. Calculated as the sum of daily abnormal returns relative to the Fama-French five factors plus momentum over the corresponding horizon (1-month, 2-month, 3-month, 6-month, or 12-month), with sales transactions multiplied by -1. A transaction is a high-return trade if its *CAR* exceeds the pooled top 20th percentile for that horizon; the top 10th percentile is used in the robustness test.	CRSP, PTR
%($high-return)	Dollar value of the politician's high-return stock trades in month *t* divided by the dollar value of stock trades with a usable *CAR* at the corresponding horizon, in percent. Politician-months without such trades are coded zero.	CRSP, PTR
1{high-return}	Indicator variable equal to one if at least one high-return stock trade is observed for the politician in month *t*, and zero otherwise.	CRSP, PTR
<u>Other public attention measures</u>		
Google_trends	Monthly United States search interest for the politician's name, summed over months *t-3* to *t-1*. The natural logarithm of one plus the variable is used in regressions.	Google Trends
Wiki_views	Monthly Wikipedia pageviews for the politician's page, summed over months *t-3* to *t-1*. The natural logarithm of one plus the variable is used in regressions.	Wikimedia

Table A.2. Keyword definitions for Twitter attention queries

Keyword Category	*Terms Included*
Congressional keywords	"congressional", "congress", "senate", "senator", "congressman", "politician", "lawmaker"
Trading-related keywords	"insider trading", "financial investment", "stock investment", "stock trading", "stock holding", "options holding", "options trading", "derivatives holding", "derivatives trading", "purchase stock", "sell stock"
Additional specification	Individual attention queries replace the congressional keywords with the politician's full name.

Internet Appendix

Internet Appendix B. PTR retrieval, reconstruction, and validation

B.1. Filing sources and formats

We retrieve Periodic Transaction Reports (PTRs) from the official Senate and House disclosure portals to cover transactions executed from January 2014 through December 2022. Because a PTR may be filed after the underlying transaction, the retrieval window extends through 2023. The reports enter the data in three formats: (i) electronic records, (ii) printed scans that retain the standard PTR table, and (iii) handwritten or nonstandard scans. Electronic reports in PDF or HTML formats can be parsed directly. Printed scans are processed with a fine-tuned optical character recognition (OCR) procedure when image quality and table structure permit. Remaining scanned records are collected manually.

Across the 2014 to 2022 sample, we identify 7,787 PTRs, including 1,550 Senate filings and 6,237 House filings. Of these, 210 Senate filings (14%) and 1,810 House filings (29%) are available only as scanned images. The greater prevalence of scanned filings in the House is one reason that relying only on machine-readable reports would materially understate congressional trading activity.

The pooled source files contain 132,377 transaction records before common parsing screens. We remove superseded reports, filings by former members, and records missing the transaction date, transaction type, or reported amount range. The resulting sample contains 115,412 records: 51,559 electronic records, 4,340 OCR-recovered records, and 59,513 manually collected records.

Panel A. Printed standard-format scan

Report any purchase, sale, or exchange by you, your spouse, or dependent child **within 30 days** of receiving written notification of such transaction. Report any stocks, bonds, commodity futures, and other securities when the amount of the transaction exceeded $1,000. Include transactions that resulted in a loss. Do not report a transaction involving an excepted investment fund, any real property, or a transaction between you, your spouse, or dependent child. Please clarify which two assets are involved in any reportable exchange. In no event may this disclosure be filed more than 45 days after such transaction.		Transaction Type (x)			Transaction Date (Mo., Day, Yr.)	Amount of Transaction (x)										
Identification of Assets		Purchase	Sale	Exchange		$1,001 - $15,000	$15,001 - $50,000	$50,001 - $100,000	$100,001 - $250,000	$250,001 - $500,000	$500,001 - $1,000,000	Over $1,000,000***	$1,000,001 - $5,000,000	$5,000,001 - $25,000,000	$25,000,001 - $50,000,000	Over $50,000,000
Example: (S) Spouse (DC) Dependent Child (J) Joint	IBM Corp. (stock) NYSE	X			2/1/1X		X			E	X	A	M	P	L	E
	(DC) Microsoft (stock) NASDAQ/OTC		X		2/27/1X				X	E	X	A	M	P	L	E
1	(S) Kite Pharma, Inc (stock) NASDAQ		X		12/17/2014								X			
2	(S) Kite Pharma, Inc (stock) NASDAQ		X		12/18/2014								X			

Panel B. Handwritten scan

	FULL ASSET NAME	TYPE OF TRANS-ACTION			DATE OF TRANS-ACTION	DATE NOTIFIED OF TRANS-ACTION	AMOUNT OF TRANSACTION									
JT	Provide full name, not ticker symbol.	PURCHASE	SALE	EXCHANGE	(MO/DA/YR)	(MO/DA/YR)	A $1,000-$15,000	B $15,001-$50,000	C $50,001-$100,000	D $100,001-$250,000	E $250,001-$500,000	F $500,001-$1,000,000	G $1,000,001-$5,000,000	H $5,000,001-$25,000,000	I $25,000,001-$50,000,000	J Over $50,000,000
JT	Example: Mega Corp. Common Stock		X		8/14/12	8/14/12		X								
	ALTRIA GROUP - STOCK		X		2-12-14	2-17-14	X									
	HOST HOTELS - STOCK		X		2-12-14	2-17-14	X									
	HUNTINGTON INGALLS- STOCK		X		2-12-14	2-17-14	X									

Figure B.1. Examples of scanned PTR formats
Panel A shows an identity-free printed standard-form crop suitable for OCR when legible. Panel B shows identity-free handwritten entries that require manual transcription.

B.2. Recovery of structured scans

The OCR procedure has five components. It is designed to systematically detect and extract tabular transaction information from printed PTRs. The procedure is optimized for layouts featuring pre-defined column headers such as "Assets," "Trading Date," "Amount of Transaction," and checkbox indicators for trade type and amount ranges. The pipeline is not applied when the layout or image quality prevents reliable field identification. The five procedure components are:

1. Image preprocessing. Each scanned file is imported, reoriented based on aspect ratio, and converted into RGB format. Orientation correction is applied if the document appears rotated.

2. Masking of irrelevant regions. Using keyword-based detection via a preliminary OCR pass, visual masks are placed over irrelevant text regions, such as headers, asset examples, and marginal notes, to reduce noise. Mask boundaries are dynamically set depending on the location of key terms and table elements.

3. Structured OCR parsing. Core table data are extracted using hybrid OCR tools, focusing on cell-level text and positional coordinates. A valid transaction row must contain a recognizable trading date. Coordinates for trade type and amount range fields are validated by spatial consistency, and if necessary, re-estimated based on inferred cell widths.

4. Symbol-to-category mapping. PTR forms use "X" marks or checkboxes to indicate trade types (purchase, sale, exchange) and value brackets (e.g., \$15,001–\$50,000). For each coordinate pair, cropped image segments are compared to a reference set of symbol templates. The most visually similar symbol is mapped to its corresponding transaction category.

5. Data structuring. Extracted records are organized into a structured format, capturing the following fields: asset description (including owner type, asset name, and optional ticker), trading date, trade type, and amount range. The procedure accommodates variability in date formats and recognizes common OCR errors, such as misreading table lines as numerals (e.g., "20/3/151").

The structured OCR procedure recovers transaction information from 170 of the 210 scanned Senate PTRs, an 81% recovery rate, and 605 of the 1,810 scanned House PTRs, a 33% recovery rate. The remaining 40 Senate filings and 1,205 House filings proceed to manual review and transcription.

B.3. Manual transcription

A team of trained research assistants reviews filings that cannot be recovered reliably through the OCR pipeline. These include handwritten entries, free-form disclosures, nonstandard grids, and scans with poor image quality. The research assistants transcribe the same fields produced by the automated procedure: owner, asset description, transaction date, transaction type, and reported amount range. We apply the same parsing rules and sample restrictions to every extraction channel.

Manual transcription contributes 59,513 of the 115,412 parsed transaction records (51.6%). After asset classification, the manual channel contributes 57,344 of the 112,327 records with identified asset types. It also contributes 37,532 of the 77,304 CRSP-matched public-equity purchases and sales in *Sample G* (48.6%).

B.4. Asset, ticker, and date recovery

A further challenge in the reconstruction of PTRs arises from the unstructured nature of asset descriptions. In the standardized electronic format, tickers are typically indicated in parentheses, and asset types are specified in brackets, often using abbreviations such as "(AAPL)" and "[ST]". This convention provides a clear and organized representation of the relevant information. However, many filings, particularly scanned submissions and a substantial subset of electronic reports, do not follow this standard. In these cases, tickers and asset types may appear in different positions within the text, be embedded in narrative descriptions, or be implied without explicit labeling. This irregularity complicates systematic extraction and motivates the use of a large language model (DeepSeek-V3) to recover tickers, asset categories, and trading dates in a consistent manner.

The procedure consists of three steps. First, the model is prompted to parse each raw asset description and return two outputs, the ticker symbol and the associated asset type such as stock, fund, or option. To ensure consistency and to avoid spurious classification, we design the following prompt:

"*Return two one-word outputs separated by a semicolon (;). No other words needed. The first is the ticker from this description: {description}. The second is the asset type (stock, fund, option, etc.). Return '' for any part you are not 100% sure about.*"

This instruction requires the model to produce only two tokens, thereby reducing the likelihood of extraneous content in the output.

Second, we introduce a validation step in which the model re-examines the initial classification against the original asset description. The purpose is to filter out inconsistent matches and securities that do not correspond to public equities or funds. The validation prompt is as follows:

"*Double check if '{description}' matches {classification}. Return 'ticker;asset type' only. Skip if not public equity/fund. Return '' for any mismatch or uncertainty.*"

Through this step, the model either confirms the classification or discards it, preventing erroneous matches from entering the dataset.

Finally, we apply a similar approach to normalize trading dates, which can be highly variable in hand-written or scanned forms. Dates frequently lack years or use ambiguous separators. To recover standardized dates, the model is prompted as follows:

"*From this trading date: {date_str}, return only the interpreted date in format yyyy/mm/dd. If no year in the string, use the filing year {filing_year}. Assume month/date/year unless clearly invalid. Return only the date string. No other words.*"

This prompt requires the model to output a single normalized date string, ensuring comparability across filings. When the year is missing, the filing year is used as a reference point, and ambiguous formats are resolved through standardized assumptions.

By applying this layered approach, we enhance the completeness and quality of PTR data in several dimensions. Tickers and asset types that would otherwise remain unstructured or ambiguously described are consistently identified, while strict validation safeguards minimize the risk of misclassification. The standardized trading dates further enable direct integration of transaction records into a coherent panel dataset suitable for empirical analysis. The empirical distribution of recovered and missing tickers, asset types, and trading dates is summarized in Table 1.

B.5. Sample contribution and validation

Asset classification yields 112,327 records with identified asset types: 51,126 electronic records, 3,857 OCR-recovered records, and 57,344 manually transcribed records. These records consist of 99,762 House transactions and 12,565 Senate transactions. *Sample G* contains 77,304 CRSP-matched public-equity purchases and sales, of which 37,174 are electronic, 2,598 are recovered by OCR, and 37,532 are manually transcribed.

To evaluate the accuracy of the reconstructed transaction data, we conduct a random audit of extracted records across both the Senate and House samples. From the full set of recovered PTRs, we draw a random sample of 103 transaction entries filed by senators and 108 filed by representatives. Each record in the sample is manually reviewed to assess the fidelity of key variables, including asset name, trading date, trade type, and transaction amount range.

For the senator sample, we find that 98 percent of asset names are correctly captured, and both the trading date and amount range are recorded with perfect accuracy. The trade type field is also correctly identified in 98 percent of cases. For the representative sample, the accuracy rates are similarly high: 96 percent for asset names, 96 percent for trading dates, and 100 percent for both trade type and amount range. These results demonstrate that our combined procedure consisting of algorithmic extraction supplemented by human verification achieves a high degree of precision in capturing transaction-level information from scanned PTRs.

Internet Appendix C. Additional analyses and robustness

C.1. Nancy Pelosi: abnormal returns and top-tail trades

Section 2.4 uses a single politician, Nancy Pelosi, as an example to illustrate why average performance and right-tail performance may diverge. Table C.1 reports Pelosi's abnormal return distribution and percentile rank. For each return horizon, we rank Pelosi's own trades across all politicians by CAR, and compute the value-weighted mean CAR over all trades, over the top-20% CAR trades and over the top-10% CAR trades, together with the CAR of her single best trade. Panel A reports these statistics, and Panel B reports her percentile rank in the cross-politician distribution. The case is illustrative: it shows that a politician's average performance need not reveal how her most profitable trades performed, and it is not evidence that any particular trade was informed.

C.2. Univariate tests of CARs for alternative power measures

The Table 3 univariate tests of abnormal returns by committee power use top-five committee leadership as the political power measure. Table C.2 asks whether the absence of average outperformance of these powerful politicians depends on the measure choice. It repeats the univariate comparison of politician-month value-weighted CARs under four alternative definitions: chair or ranking member of a top-three committee, membership of a top-three committee, membership of a top-five committee, and core congressional party leadership as defined in Wei and Zhou (2025). Each panel compares months in which a politician holds the position with all other politician-months. The results are discussed in Section 2.4.

C.3. Top-five committee leadership and CARs

Table C.3 examines the heterogeneity of abnormal returns in committee power in a regression, which holds constant other characteristics that may be related to returns. Politician-month value-weighted CARs are regressed on *Top5_leader* at each of the five horizons, controlling for politician-specific Twitter attention, general attention to congressional trading, and tenure. Panel A includes year fixed effects, so the coefficient reflects overall variation in leadership status, both across politicians and over time. Panel B adds politician fixed effects, so the coefficient reflects only within-politician variation, i.e., changes in a politician's own leadership status during the sample. The results are discussed in Section 2.4.

C.4. Chamber heterogeneity in the response to attention

The reputational cost of controversial trading may differ across the two chambers. Senators represent statewide constituencies, serve six-year terms, and typically receive greater national coverage than representatives, so the same volume of discussion may carry a larger reputational cost for a senator. We therefore ask whether the relationship between politician-specific Twitter attention and trading is more negative for senators, and whether any chamber difference is larger for politicians whose committee positions already make personal trading visible.

Table C.4 reports two specifications. The chamber specification adds the interaction of *Ln(Attention_total)* with *Senate* to the baseline model. The chamber and leadership specification adds *Top5_leader*, its interaction with attention, and the corresponding triple interaction. The *Senate* indicator itself is absorbed by the politician fixed effects, because chamber does not change within politician in our sample. Panel A uses the number and the dollar value of stock trades, and Panel B uses *%($high-return)* at the 1- and 12-month CAR horizons. Both panels use the full panel of 28,206 politician-months.

The chamber difference on its own is limited. In the chamber specification, the interaction between attention and *Senate* is negative for all four outcomes but is not statistically significant: -0.0385 and -0.247 for the number and the value of stock trades in Panel A, and -0.430 and -0.340 for the high-return trade value share at the 1- and 12-month horizons in Panel B. The picture is sharper once committee leadership enters. The triple interaction is -0.856 for stock trade value in Panel A, and -1.332 and -2.720 for the high-return trade value share in Panel B, each significant at the 1% level, while the corresponding estimate for the number of stock trades stays small and insignificant. Chamber alone therefore reveals limited heterogeneity, whereas chamber combined with committee leadership indicates that the stronger response to attention among powerful politicians is concentrated among senators.

C.5. Presidential election heterogeneity in the response to attention

Reputational exposure also varies over the political cycle. Political competition and media coverage intensify as a presidential election approaches, so the same discussion of a politician may be more costly in the months just before the election. We therefore compare the three months up to and including the presidential election month with months 4 through 24 before that election.

Table C.5 reports the election-window specification, which interacts *Ln(Attention_total)* with *President_elect*, and the election-window and leadership specification, which adds *Top5_leader* and the corresponding triple interaction. Months outside the two windows are excluded, which leaves 13,987 politician-months. Panel A uses the number and the dollar value of stock trades, and Panel B uses *%($high-return)* at the 1- and 12-month CAR horizons.

Attention is more negatively related to trading inside the election window. In Panel A, the interaction is -0.0701 for the number of stock trades and -0.330 for stock trade value, both significant at the 5% level, and the estimates are similar once the leadership terms are added. In Panel B, the interaction is -0.529 at the one-month horizon and significant at the 5% level, while the twelve-month estimate is negative and insignificant. Adding committee leadership again produces the largest differentials: the triple interaction is -0.115 and -1.429 for the two trade volume outcomes and -3.392 and -2.636 for the high-return trade value share, significant at the 5% level or better in all four columns. Trading by top-five committee leaders is therefore most sensitive to attention when electoral stakes are highest.

C.6. Filing format: complete-horizon results

Table C.6 reports the complete-horizon counterparts to Table 10, Panels B and C. It reports CARs and high-return-trade measures for the one-, two-, three-, six-, and twelve-month horizons; the trade-volume rows remain in Table 10. High-return trades use the main top-20% definition. The results are discussed in Section 5.4.

C.7. Filing format: alternative top-10% high-return trades

Table C.7 repeats the high-return-trade comparisons from Table 10, Panels B and C, using the alternative top-10% definition over all five CAR horizons. The results are discussed in Section 5.5.

C.8. Other measures of public attention

Politician-specific Twitter attention may increase when a politician is in the news for any reason. A politician who is being discussed because of a committee controversy, an electoral challenge, or broader news coverage may also act cautiously in trading that month for reasons unrelated to scrutiny of personal trading. If that is what the baseline captures, adding a measure of how prominent a politician is in a given month should absorb the Twitter attention estimates.

Table C.8 adds two controls to the baseline specification: in Panel A, Ln(Google_trends) is the log of one plus monthly United States search interest for the politician, summed over the preceding three months. In Panel B, Ln(Wiki_views) is built the same way from Wikipedia pageviews of the politicians.

The baseline relationship is largely unchanged after controlling for broader public attention. In Panel A, the Twitter coefficient remains negative and significant for all four trade volume outcomes after controlling for Google Trends, with estimates close to those in Table 6. In Panel B, controlling for Wikipedia pageviews leaves the Twitter estimates virtually unchanged, while the pageview coefficients are small and insignificant throughout. Economically, a one-standard-deviation increase in total Twitter attention remains associated with 1.61 fewer all-asset trades and $161,151 lower trade value per month, and with 1.12 fewer stock trades and $77,704 lower stock trade value. These results indicate that the baseline relationship is distinct from broader fluctuations in public attention to individual politicians.

Table C.1. Nancy Pelosi: abnormal returns and top-tail trades

This table summarizes Nancy Pelosi's trading performance over the sample period, January 2014 to December 2022, using her CRSP-matched public equity trades. For each politician and each return horizon, the politician's own trades are ranked by their FF5 plus momentum cumulative abnormal return (CAR). Panel A reports for Pelosi the value-weighted mean CAR over all her trades, over her top-20% CAR trades, and over her top-10% CAR trades, and the CAR of her single best trade. Panel B reports Pelosi's percentile rank in the corresponding cross-politician distribution.

Panel A. Pelosi's VW CARs

Horizon	*Mean VW CAR (all trades)*	*Mean VW CAR (top-20% trades)*	*Mean VW CAR (top-10% trades)*	*Max CAR (best trade)*
1-month	0.0123	0.1074	0.1224	0.1473
2-month	0.0063	0.1524	0.2001	0.2017
3-month	-0.0118	0.1442	0.1800	0.1990
6-month	-0.0205	0.2922	0.3526	0.3728
12-month	-0.0537	0.3624	0.5631	0.6624

Panel B. Pelosi's percentile rank among politicians

Horizon	*Percentile (all trades)*	*Percentile (top-20% trades)*	*Percentile (top-10% trades)*	*Percentile (best trade)*
1-month	75.5	66.1	56.4	48.0
2-month	63.6	69.0	67.4	46.4
3-month	34.5	50.5	46.4	41.7
6-month	33.6	78.6	74.8	50.9
12-month	22.5	67.6	79.4	58.1

Table C.2. Univariate tests of CARs for alternative power measures
This table reports univariate comparisons of value-weighted FF5 plus momentum cumulative abnormal returns (VW CARs) at the politician-month level for four alternative definitions of political power. The sample includes all politician-months with at least one CRSP-matched public equity trade with a valid abnormal return. Panel A compares months in which the politician chaired or was the ranking member of one of the three highest-ranked powerful committees in the politician's chamber, based on Stewart III (2012), with all other politician-months. Panel B repeats the comparison for months in which the politician served on a top-three committee. Panel C repeats the comparison for months in which the politician served on a top-five committee. Panel D repeats the comparison for months in which the politician held a core congressional party leadership position, including the Speaker of the House, House and Senate party floor leaders, party whips, and conference or caucus chairpersons, as defined in Wei and Zhou (2025). For each group, means and medians are reported together with tests against zero; the difference columns report mean and median differences with tests of equality. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Top-3 chair & ranking members vs others

	Top-3 chair & rank months		*Other months*		*Difference: (1) − (2)*	
	(1)		(2)		(3)	
	Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*
CAR (1-month)	0.0008	-0.0001	-0.0024**	-0.0001	0.0032	0.0000
CAR (2-month)	-0.0016	-0.0050	-0.0024*	-0.0005	0.0008	-0.0045
CAR (3-month)	-0.0027	0.0017	-0.0025	-0.0007	-0.0002	0.0024
CAR (6-month)	-0.0089	0.0022	-0.0044*	-0.0010	-0.0045	0.0032
CAR (12-month)	0.0099	0.0229	-0.0089***	-0.0026	0.0188	0.0255*

Panel B. Top-3 committee members vs others

	Top-3 committee months		*Other months*		*Difference: (1) − (2)*	
	(1)		(2)		(3)	
	Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*
CAR (1-month)	-0.0021	-0.0003	-0.0025*	0.0001	0.0004	-0.0004
CAR (2-month)	-0.0031	-0.0003	-0.0019	-0.0007	-0.0012	0.0004
CAR (3-month)	-0.0043*	0.0005	-0.0011	-0.0012	-0.0032	0.0017
CAR (6-month)	-0.0062*	-0.0007	-0.0032	-0.0010	-0.0030	0.0003
CAR (12-month)	-0.0072	-0.0006	-0.0094**	-0.0031	0.0023	0.0025

Panel C. Top-5 committee members vs others

	Top-5 committee months		*Other months*		*Difference: (1) − (2)*	
	(1)		(2)		(3)	
	Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*
CAR (1-month)	-0.0013	-0.0002	-0.0040**	0.0000	0.0027	-0.0002
CAR (2-month)	-0.0016	0.0000	-0.0036	-0.0013	0.0020	0.0013
CAR (3-month)	-0.0023	0.0000	-0.0029	-0.0013	0.0007	0.0013
CAR (6-month)	-0.0052*	-0.0012	-0.0034	-0.0005	-0.0018	-0.0007
CAR (12-month)	-0.0054	-0.0002	-0.0132**	-0.0047*	0.0077	0.0045

Panel D. Core party leaders vs others

	Core party leader months		*Other months*		*Difference: (1) − (2)*	
	(1)		(2)		(3)	
	Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*
CAR (1-month)	0.0065	0.0042	-0.0024**	-0.0002	0.0089	0.0044
CAR (2-month)	-0.0016	-0.0052	-0.0024*	-0.0006	0.0008	-0.0046
CAR (3-month)	-0.0065	-0.0063	-0.0025	-0.0007	-0.0041	-0.0056
CAR (6-month)	0.0078	-0.0117	-0.0046**	-0.0009	0.0125	-0.0108
CAR (12-month)	0.0025	-0.0054	-0.0086***	-0.0022	0.0111	-0.0032

Table C.3. Top-five committee leadership and CARs

This table reports estimates of politicians' monthly value-weighted FF5 plus momentum cumulative abnormal returns (VW CARs) on *Top5_leader*, an indicator equal to one in months in which the politician serves as chair or ranking member of one of the five highest-ranked powerful committees in the politician's chamber, based on Stewart III (2012). The dependent variable is the VW CAR measured over horizons of one to twelve months, in columns (1) to (5). The sample includes all politician-months with at least one CRSP-matched public equity trade whose abnormal return is valid at all five horizons and with non-missing controls, giving 4,952 observations in every column. Panel A includes year fixed effects. Panel B adds politician fixed effects, so that the estimate comes from within-politician variation. Definitions for all variables are provided in Appendix Table A.1. Standard errors are clustered at the politician level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Top-five leadership and CARs

Dependent variable:	*VW CAR*				
CAR horizon:	1-Month	2-Month	3-Month	6-Month	12-Month
	(1)	(2)	(3)	(4)	(5)
Top5_leader	0.00421	0.00637	0.00802	0.00595	0.0128
	(0.00275)	(0.00416)	(0.00510)	(0.00919)	(0.0112)
Ln(Attention_total)	-0.00100	0.000780	0.00159	0.00424	0.00293
	(0.00100)	(0.000828)	(0.00172)	(0.00259)	(0.00259)
Ln(Attention_total_other)	0.0000525	0.000128	0.000100	0.000322	0.000713
	(0.000234)	(0.000284)	(0.000334)	(0.000496)	(0.000746)
Ln(Tenure)	0.000380	-0.000390	-0.00224	0.00165	0.00303
	(0.00159)	(0.00180)	(0.00248)	(0.00357)	(0.00465)
Constant	Yes	Yes	Yes	Yes	Yes
Politician FE	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	4,952	4,952	4,952	4,952	4,952
Adjusted R-squared	-0.001	0.001	0.003	0.003	-0.000

Panel B. Within-politician variation

Dependent variable:	*VW CAR*				
CAR horizon:	1-Month	2-Month	3-Month	6-Month	12-Month
	(1)	(2)	(3)	(4)	(5)
Top5_leader	0.00151	0.000274	0.00290	0.00198	0.00230
	(0.00292)	(0.00488)	(0.00630)	(0.0118)	(0.0136)
Ln(Attention_total)	-0.00206	-0.000379	-0.000792	-0.000688	-0.00114
	(0.00142)	(0.00151)	(0.00192)	(0.00265)	(0.00259)
Ln(Attention_total_other)	-0.000264	-0.00000935	0.00114	0.00254	0.00162
	(0.000760)	(0.00119)	(0.00150)	(0.00205)	(0.00238)
Ln(Tenure)	-0.00277	-0.00701	-0.00638	-0.00382	-0.0217
	(0.00544)	(0.00844)	(0.0115)	(0.0139)	(0.0162)
Constant	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	4,952	4,952	4,952	4,952	4,952
Adjusted R-squared	0.094	0.031	0.021	0.057	0.035

Table C.4. Chamber heterogeneity in the response to attention

This table reports estimates examining whether the relationship of politician-specific Twitter attention with trading differs between senators and representatives and whether this chamber difference is larger for top-five committee leaders. *Senate* equals one for senators and zero for representatives. Two specifications are reported: the chamber specification interacts attention with *Senate*, and the chamber and leadership specification adds the interaction with *Top5_leader*. Panel A uses the number and the dollar value of stock trades, *Ln(#trade_stock)* and *Ln($trade_stock)*. Panel B uses *%($high-return)* at the 1- and 12-month CAR horizons. All specifications include politician and year fixed effects. Definitions for all variables are provided in Appendix Table A.1. Standard errors are clustered at the politician level and reported in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Panel A. Trade volume

Dependent variable:	*Trade volume, stocks*			
Specification:	*Chamber*		*Chamber and leadership*	
Outcome:	Ln(#trade_stock)	Ln($trade_stock)	Ln(#trade_stock)	Ln($trade_stock)
	(1)	(2)	(3)	(4)
Ln(Attention_total) × Senate	-0.0385	-0.247	-0.0324	-0.160
	(0.0347)	(0.169)	(0.0394)	(0.169)
Ln(Attention_total)	-0.0228*	-0.0922	-0.0226*	-0.0944
	(0.0134)	(0.0871)	(0.0135)	(0.0877)
Ln(Attention_total) × Senate			-0.0243	-0.856***
× Top5_leader			(0.0719)	(0.295)
Ln(Attention_total) ×			-0.0207	0.264
Top5_leader			(0.0602)	(0.255)
Senate × Top5_leader			-0.0291	-0.766
			(0.150)	(0.841)
Top5_leader			0.0740	0.874
			(0.141)	(0.761)
Constant	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Politician Control	Yes	Yes	Yes	Yes
Other Attention Control	Yes	Yes	Yes	Yes
Observations	28,206	28,206	28,206	28,206
Adjusted R-squared	0.542	0.436	0.542	0.438

Panel B. Share of high-return trades

Dependent variable:	*%($high-return)*			
Specification:	*Chamber*		*Chamber and leadership*	
CAR horizon:	1 month	12 months	1 month	12 months
	(1)	(2)	(3)	(4)
Ln(Attention_total) × Senate	-0.430	-0.340	-0.288	-0.0974
	(0.291)	(0.369)	(0.290)	(0.339)
Ln(Attention_total)	-0.291	-0.338	-0.295	-0.347*
	(0.182)	(0.207)	(0.184)	(0.209)
Ln(Attention_total) × Senate ×			-1.332***	-2.720***
Top5_leader			(0.456)	(0.534)
Ln(Attention_total) ×			0.386	1.111**
Top5_leader			(0.399)	(0.458)
Senate × Top5_leader			-2.257	-1.133
			(1.660)	(1.945)
Top5_leader			1.740	0.862
			(1.512)	(1.600)
Constant	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Politician Control	Yes	Yes	Yes	Yes
Other Attention Control	Yes	Yes	Yes	Yes
Observations	28,206	28,206	28,206	28,206
Adjusted R-squared	0.128	0.123	0.129	0.124

Table C.5. Presidential election heterogeneity in the response to attention

This table reports estimates examining whether the relationship of politician-specific Twitter attention with trading differs near presidential elections and whether this election-window difference is larger for top-five committee leaders. *President_elect* equals one during the three months up to and including the presidential election month, and zero during months 4 through 24 before that election. Months outside that range are excluded. Two specifications are reported: the election-window specification interacts attention with *President_elect*, and the election-window and leadership specification adds the interaction with *Top5_leader*. Panel A uses *Ln(#trade_stock)* and *Ln($trade_stock)*, and Panel B uses *%($high-return)* at the 1- and 12-month CAR horizons. All specifications include politician and year fixed effects. Definitions for all variables are provided in Appendix Table A.1. Standard errors are clustered at the politician level and reported in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Panel A. Trade volume

Dependent variable:	*Trade volume, stocks*			
Specification:	*Election window*		*Election window and leadership*	
Outcome:	Ln(#trade_stock)	Ln($trade_stock)	Ln(#trade_stock)	Ln($trade_stock)
	(1)	(2)	(3)	(4)
Ln(Attention_total) × President_elect	-0.0701**	-0.330**	-0.0679**	-0.299**
	(0.0331)	(0.151)	(0.0335)	(0.149)
Ln(Attention_total)	-0.0189	-0.0764	-0.0158	-0.0457
	(0.0189)	(0.0921)	(0.0201)	(0.0956)
President_elect	-0.0303**	-0.140	-0.0325**	-0.150*
	(0.0145)	(0.0880)	(0.0148)	(0.0896)
Ln(Attention_total) × President_elect × Top5_leader			-0.115**	-1.429***
			(0.0567)	(0.425)
Ln(Attention_total) × Top5_leader			-0.0411*	-0.397***
			(0.0223)	(0.119)
President_elect × Top5_leader			0.0556	0.369
			(0.0804)	(0.490)
Top5_leader			0.0887	0.790
			(0.122)	(0.826)
Constant	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Politician Control	Yes	Yes	Yes	Yes
Other Attention Control	Yes	Yes	Yes	Yes
Observations	13,987	13,987	13,987	13,987
Adjusted R-squared	0.562	0.456	0.562	0.457

Panel B. Share of high-return trades

Dependent variable:	*%($high-return)*			
Specification:	Election window		Election window and leadership	
CAR horizon:	1 month	12 months	1 month	12 months
	(1)	(2)	(3)	(4)
Ln(Attention_total) ×	-0.529**	-0.284	-0.422**	-0.258
President_elect	(0.238)	(0.404)	(0.207)	(0.421)
Ln(Attention_total)	-0.384**	-0.127	-0.402**	0.0207
	(0.170)	(0.308)	(0.182)	(0.303)
President_elect	-0.576	0.538	-0.548	0.494
	(0.358)	(0.371)	(0.361)	(0.373)
Ln(Attention_total) ×			-3.392***	-2.636***
President_elect × Top5_leader			(0.997)	(0.995)
Ln(Attention_total) ×			0.187	-1.837***
Top5_leader			(0.209)	(0.367)
President_elect × Top5_leader			-0.183	1.194
			(1.229)	(2.066)
Top5_leader			1.454	1.316
			(1.606)	(1.705)
Constant	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Politician Control	Yes	Yes	Yes	Yes
Other Attention Control	Yes	Yes	Yes	Yes
Observations	13,987	13,987	13,987	13,987
Adjusted R-squared	0.136	0.118	0.136	0.119

Table C.6. Filing format of politicians' PTRs: complete-horizon results

This supplementary table reports the complete 1-, 2-, 3-, 6-, and 12-month CAR and high-return-trade results corresponding to Table 10, Panels B and C. Trade-volume rows remain in the main Table 10 and are not repeated here. The high-return definition is the main specification: signed CAR strictly above the pooled 80th percentile among all transactions with nonmissing CAR at the corresponding horizon. All samples, aggregation methods, columns, and tests follow Table 10. Only CARs are tested against zero in the standalone columns, with statistical significance reported by stars; for high-return measures, stars are reported only for differences.

Panel A. Across politician groups defined by PTR format (counterpart to Table 10, Panel B)

By PTR Format	*1. Electronic*		*2. Scanned*		*3. Both*		*Difference: Group 1 - 2*		*Difference: Group 1 - 3*	
	(1)		(2)		(3)		(4)		(5)	
	Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*
Transaction-level										
FF5 plus momentum cumulative abnormal return (CAR)										
CAR (1-month)	-0.0000	0.0002	-0.0003	0.0005	-0.0034***	-0.0009**	0.0002	-0.0002	0.0034***	0.0011***
CAR (2-month)	0.0001	-0.0001	-0.0002	0.0004	-0.0046***	-0.0022***	0.0003	-0.0005	0.0047***	0.0021**
CAR (3-month)	0.0001	0.0003	-0.0003	-0.0000	-0.0044**	-0.0008**	0.0004	0.0003	0.0045**	0.0011**
CAR (6-month)	0.0011	0.0014	-0.0010	0.0007	-0.0044*	-0.0019	0.0022	0.0006	0.0055**	0.0032**
CAR (12-month)	0.0052***	0.0045***	-0.0014	0.0005	-0.0106***	-0.0029*	0.0066***	0.0041**	0.0158***	0.0074***
High-return trade indicator										
1-month	0.2050	0.0000	0.1975	0.0000	0.1938	0.0000	0.0075**	0.0000**	0.0112**	0.0000**
2-month	0.2041	0.0000	0.1979	0.0000	0.1948	0.0000	0.0063**	0.0000**	0.0093*	0.0000*
3-month	0.2037	0.0000	0.1993	0.0000	0.1932	0.0000	0.0044	0.0000	0.0105**	0.0000**
6-month	0.1995	0.0000	0.2005	0.0000	0.1990	0.0000	-0.0010	0.0000	0.0004	0.0000
12-month	0.2009	0.0000	0.2013	0.0000	0.1952	0.0000	-0.0004	0.0000	0.0057	0.0000

Panel A (continued). Politician-level results

By PTR Format	*1. Electronic*		*2. Scanned*		*3. Both*		*Difference: Group 1 - 2*		*Difference: Group 1 - 3*	
	(1)		(2)		(3)		(4)		(5)	
	Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*
Politician-level										
FF5 plus momentum cumulative abnormal return (CAR)										
CAR (1-month)	-0.0026	-0.0001	0.0013	-0.0023	0.0003	-0.0011	-0.0039	0.0021	-0.0029	0.0009
CAR (2-month)	-0.0050	-0.0016	0.0097	0.0007	-0.0023	-0.0056	-0.0147	-0.0022	-0.0027	0.0041
CAR (3-month)	0.0001	-0.0008	-0.0016	-0.0007	-0.0061	-0.0017	0.0017	-0.0001	0.0062	0.0010
CAR (6-month)	0.0007	-0.0040*	0.0038	0.0022	-0.0241*	-0.0114***	-0.0031	-0.0062	0.0248	0.0073
CAR (12-month)	-0.0071	0.0002	0.0202	0.0056	-0.0294*	-0.0178**	-0.0273	-0.0055	0.0223	0.0180
% of trades that are high return										
1-month	21.95	18.20	18.92	15.96	19.36	18.12	3.03	2.25	2.59	0.08
2-month	19.62	18.12	22.64	18.82	17.69	17.14	-3.02	-0.71	1.93	0.97
3-month	20.47	17.85	22.44	17.97	19.34	18.92	-1.97	-0.13	1.14	-1.07
6-month	20.42	17.05	19.52	18.24	16.47	16.67	0.90	-1.19	3.95	0.38
12-month	19.44	16.72	22.90	19.23	17.37	16.54	-3.46	-2.51	2.07	0.18
% of trade dollars in high-return trades										
1-month	21.18	17.21	17.22	12.02	19.16	15.02	3.96	5.20*	2.02	2.19
2-month	18.04	15.52	20.25	14.07	18.65	13.86	-2.21	1.45	-0.61	1.66
3-month	18.79	15.49	20.38	15.72	17.53	14.45	-1.58	-0.23	1.26	1.04
6-month	19.22	15.23	18.32	14.44	16.18	13.13	0.90	0.79	3.03	2.10
12-month	17.94	15.09	21.42	17.71	15.94	12.46	-3.48	-2.62	2.00	2.63

Panel B. Following switches to scanned filings (counterpart to Table 10, Panel C)

	Electronic records			*Scanned records*			*Difference*	
	(1)			(2)			(3) *Electronic - Scanned*	
	Mean	*Median*	*Obs*	*Mean*	*Median*	*Obs*	*Mean*	*Median*
Transaction-level								
FF5 plus momentum cumulative abnormal return (CAR)								
CAR (1-month)	-0.0041*	-0.0014*	3,577	0.0063	0.0025	138	-0.0104	-0.0039
CAR (2-month)	-0.0046	-0.0015	3,567	0.0078	0.0039	138	-0.0125	-0.0054
CAR (3-month)	-0.0058*	-0.0036**	3,558	0.0101	0.0084	138	-0.0160	-0.0120*
CAR (6-month)	-0.0067	-0.0042*	3,539	0.0136	0.0173	137	-0.0203	-0.0215*
CAR (12-month)	-0.0152***	-0.0077**	3,496	0.0134	0.0382*	136	-0.0285	-0.0458**
High-return trade indicator								
1-month	0.2158	0.0000	3,577	0.1667	0.0000	138	0.0492	0.0000
2-month	0.2150	0.0000	3,567	0.1957	0.0000	138	0.0194	0.0000
3-month	0.2102	0.0000	3,558	0.1739	0.0000	138	0.0363	0.0000
6-month	0.2173	0.0000	3,539	0.1971	0.0000	137	0.0202	0.0000
12-month	0.2068	0.0000	3,496	0.1838	0.0000	136	0.0230	0.0000
Politician-level								
FF5 plus momentum cumulative abnormal return (CAR)								
CAR (1-month)	-0.0009	-0.0007	19	-0.0273	-0.0065	19	0.0247	0.0058
CAR (2-month)	-0.0112	0.0001	19	-0.0172	-0.0038	19	0.0034	0.0131
CAR (3-month)	-0.0148	-0.0053	19	-0.0237	-0.0004	19	0.0116	0.0078
CAR (6-month)	-0.0228	-0.0097	19	-0.0180	-0.0125	19	-0.0033	0.0027
CAR (12-month)	-0.0213	-0.0176	19	-0.0665	-0.0027	19	0.0719	0.0342
% of trades that are high return								
1-month	22.57	21.31	19	12.31	0.00	19	11.82***	11.72***
2-month	22.50	21.36	19	18.74	0.00	19	1.23	9.76
3-month	23.85	21.77	19	17.92	11.11	19	6.22	9.76
6-month	19.96	19.61	19	15.53	0.00	19	2.32	13.37
12-month	19.91	19.95	19	18.13	0.00	19	2.02	12.08
% of trade dollars in high-return trades								
1-month	23.41	19.24	19	9.96	0.00	19	13.53***	15.22***
2-month	23.80	17.91	19	18.42	0.00	19	3.67	12.78
3-month	25.05	19.60	19	15.49	2.76	19	8.94	10.63*
6-month	19.51	17.46	19	11.94	0.00	19	6.66	12.47
12-month	15.53	13.95	19	14.32	0.00	19	-0.89	6.10

Table C.7. Filing format of politicians' PTRs: alternative top-10% high-return trades
This supplementary table repeats the high-return-trade results corresponding to Table 10, Panels B and C, using an alternative top-10% definition. A high-return trade is one whose signed CAR is strictly above the pooled 90th percentile among all transactions with nonmissing CAR at the corresponding horizon. The table reports the complete 1-, 2-, 3-, 6-, and 12-month horizons. All samples, aggregation methods, columns, and tests otherwise follow Table 10; stars are reported only for between-group differences.

Panel A. Across politician groups defined by PTR format (counterpart to Table 10, Panel B)

Group by PTR Format	*1. Electronic*		*2. Scanned*		*3. Both*		*Difference: Group 1 - 2*		*Difference: Group 1 - 3*	
	(1)		(2)		(3)		(4)		(5)	
	Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*
Transaction-level										
High-return trade indicator										
1-month	0.1063	0.0000	0.0950	0.0000	0.1002	0.0000	0.0113***	0.0000***	0.0061*	0.0000*
2-month	0.1052	0.0000	0.0951	0.0000	0.1033	0.0000	0.0102***	0.0000***	0.0019	0.0000
3-month	0.1037	0.0000	0.0969	0.0000	0.1026	0.0000	0.0068***	0.0000***	0.0010	0.0000
6-month	0.1055	0.0000	0.0951	0.0000	0.1033	0.0000	0.0104***	0.0000***	0.0022	0.0000
12-month	0.1046	0.0000	0.0974	0.0000	0.1002	0.0000	0.0072***	0.0000***	0.0044	0.0000
Politician-level										
% of trades that are high return										
1-month	12.45	8.11	9.38	4.18	10.01	7.96	3.07	3.93**	2.44	0.15
2-month	10.75	7.83	9.69	5.66	9.66	8.43	1.06	2.17	1.09	-0.60
3-month	10.67	6.98	9.40	4.79	10.52	8.68	1.27	2.19*	0.15	-1.70
6-month	12.68	8.05	10.11	6.12	7.85	6.75	2.57	1.93	4.84*	1.31
12-month	11.30	7.18	10.11	7.21	9.20	8.10	1.19	-0.03	2.10	-0.92
% of trade dollars in high-return trades										
1-month	11.63	7.14	8.49	2.47	11.36	6.34	3.14	4.67**	0.27	0.81
2-month	9.66	5.55	8.61	4.59	10.88	6.58	1.05	0.96	-1.22	-1.03
3-month	9.49	5.39	8.04	1.98	8.99	6.20	1.45	3.41*	0.50	-0.81
6-month	11.96	5.79	8.71	3.06	6.28	3.42	3.25	2.73	5.67**	2.37
12-month	10.10	5.29	9.19	4.82	8.50	5.04	0.91	0.48	1.60	0.26

Panel B. Following switches to scanned filings (counterpart to Table 10, Panel C)

	Electronic records			*Scanned records*			*Difference*	
	(1)			(2)			(3) *Electronic - Scanned*	
	Mean	*Median*	*Obs*	*Mean*	*Median*	*Obs*	*Mean*	*Median*
Transaction-level								
High-return trade indicator								
1-month	0.1216	0.0000	3,577	0.1087	0.0000	138	0.0129	0.0000
2-month	0.1194	0.0000	3,567	0.1014	0.0000	138	0.0180	0.0000
3-month	0.1197	0.0000	3,558	0.1087	0.0000	138	0.0110	0.0000
6-month	0.1209	0.0000	3,539	0.0876	0.0000	137	0.0333	0.0000
12-month	0.1130	0.0000	3,496	0.0735	0.0000	136	0.0395	0.0000
Politician-level								
% of trades that are high return								
1-month	13.76	11.71	19	9.11	0.00	19	7.20	4.17*
2-month	13.49	10.00	19	11.33	0.00	19	0.02	4.08
3-month	11.43	11.11	19	14.49	0.00	19	-3.81	0.00
6-month	10.96	10.00	19	9.08	0.00	19	1.07	5.62
12-month	9.13	8.33	19	12.29	0.00	19	-1.51	0.00
% of trade dollars in high-return trades								
1-month	16.35	10.96	19	7.66	0.00	19	9.62*	5.11**
2-month	15.50	12.90	19	11.27	0.00	19	2.84	3.00
3-month	10.54	7.19	19	9.79	0.00	19	-1.27	0.24
6-month	9.14	8.08	19	9.13	0.00	19	-0.97	2.60
12-month	7.52	4.66	19	9.84	0.00	19	-3.00	0.00

Table C.8. Social media attention and trade volume: other measures of public attention
This table reports estimates examining how politician-specific Twitter attention relates to congressional trading volume after controlling for broader measures of public interest in a politician. *Ln(#trade_all)* and *Ln($trade_all)* are the logarithm of one plus the total number and total value of politicians' trades in Sample D, which includes all parsed transaction records. *Ln(#trade_stock)* and *Ln($trade_stock)* are constructed using "Public stock plus" trades in Sample G only. *Ln(Google_trends)* is the log of one plus monthly United States search interest for the politician, summed over the three months prior. *Ln(Wiki_views)* is the corresponding measure built from Wikipedia pageviews. Panel A adds Google Trends and Panel B adds Wikipedia pageviews. The Google Trends sample is smaller because search interest is not reported for every politician-month. All specifications include politician and year fixed effects. Definitions for all variables are provided in Appendix Table A.1. Standard errors are clustered at the politician level and reported in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Panel A. Google Trends search interest

Dependent variable:	*Trade volume*			
Outcome:	Ln(#trade_all)	Ln($trade_all)	Ln(#trade_stock)	Ln($trade_stock)
	(1)	(2)	(3)	(4)
Ln(Attention_total)	-0.0511**	-0.268***	-0.0457**	-0.237**
	(0.0208)	(0.0992)	(0.0204)	(0.0964)
Ln(Google_trends)	0.0428***	0.254***	0.0452***	0.274***
	(0.0130)	(0.0761)	(0.0116)	(0.0674)
Constant	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Politician Control	Yes	Yes	Yes	Yes
Other Attention Control	Yes	Yes	Yes	Yes
Observations	27,528	27,528	27,528	27,528
Adjusted R-squared	0.493	0.423	0.479	0.412

Panel B. Wikipedia pageviews

Dependent variable:	*Trade volume*			
Outcome:	Ln(#trade_all)	Ln($trade_all)	Ln(#trade_stock)	Ln($trade_stock)
	(1)	(2)	(3)	(4)
Ln(Attention_total)	-0.0484**	-0.250**	-0.0433**	-0.224**
	(0.0204)	(0.0981)	(0.0200)	(0.0951)
Ln(Wiki_views)	0.00306	0.0157	0.00189	0.00761
	(0.00314)	(0.0194)	(0.00259)	(0.0169)
Constant	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Politician Control	Yes	Yes	Yes	Yes
Other Attention Control	Yes	Yes	Yes	Yes
Observations	28,206	28,206	28,206	28,206
Adjusted R-squared	0.552	0.442	0.541	0.435