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CAPITAL IN THE CAPITOL:
CONGRESSIONAL TRADES RESEMBLE UNINFORMED RETAIL TRADING

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ABSTRACT

Do elected officials exploit informational advantages for personal financial gain? This question has attracted heightened attention amid increased scrutiny of congressional stock trading, particularly following the COVID-19 pandemic. Prior research finds little evidence that legislators outperform the market, but existing studies rely on limited time periods and offer limited insight into the mechanisms underlying trade timing. We revisit this question by constructing a novel dataset covering the stock trading activity of all U.S. members of Congress and their immediate families from 2012 to 2023. We find that, on average, legislators' portfolios underperform or, at best, match market benchmarks after the STOCK Act. What explains this mediocre performance? We show that legislators' positions track financial professionals' recommendations, and that their timing largely reflects prevailing market sentiment, estimated from retail investors' social media posts, rather than anticipating future price changes. Together, these results suggest that legislators' observable trading behavior is more consistent with public-signal-following than with systematically profitable use of private information.

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1 Introduction

Why would members of Congress dedicate much of their time and energy to raising millions of dollars for elections just to retain a job that pays $174,000 a year? One narrative suggests that legislators are rent-seeking, gaining financial benefits while in office (e.g., Eggers and Hainmueller 2009; Querubin and Snyder 2011). Following this logic, a popular perception is that corrupt insider trading is widespread among members of Congress, who leverage non-public information obtained through their public service to enrich themselves.[1]

Recently, stock trading by politicians has drawn renewed attention when several Senators were reported to have averted substantial short-term losses at the start of the COVID-19 pandemic. These politicians were accused of using intelligence from a closed Senate meeting about the COVID-19 outbreak to inform their stock transactions.[2] In the wake of this scandal, public scrutiny has shifted from whether members of Congress *beat the market* to whether their trades exhibit *suspicious timing* or reflect conflicts of interest.[3] The timing dimension is especially salient because it generates concrete narratives of corruption even when trades are ultimately unprofitable. For example, the wife of California Representative Alan Lowenthal sold Boeing shares in March 2020, one day before a House committee on which her husband sits released damaging findings on Boeing aircraft. Another example involves Florida Democrat Lois Frankel, who sold stock in First Republic Bank and bought shares in JPMorgan Chase a few weeks prior to the collapse and acquisition of the former in April 2023. Neither legislator made money on these trades.

[1] A recent survey found that Americans overwhelmingly (86%) support banning members of Congress from trading stock in individual companies. `https://publicconsultation.org/united-states/stock-trading-by-members-of-congress`.

[2] These senators, including Richard Burr, Dianne Feinstein, Jim Inhofe, Kelly Loeffler, and David Perdue, were not charged in subsequent investigations by the DOJ and the SEC. See `https://www.nytimes.com/2020/05/26/us/politics/senators-stock-trades-investigation.html`.

[3] On conflicts of interest, a New York Times analysis found that nearly half of the members of Congress who reported stock trades sat on Congressional committees that oversee the companies they traded. `https://www.nytimes.com/interactive/2022/09/13/us/politics/congress-stock-trading-investigation.html`. Regarding violations of the STOCK Act (i.e., breaking the 45-day financial disclosure rule), see `https://www.businessinsider.com/congress-stock-act-violations-senate-house-trading-2021-9`.

Despite frequent media reports and widespread public concern, several studies have concluded that members of Congress are only mediocre investors, investing similarly to average investors, during 2004–2008 (Eggers and Hainmueller 2013) and during 2012–2020 (Belmont et al. 2022). Previous literature, however, mostly evaluates whether politicians' aggregate portfolios outperform a benchmark over a particular sample window. This approach leaves two core issues unresolved. First, portfolio-level performance can mask abnormal returns from individual trades, including those plausibly linked to members' committee jurisdictions or other channels of access. Second, portfolio comparisons are largely silent on when members trade — precisely the dimensions that motivate public concern. An informed trade may be unprofitable yet still reflect unethical use of nonpublic information; conversely, a profitable or loss-avoiding trade need not be informed. In this paper, we address these gaps.

Using a novel dataset of congressional stock trading from 2012 to 2023, we begin by re-estimating buy-and-hold abnormal returns at the trade level across multiple horizons and a range of benchmarks (CRSP, industry-size, DGTW, Fama-French, Carhart four-factor), and we test for heterogeneity among legislators with greater potential access to information, including frequent traders, party leaders, and legislators trading in industries overseen by their committees. Across specifications, congressional trades do not generate abnormal profits; on average, legislators' portfolios underperform or at best match the market, industry, and factor-adjusted benchmarks, and the magnitudes are small.

We then revisit the puzzle of congressional stock trading by directly studying timing. We benchmark each buy-sell decision against professional market consensus measured in I/B/E/S, using both the level of analyst recommendations and recent recommendation revisions. Legislators trade in the direction of analyst consensus: moving the average recommendation one notch toward a more bearish consensus (e.g., from Buy to Hold) predicts a 4.7 percentage point lower probability that a trade is a purchase, and legislators tilt away from buying following recent downgrades. We also report robustness checks, including a lead–lag test and an event-study around revision weeks, and find little evidence that congressional trades predict future analyst revisions or systematically anticipate upgrades and downgrades. Taken together, the timing evidence is consistent with legislators' trades aligning with publicly observable professional signals.

Finally, we study timing against retail signals, using social-media-based measures of investor attention and sentiment. Using social media posts from StockTwits, we show that legislators tend to trade stocks that are already attracting elevated retail attention and experiencing rising posting activity in the weeks leading up to the trade, rather than trading ahead of attention cycles. In the trade week, StockTwits posting activity is about 2.6% higher than in the week before the trade, and attention declines in the weeks that follow. Using Twitter/X sentiment from Context Analytics (S-Score), we show that legislators' buy-sell decisions also track prevailing market mood: purchases are more common when sentiment is unusually bullish and less common when sentiment is unusually bearish. In specifications with legislator and date fixed effects, a one-unit increase in S-Score (one standard deviation relative to the stock's recent history) raises the probability that a trade is a purchase by 1.83 percentage points. With an unconditional purchase rate of 51.6%, this implies a shift from 51.6% to 53.4% for a one-standard-deviation increase in sentiment. For comparison, predicted purchase shares are about 48% when S-Score equals -2 and about 55% when S-Score equals $+2$. We find little evidence that congressional trades anticipate future price changes; instead, they align with publicly observable signals from both professionals and retail investors.

Beyond informing ongoing legislative efforts aimed at increasing transparency in Congressional trading, this research contributes to the growing literature on the interactions between financial markets and political elites (Benton and Philips 2020; Fowler 2006; Roberts 1990*b*). In finance, recent work studies how politicians' ideology maps into portfolio choice (Aiken, Ellis, and Kang 2020), how executives enter politics (Babenko, Fedaseyeu, and Zhang 2023), and how political polarization can shape stock-market outcomes during the COVID-19 pandemic (Sheng, Sun, and Wang 2024). Our evidence on trade-level returns and the timing of legislators' trades complements this work and connects to research that uses social media to measure market signals (Cookson et al. 2025; Cookson, Niessner, and Schiller 2026).

A vast body of literature studying the influence of money in American politics focuses on campaign contributions (e.g., Ansolabehere, de Figueiredo, and Snyder 2003; Fouirnaies and Hall 2018), lobbying (e.g., Payson 2020), firms' non-market strategies (Li and Disalvo 2023), and political connections (Goldman, Rocholl, and So 2008; Jayachandran 2006; Roberts 1990*a*). This paper speaks to a less-studied yet important conversation on the financial influence of politicians' behavior.

This research also resonates with a broad body of literature on accountability and political selection (Besley 2006; Caselli and Morelli 2004; Ferejohn 1986; Przeworski, Stokes, and Manin 1999). Politicians are expected to be "virtuous" while holding the public's trust.[4] As such, an agency problem arises when elected representatives use their political power to further their own special interests rather than those of the electorate. When the motivations of legislators are economic (Diermeier, Keane, and Merlo 2005) and institutions that ensure accountability (like the STOCK Act) fail to constrain their behavior, politicians can abuse their power and seek rents. This paper studies politicians' corruption and wealth accumulation by testing whether they receive direct financial benefits from their seats (Eggers and Hainmueller 2009; Querubin and Snyder 2011).

The results from this paper have implications beyond academia. The perception of Congressional insider trading has greatly impacted the investor community. As of March 2026, traders have invested at least $650 million in attempts to mimic the trades of members of Congress.[5] This strategy capitalizes on the presumption that Congressional insider trading exists and legislators gain excessive profits by choosing the right timing to trade using insider information. Our results question the very foundations of this strategy.

[4] Federalist No. 57.

[5] Autopilot, a fintech trading platform, has attracted at least $350 million to its famous Pelosi Tracker. Two ETFs, named after Nancy Pelosi (ticker: NANC) and the Republican Party (ticker: GOP), have raised more than $299 million (as of March 2026) to track Democrats' and Republicans' stock trades. See Appendix A.1 for a detailed discussion on the impact of Congressional trading on the financial market.

2 New Dataset on Congressional Trading

In response to growing concerns over these practices, the Stop Trading on Congressional Knowledge Act (STOCK Act) was passed in 2012. This bipartisan bill seeks to prevent members of Congress from using non-public information for personal investment gains by mandating the disclosure of any trades (by their own or their immediate family members) exceeding $1,000 within 45 days of the transaction. It allows us to collect the data from the self-reported Periodic Transaction Reports of senators and House members.

This novel dataset we compile covers all trades from 2012 to 2023, which contains the transaction date, name, unique identifier of the legislator, ownership, asset name, asset ticker, transaction position (buy or sell), and amount. Under the STOCK Act, members are only required to report the dollar range within which each asset falls, not the exact amount. We assume the transaction is valued at the lower bound of the reported brackets ($1,000, $15,000, $50,000, $100,000, and $250,000) they report.[6] We consolidate trades for the same elected official on the same date in the same security and filter our sample to include only transactions involving publicly listed securities and discard transactions of other securities, such as private bonds, mutual fund stakes, hedge fund stakes. Additionally, we use OpenSecrets' personal finances data to validate our data collection, as some of these extra sources track year-end personal finance data and capture trades not reported on time.[7] A detailed description of the data collection process can be found in Appendix A.2. Data on stock volume, price, and company information, and the Center for Research in Security Prices (CRSP) Value Weighted Index, are sourced from the Wharton Research Data Services (WRDS).[8]

Since 2012, a total of 334 members of Congress have reported trading stocks of 3,403 different public firms. Most trades fall under $15,000. Appendix A.3 provides further insights

[6] Alternatively, Milyo and Groseclose (1999) assume the value of each transaction follows an exponential distribution and impute the expected value as the midpoint value of each bracket. Alternative calculations of value do not alter our main conclusions.

[7] `https://www.opensecrets.org/personal-finances`.

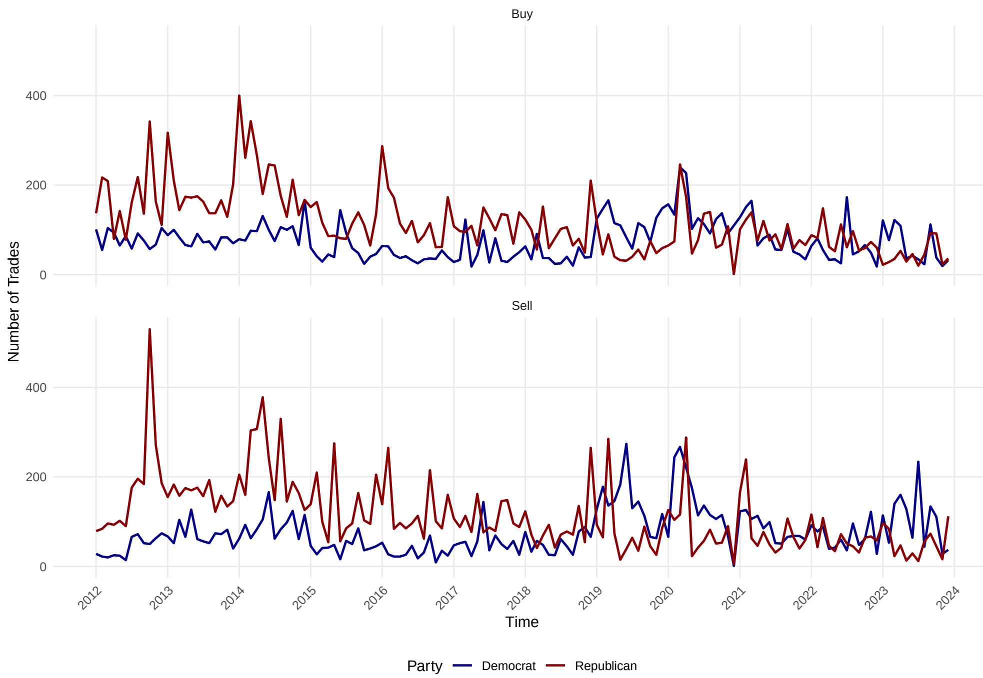
[8] `https://wrds-www.wharton.upenn.edu`.

into the characteristics and patterns of stock trading by members of Congress. One major takeaway we note is that the distribution of stock trades made by members of Congress is highly skewed. For instance, Rohit Khanna (Democrat, CA-17) alone executed 12,020 trades (approximately 16.9% of all trades), with 81% valued below $15,000. Michael McCaul (Republican, TX-10) made 4,482 trades at considerably higher stakes, with 28% exceeding $50,000. In contrast, 33 legislators reported only a single trade. This skewness suggests that analyses are sensitive to individual-level performance and that different weighting strategies may yield different results.[9] Figure 1 plots the monthly number of reported stock trades by members of Congress in our sample, separately for purchases (top panel) and sales (bottom panel). We exclude two outliers, Representatives Rohit Khanna and Michael McCaul, who account for a disproportionate share of trading activity.

Two patterns stand out. First, trading volume is highly episodic: month-to-month activity fluctuates substantially, ranging from fewer than 10 trades to nearly 1,000 trades in some months (or over 1,400 when including the two excluded outliers). Second, there is a pronounced partisan gap early in the sample: Republicans trade more frequently than Democrats prior to roughly 2019 in both purchases and sales, but this gap narrows markedly thereafter as the two series converge. Overall, trading remains pervasive throughout the period, indicating that disclosure requirements under the STOCK Act have not eliminated active trading by legislators. These descriptive patterns motivate our next analyses, which ask whether congressional trades are informed.

[9] See Eggers and Hainmueller (2013) for a discussion of weighting choices: (i) trade-equal (weight each trade equally) versus trade-value (weight by amount invested, thus giving more weight to larger-dollar trades), and (ii) member-equal (weight each legislator equally) versus aggregated (weight by portfolio size). In our analysis, the main results weight each trade equally. Consistent with Eggers and Hainmueller (2013), our conclusions do not depend on the weighting schemes.

Figure 1: **Trade Frequency Over Time.** Republicans consistently traded more frequently than Democrats prior to 2019, both in terms of purchases and sales. The partisan gap narrows considerably thereafter.



3 Legislators Do Not Beat the Market Since the STOCK Act

Do politicians leverage time-sensitive private information for personal financial gains? A first step to address this question is to compare the returns from legislators' portfolios with those of average investors (i.e., the market benchmark). We use buy-and-hold abnormal returns (BHARs), which measure the compound return a legislator earns on a specific trade relative to what a passive investor would have earned over the same holding period.[10] We remove independents and trades with missing positions in the analysis.

Table 1 reports "insider profits" for all Congressional trades across different benchmarks. The first row compares to the CRSP value-weighted market index (the broadest benchmark) and shows that, on average, trades slightly underperform the market across all horizons — for example, by 5 basis points (0.05%) over 10 trading days (half-month) and by 26

[10]BHARs are the standard approach in the finance literature for measuring abnormal performance around discrete events. See, for example, Barber and Lyon (1997).

Table 1: **Abnormal Returns of Congressional Trading**

	Half Month	One Month	Three Months	Six Months	One Year
All	-0.0005	-0.0010	-0.0015	-0.0038	-0.0026
	(0.0002)	(0.0003)	(0.0005)	(0.0009)	(0.0020)
All (Value Weighted)	0.0011	0.0024	0.0006	0.0024	0.0115
	(0.0007)	(0.0010)	(0.0017)	(0.0026)	(0.0047)
All (Industry-size)	-0.0004	-0.0004	-0.0001	0.0014	0.0026
	(0.0002)	(0.0002)	(0.0004)	(0.0006)	(0.0010)
All (Fama French)	-0.0005	-0.0010	-0.0016	-0.0035	-0.0029
	(0.0002)	(0.0003)	(0.0005)	(0.0008)	(0.0017)
Buy	-0.0015	-0.0018	-0.0022	-0.0048	-0.0069
	(0.0003)	(0.0004)	(0.0007)	(0.0011)	(0.0018)
Sell	0.0006	-0.0001	-0.0008	-0.0029	0.0019
	(0.0003)	(0.0005)	(0.0008)	(0.0013)	(0.0037)
House	-0.0006	-0.0009	-0.0014	-0.0033	-0.0021
	(0.0002)	(0.0003)	(0.0006)	(0.0010)	(0.0024)
Senate	0.0003	-0.0012	-0.0019	-0.0062	-0.0047
	(0.0005)	(0.0007)	(0.0013)	(0.0019)	(0.0030)
Democrat	-0.0009	-0.0011	-0.0007	-0.0049	-0.0098
	(0.0003)	(0.0005)	(0.0008)	(0.0013)	(0.0020)
Republican	-0.0001	-0.0009	-0.0023	-0.0028	0.0039
	(0.0003)	(0.0004)	(0.0007)	(0.0012)	(0.0034)
Frequent Trader	-0.0003	-0.0008	-0.0015	-0.0047	-0.0079
	(0.0002)	(0.0003)	(0.0006)	(0.0009)	(0.0014)
Leader	0.0001	0.0003	-0.0035	-0.0103	-0.0437
	(0.0024)	(0.0030)	(0.0055)	(0.0081)	(0.0128)
Committee Oversight	-0.0013	-0.0027	-0.0058	-0.0160	-0.0277
	(0.0007)	(0.0010)	(0.0017)	(0.0023)	(0.0037)

Note: Entries report mean abnormal returns with standard errors in parentheses. Returns are measured from the day of the trade over horizons of half-month, 1-month, 3-months, 6-months, and 12-months. The first row compares to the CRSP value-weighted benchmark. The Value Weighted row weights by trade amount. Industry-size compares to an industry benchmark that matches on 4-digit SIC and size quintile. The Fama French row reports abnormal returns using the Fama French model. Subgroups are defined by: Buy/Sell = trade position; House/Senate = chamber; Democrat/Republican = party; Frequent Trader = having $\geq$50 trades/year; Leader = party leaders (majority or minority); Committee Oversight = trades in industries matched to the legislator's committee(s) based on 4-digit SIC codes.

basis points (0.26%) over 255 trading days (one year). The second row weights trades by dollar value to test whether legislators allocate more capital to their most informed bets. It tells a different story: value-weighted returns are consistently positive, outperforming by 11 basis points at half a month and 115 basis points at one year, suggesting that larger trades tend to do better. A skeptic might argue that legislators invest in riskier sectors that naturally outperform the broad market. To address this concern, the third row compares returns to industry-size matched portfolios, which control for the possibility that legislators simply trade in sectors that happen to perform well, and finds results hovering close to zero. Alternatively, legislators might tilt toward small-cap stocks that carry known risk premia. The fourth row reports alphas from the Fama-French three-factor model, which adjusts for the betas on the market risk premium, size (SMB), and value (HML) factors. Again, it reports underperformance across all horizons, such as 10 basis points at one month. Our null result holds across the three equal-weighted benchmarks and across five time horizons. Even for the one specification that shows positive abnormal returns, value-weighting, the magnitude is modest: the largest point estimate implies an abnormal gain of roughly $115 per $10,000 invested over a year.[11] Appendix A.4 reports the full estimates from various weighting specifications and asset pricing models (CRSP, industry-size, Daniel–Grinblatt–Titman–Wermers (DGTW), Fama-French, Carhart four-factor). The estimates from these alternative models are substantively similar to those in Table 1.

Performance in subgroups helps assess whether the overall patterns hold universally. Rows 5 and 6 split trades by position, showing that sales generally fare better than purchases. Rows 7 and 8 divide by chamber, with Senate trades performing worse than House trades and losing 47 basis points at one year. Rows 9 and 10 compare parties, where Democratic trades underperform more clearly, falling short by 98 basis points at one year. The final three rows examine narrower groups with greater potential access to information. Fre-

[11] The positive value-weighted result should be interpreted cautiously: weighting by disclosed amount gives disproportionate influence to a small number of large trades and changes the estimand. Appendix A.4 reports results under member-equal weighting and excluding the two highest-volume traders; the null result is robust to both.

quent traders steadily lose value over time, party leaders see sharp declines exceeding four percentage points at one year, and trades tied to committee oversight also show consistent underperformance. If insider trading were prevailing and profitable, we would expect legislators who sit closest to material nonpublic information to enjoy the highest returns. The data show the opposite: party leaders underperform by 4.37 percentage points at one year (SE = 1.28), and committee-oversight trades underperform by 2.77 percentage points (SE = 0.37). The pattern is difficult to reconcile with the insider-trading hypothesis but consistent with a world in which political information is noisy, non-tradable, or already incorporated into prices by the time legislators act.

Appendix A.5 examines the relationship between politicians' characteristics and abnormal returns. We regress one-month buy-and-hold abnormal returns on factors plausibly linked to informational advantages (i.e., party leadership, seniority, and committee oversight) while controlling for party, chamber, and trade year. The results are consistent with political influence not translating into systematically higher trading profits. It is commonly argued that enforcement of the STOCK Act's 45-day disclosure requirement is minimal. In Appendix A.6, we examine the returns of trades that violate this rule. The evidence shows little statistically significant advantage from delaying reports.

4 Congressional Trade Timing and Public Information

The abnormal return evidence suggests that congressional trades do not systematically outperform, but realized performance is an imperfect diagnostic of informed trading: even informed investors need not earn ex post abnormal returns (e.g., Bhattacharya 2014; Lakonishok and Lee 2001). We therefore turn to a more direct test based on timing. Specifically, we examine whether legislators' buy-sell decisions appear unusual relative to publicly observable measures of market consensus, or instead correlate with information that is broadly available to market participants.

4.1 The Timing of Congressional Trades Largely Follows Financial Advisors

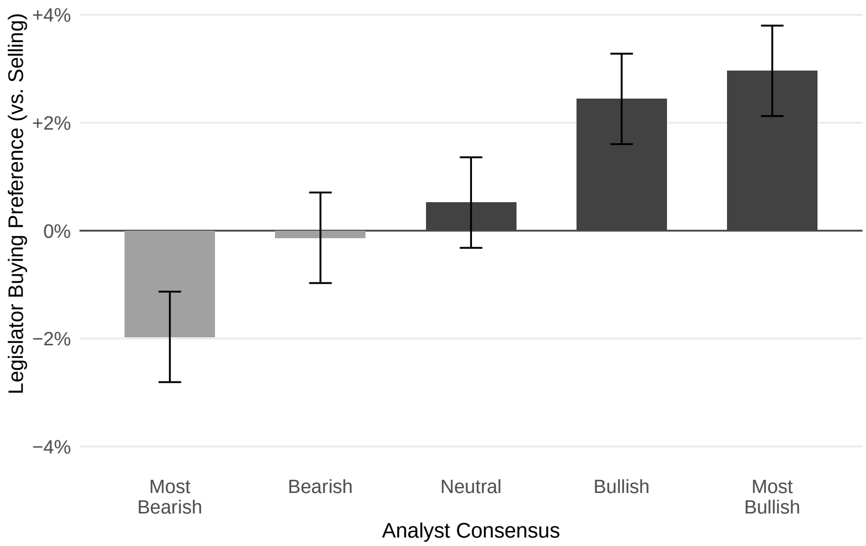
We ask whether congressional transactions appear "suspicious" in the sense of deviating from the information set available to ordinary market participants. We thereby propose a first test of whether legislators' transaction decisions reflect unusual timing by using professional analysts' recommendations as a proxy for market consensus. We measure analyst sentiment using I/B/E/S (Institutional Brokers' Estimate System), a commonly used commercial database in finance that records stock recommendations issued by sell-side analysts at brokerage firms. I/B/E/S maps brokerage-specific recommendation labels to a standardized five-point scale, where 1 = Strong Buy and 5 = Strong Sell, so lower values indicate a more bullish consensus.

We summarize analyst sentiment at the stock-month level using two measures: 1) *Avg Rec* is the average standardized recommendation across all analysts covering the stock in that month, and 2) *Buy Share* is the fraction of outstanding recommendations that are Buy or Strong Buy (ratings 1 or 2).[12] Then, to capture changes in professional opinion, we use analyst-level recommendation revisions: for each congressional trade, we count upgrades and downgrades for that stock over the 30 calendar days prior to the trade date. We then define *Upgrade* as an indicator equal to one when upgrades exceed downgrades, and *Downgrade* as an indicator equal to one when downgrades exceed upgrades (the omitted category is no net change, including ties).

Figure 2 examines whether legislators' buy-sell decisions align with the prevailing direction of professional analyst advice. We assign each congressional trade to a quintile based on the stock's Buy Share in the month of the trade, ranging from Most Bearish (lowest Buy Share) to Most Bullish (highest Buy Share). The vertical axis reports legislators' buying

[12]Because the consensus variables are aggregated at the monthly level, a trade early in the month may be matched with recommendations issued later that month. In practice, analyst consensus is highly persistent within months (the median stock receives fewer than one recommendation change per month), so this measurement choice has negligible impact on the estimates. The key results rely on the revision indicators (*Upgrade* and *Downgrade*), which use an exact 30-day trailing window and are not subject to this concern.

Figure 2: **Legislators' Positions and Professional Advice.** The figure plots legislators' buying preference against analyst consensus from I/B/E/S; error bars show 95% confidence intervals.



preference, defined as the share of congressional trades that are purchases minus 50 percentage points; positive values indicate that purchases are more common than sales within that quintile. The relationship is monotonic. In the most bearish quintile, legislators' buying preference is -1.97 percentage points (buy share = 48.03%). In the most bullish quintile, buying preference is $+2.96$ percentage points (buy share = 52.96%). The first three quintiles lie close to zero, while both the Bullish and Most Bullish quintiles show elevated buying preferences, indicating that legislators tilt toward purchases when the analyst consensus is bullish. If legislators systematically traded on material nonpublic information, there is no clear reason their trades should line up so closely with an easily observed, widely disseminated signal. Instead, Figure 2 is consistent with legislators trading in the direction of public analyst sentiment.

This simple comparison from Figure 2 warrants closer examination. Using trade-level information, we estimate the following linear probability model:

$$Buy_i = \beta_1 \times Upgrade_i + \beta_2 \times Downgrade_i + \Gamma \cdot \mathbf{X}_i + \alpha_j + \gamma_t + \epsilon_i \quad (1)$$

where Buy_i is an indicator variable that equals one if trade i is a purchase and zero if a sale. $Upgrade_i$ equals one if the net change in analyst recommendations over the 30 days before the trade is positive (more upgrades than downgrades), and $Downgrade_i$ equals one if the net change is negative. The specification also includes a vector of stock-level controls ($\mathbf{X}_i$) that are known to predict trading behavior — momentum (6-month stock return), log market capitalization, and log analyst coverage — as well as legislator fixed effects (α_j) to absorb time-invariant trader characteristics, and date fixed effects (γ_t) to absorb market-wide conditions on each trading day. We cluster the standard errors at the legislator level.

Table 2 reports trade-level linear probability models in which the outcome variable equals one for purchases and zero for sales. Column 1 begins with the simplest specification, regressing the buy indicator on the average analyst recommendation (*Avg Rec*). A one-unit increase in Avg Rec (roughly a one-notch shift in consensus recommendation, such as from Strong Buy to Buy) is associated with a 3.9 percentage point lower probability of buying (SE = 1.2). To absorb time-invariant differences across legislators, such as baseline trading propensity or risk tolerance, Column 2 adds legislator and date fixed effects. The estimate strengthens to 4.7 percentage points (SE = 0.7), suggesting that the relationship is not driven by compositional differences across traders or daily market-wide conditions. Given an outcome mean of 50.8% purchases, this magnitude implies that moving from a relatively bullish to a more bearish consensus is associated with a drop in the buy probability from about 50.8% to 46.1%.

The preceding analysis uses monthly consensus levels, which provide a useful descriptive benchmark but are measured with some timing imprecision (see the preceding footnote).

Table 2: **Legislators Follow Analyst Recommendations**

	Buy (=1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg Rec	-0.0392	-0.0468				
	(0.0121)	(0.0072)				
Upgrade			0.0173	0.0160	0.0185	0.0178
			(0.0088)	(0.0082)	(0.0069)	(0.0068)
Downgrade			-0.0318	-0.0337	-0.0325	-0.0342
			(0.0074)	(0.0066)	(0.0066)	(0.0064)
Momentum						-0.0271
						(0.0310)
Log(Market Cap)						-0.0087
						(0.0032)
Log(Analyst Coverage)						0.0183
						(0.0052)
Observations	68,163	68,163	68,163	68,163	68,163	68,163
Outcome Mean	0.508	0.508	0.508	0.508	0.508	0.508
Legislator FE	No	Yes	No	Yes	Yes	Yes
Date FE	No	Yes	No	No	Yes	Yes
Stock Controls	No	No	No	No	No	Yes

Note: Robust standard errors clustered by legislator in parentheses. The dependent variable equals one if the trade is a buy, zero if a sell. *Avg Rec* is the mean analyst recommendation (1=strong buy to 5=strong sell); lower values indicate more bullish consensus. *Upgrade* equals one if net analyst recommendation changes in the 30 days before the trade is positive (more upgrades than downgrades). *Downgrade* equals one if the net change is negative. Stock Controls include Momentum (6-month stock return), Log(Market Cap) (market capitalization), and Log(Analyst Coverage) (number of analysts covering the stock). Legislator FE controls for time-invariant legislator characteristics. Date FE absorbs market-wide conditions on each trading day.

We now turn to a sharper test using recommendation *revisions* measured over the exact 30-day window before each trade, which avoids the within-month timing concern. We focus on revisions in analyst sentiment in the 30 days prior to each trade. In specifications that include legislator and date fixed effects (Column 5), net upgrades increase the probability of buying by 1.85 percentage points (SE = 0.69), while net downgrades decrease it by 3.25 percentage points (SE = 0.66). Relative to the 50.8% baseline, these estimates correspond to buy probabilities of roughly 52.7% following net upgrades and 47.6% following net downgrades. Finally, to rule out the possibility that results are driven by stock characteristics that predict both analyst sentiment and trading, Column 6 adds controls for momentum, firm size, and analyst coverage. The results are stable (Upgrade = 1.78 pp, SE = 0.68; Downgrade = -3.42 pp, SE = 0.64). Across specifications, downgrades are associated with a larger shift in trade direction than upgrades.

Appendix A.7 reports a battery of robustness checks and alternative specifications, including subsamples of legislators with greater potential access to information, sensitivity to the recommendation window length, a lead–lag timing test that asks whether congressional trades predict future analyst revisions (as would be expected under a common information shock), and an event-study around analyst revision weeks that tests for anticipation by examining whether legislators systematically shift toward buys in the weeks before upgrades or toward sells in the weeks before downgrades. Together, these checks are consistent with the main results reflecting alignment between legislators' trades and observable analyst signals.

4.2 The Timing of Congressional Trades Largely Follows Market Sentiment Movements

Professional analysts provide one proxy for market consensus, but many stocks also enter the spotlight through retail attention and contemporaneous sentiment. We therefore examine whether legislators trade when a stock is already attracting unusual attention from the crowd, and whether their buy-sell decisions align with publicly observable sentiment.

We measure retail investor attention using StockTwits, a social media platform where users post short messages about stocks. Users tag stocks with "cashtags" (e.g., $AAPL), which directly link posts to specific tickers, and can optionally label posts as "Bullish" or "Bearish" (see Figure A.8.1). Our data, provided as in Li, Al Ansari, and Kaufman (2025), span May 2008 through January 2024 and include roughly 501 million posts. We focus on posts that mention at least one ticker, yielding 241 million message-ticker pairs across 25,700 unique symbols. For each post, we observe the timestamp, an anonymous user identifier, the ticker mentioned, and any sentiment tag; among tagged posts, 30% are bullish and 5% are bearish, with the remaining 65% unlabeled. We aggregate these messages to a ticker-week panel by counting all StockTwits mentions for each stock in each calendar week. We then identify weeks in which at least one legislator traded a given stock, yielding $53,738$ unique ticker-week trade events. The event-study sample includes all observations within five weeks before and after each trade for a total of $585,699$ ticker-week observations across $3,210$ stocks that appear in both datasets.

Using this data, we measure abnormal attention by comparing current posting activity to a stock's recent history. Following Da, Engelberg, and Gao (2011), for each ticker i in week w, we compute:

$$AVolume_{i,w} = \log(1 + Posts_{i,w}) - \log\left[Median(1 + Posts_{i,w-1}, \ldots, 1 + Posts_{i,w-8})\right]$$

This measure captures the current level of attention, $\log(1 + Posts_{i,w})$, relative to the logarithm of the median attention over the prior eight weeks. The median baseline is robust to transitory spikes in posting activity (e.g., viral posts or earnings weeks), and the log transformation yields a scale that is comparable across stocks.[13] A positive value indicates that the stock is receiving unusually high attention relative to its own recent history; for

[13]Table A.8.2 shows that the results are not sensitive to alternative choices for the baseline window used to compute abnormal attention.

example, a coefficient of 0.026 corresponds to roughly 2.6% higher posting activity relative to the baseline.

We then estimate an event-study regression:

$$AVolume = \sum_{\tau=-5,\,\tau\neq-1}^{5} \beta_\tau \, \mathbb{1}\{\tau_{i,w} = \tau\} + \gamma_w + \varepsilon_{i,w}$$

where $\mathbb{1}\{\cdot\}$ is an indicator function and $\tau_{i,w}$ denotes event time in weeks (the number of weeks between calendar week w and the congressional trade week for stock i). The coefficient β_{-1} is normalized to zero, so each β_τ measures abnormal attention at event time τ relative to the week before the trade. Calendar week fixed effects (γ_w) absorb market-wide variation in StockTwits activity. We cluster standard errors by ticker to account for serial correlation within stocks.

We also measure market sentiment using Context Analytics (formerly Social Market Analytics), which processes the Twitter/X firehose using proprietary natural language processing (NLP) algorithms. Context Analytics applies security-specific topic models to identify tweets about each stock, filters to accounts deemed credible by a reputation algorithm, and assigns each tweet a sentiment score on a -1 (bearish) to $+1$ (bullish) scale. The key metric, S-Score, aggregates tweet-level sentiment using an exponentially time-weighted sum over a 24-hour window and normalizes it relative to the stock's own 20-day historical baseline. The resulting S-Score is analogous to a z-score: values above $+1$ indicate sentiment is meaningfully more positive than the stock's recent history, while values below -1 indicate unusually negative sentiment. Our sample covers December 2011 through December 2023 and includes 5.6 million stock-day observations across 2,863 tickers. The S-Score ranges from -4.25 to $+4.25$ with a mean of 0.18 and a standard deviation of 1.3. Following Context Analytics' guidance, we require at least three tweets per stock-day for reliable sentiment estimates, yielding 2.7 million observations (49% of the sample).

Using these data, we test whether congressional trades respond to sentiment using the following linear probability model:

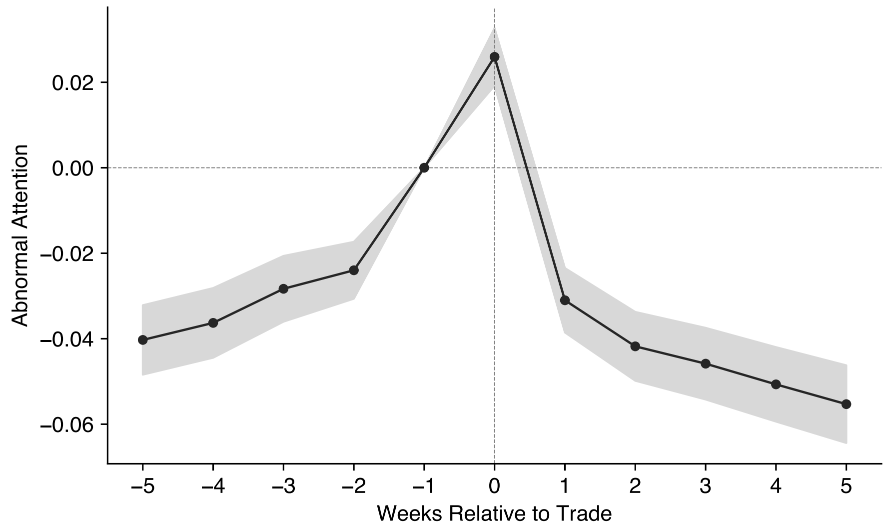
$$Buy_i = \beta_1 \times \text{S-Score}_i + \Gamma \cdot \mathbf{X}_i + \alpha_j + \gamma_t + \epsilon_i$$

where Buy_i is an indicator variable that equals one if trade i is a purchase and zero if a sale. The S-Score is benchmarked against each stock's 20-day historical sentiment, so a value of 1 indicates sentiment one standard deviation above the stock's recent average. We also include stock-level controls ($\mathbf{X}_i$) such as momentum, log market capitalization, and log tweet volume, and legislator fixed effects (α_j) and date fixed effects (γ_t).

Figure 3 provides graphical evidence that legislators trade stocks already attracting retail investor attention and that their buy-sell decisions track publicly observable sentiment. Figure 3a plots event-study estimates of abnormal StockTwits attention around congressional trade dates. The horizontal axis shows event time in weeks, where zero is the week a legislator executes a trade; the vertical axis shows estimated coefficients from a regression of abnormal attention on event-time indicators, with the week before the trade ($\tau = -1$) as the omitted reference period. Shaded bands represent 95% confidence intervals, with standard errors clustered by ticker. The figure reveals that legislators trade stocks already experiencing elevated, and rising, retail attention. During the trade week ($\tau = 0$), abnormal attention is 0.026 log points above the reference week (SE = 0.003), implying roughly 2.6% higher posting activity relative to the preceding week. More importantly, attention rises in the weeks leading up to the trade: coefficients increase from -0.040 at $\tau = -5$ toward zero by $\tau = -1$. After the trade, attention declines, with coefficients of -0.031 at $\tau = +1$ and -0.055 by $\tau = +5$. Taken together, the pattern indicates that legislators tend to trade near the peak of a retail attention cycle rather than preceding it. See Table A.8.1 for the full set of event-time coefficient estimates underlying this figure.

Figure 3: **Legislators Trade at Peak Attention and Follow Market Sentiment.**

(a) **Legislators Trade at Peak Attention.** The top panel plots event-study coefficients of abnormal StockTwits attention around congressional trade dates, with the week before the trade as the reference period; shaded bands show 95% confidence intervals.



(b) **Legislators Follow Market Sentiment.** The bottom panel plots the predicted probability of buying against Twitter sentiment (S-Score; a positive s-score indicates the market sentiment is more bullish), with an inverted histogram showing the distribution of trades; the dashed line marks 50%.

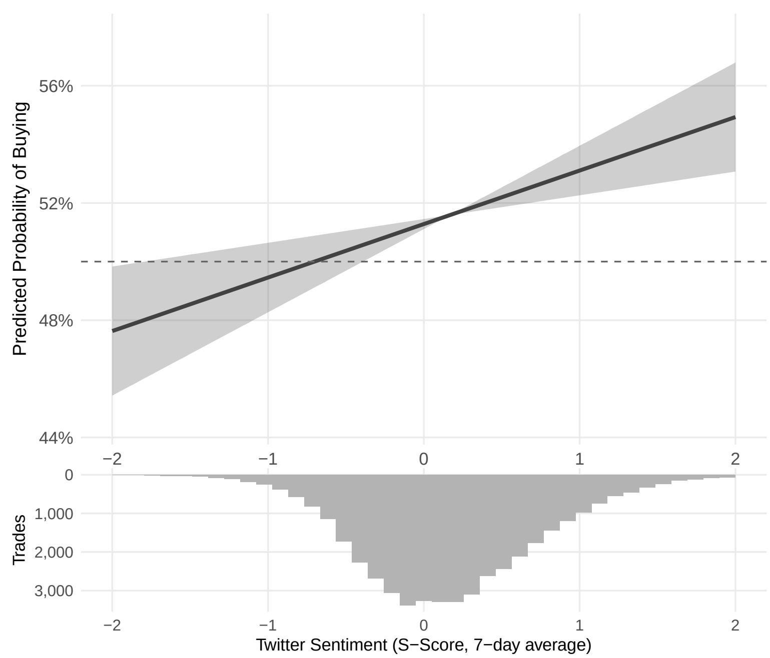


Figure 3b examines whether legislators' buy-sell decisions track market sentiment. We plot the predicted probability of buying against the Context Analytics S-Score. The solid line shows predicted probabilities from a regression of buy (=1) on S-Score with legislator and date fixed effects; the shaded band is the 95% confidence interval. Below the main plot, an inverted histogram displays the distribution of trades by S-Score, showing that most trades occur when sentiment is near its historical average. The relationship is positive and approximately linear. When S-Score equals -2 (two standard deviations more bearish than the stock's recent history), legislators buy about 48% of the time. When S-Score equals +2 (two standard deviations more bullish), they buy about 55% of the time. The dashed horizontal line at 50% marks the point of indifference between buying and selling; the regression line crosses this threshold near S-Score $= -1$, indicating that legislators are more likely to buy than sell even when sentiment is somewhat below its historical average, reflecting a slight baseline preference for buying. The pattern is consistent with legislators' buy-sell decisions tracking publicly available sentiment. If legislators possessed material nonpublic information that conflicted with prevailing sentiment, we would expect their trades to diverge from or anticipate reversals in market mood. We find no such divergence.

Table 3 reports the corresponding regression estimates of Figure 3b. The logic of this test parallels the analyst exercise: if legislators trade on private information, their decisions should be orthogonal to publicly observable sentiment. If instead they follow the crowd, their trades should align with prevailing market mood. Column 1 estimates the relationship between the continuous S-Score and the probability of buying without fixed effects. A one-unit increase in S-Score is associated with a 1.31 percentage point higher probability of buying (SE = 0.54). To account for the possibility that some legislators are inherently more inclined to buy and that market-wide conditions drive both sentiment and trading, Column 2 adds legislator and date fixed effects. The estimate increases to 1.83 percentage points (SE = 0.52). With an outcome mean of 51.6% purchases, this magnitude implies that a one-unit increase in sentiment is associated with an increase in the buy probability from about 51.6%

Table 3: **Legislators Follow Twitter Sentiment**

	Buy (=1)					
	(1)	(2)	(3)	(4)	(5)	(6)
S-Score	0.0131	0.0183				
	(0.0054)	(0.0052)				
High Sentiment			0.0164	0.0162	0.0282	0.0268
			(0.0122)	(0.0117)	(0.0108)	(0.0109)
Low Sentiment			-0.0301	-0.0261	-0.0291	-0.0331
			(0.0205)	(0.0218)	(0.0205)	(0.0192)
Momentum						-0.0114
						(0.0326)
Log(Market Cap)						-0.0052
						(0.0047)
Log(Tweet Volume)						-0.0019
						(0.0050)
Observations	45,386	45,386	45,386	45,386	45,386	45,386
Outcome Mean	0.516	0.516	0.516	0.516	0.516	0.516
Legislator FE	No	Yes	No	Yes	Yes	Yes
Date FE	No	Yes	No	No	Yes	Yes
Stock Controls	No	No	No	No	No	Yes

Note: Robust standard errors clustered by legislator in parentheses. The dependent variable equals one if the trade is a buy, zero if a sell. *S-Score* is the average normalized Twitter sentiment from Context Analytics over the 7 days before the trade, where positive values indicate bullish sentiment and negative values indicate bearish sentiment. *High Sentiment* equals one if S-Score > 1 (one standard deviation above the stock's historical mean). *Low Sentiment* equals one if S-Score < -1. Stock Controls include Momentum (6-month stock return), Log(Market Cap), and Log(Tweet Volume). Sample restricted to stock-days with at least 3 tweets per day on average.

to 53.4%; moving from moderately bearish sentiment (S-Score = -1) to moderately bullish sentiment (S-Score = +1) corresponds to an increase of about 3.7 percentage points.

Columns 3 through 6 use discrete sentiment indicators to test whether the relationship is concentrated at the extremes. In the preferred specification (Column 5), when S-Score exceeds 1 (unusually bullish), the probability of buying increases by 2.82 percentage points (SE = 1.08) in specifications with legislator and date fixed effects, which corresponds to an increase from 51.6% to about 54.4%. When S-Score is below -1 (unusually bearish), the point estimate suggests a decrease of 2.91 percentage points (SE = 2.05), though this estimate is imprecise and not statistically distinguishable from zero. The results are robust to adding stock controls in Column 6. Overall, the estimates in Figure 3 and Table 3 indicate that legislators trade stocks that are already salient to retail investors and that their buy-sell decisions move with recent public sentiment, consistent with trading that follows rather than anticipates shifts in market attention and mood. As a placebo test, Appendix A.8 shows that future sentiment does not predict current trade direction, while recent sentiment remains a significant predictor (Table A.8.4).

5 Why We Don't See Congressional Insider Trading

Our evidence is inconsistent with two straightforward stories: members are not reliably profiting on their trades (Section 3), and we find no evidence that they time trades ahead of market-moving information (Section 4). Why don't legislators use insider information to make financial decisions?

First, the simplest reason is deterrence. Insider trading by elected officials is now highly visible and politically costly: STOCK Act disclosure requirements and media trackers make concealment hard, while the reputational and electoral costs are steep. One possible loophole people raise is that politicians might use closed-door information to inform their long-term investment strategies, not just single transactions. Our results show little evidence that legislators hide insider trading by tilting their portfolios. The abnormal returns reported in Table 1 show no economically meaningful excess returns in either short (half-month) or longer (one-year) time windows, and Table A.3.1 shows that most transactions are small (\$1,000–\$15,000). The expected gain from insider trading is trivial relative to the career risk.

A second explanation is that much "inside" information is not tradable. A common narrative is that legislators obtain market-relevant information from hearings and policy briefings, but such information is noisy, contingent on legislative bottlenecks, and often diffuses through agencies, lobbyists, and industry. Legislators may possess more information than average investors through political connections — for example, Eggers and Hainmueller (2014) find that members of Congress get more profits from investing in local firms prior to the STOCK Act, which results from their familiarity with local business. But when we inspect their trades in recent years, these legislators trade disproportionately in large corporations and specific sectors (see the most traded securities in Table A.3.2), making inside information hard to convert into excess returns. To formally test the local information advantage, following Eggers and Hainmueller (2014), we confirm that legislators still overweight local and PAC-donating firms in their portfolios (see Figure A.9.1) after 2012, yet these connected trades earn no abnormal returns (see Table A.9.1). Taken together, these calculations explain why we do not see Congressional insider trading "on paper", and why our null findings are exactly what an office-seeking equilibrium would predict (Mayhew 1974).

6 Conclusion

Congressional insider trading is unethical in many ways. It incentivizes lawmakers to misappropriate information and manipulate the legislative process for personal gain (Bainbridge 2010). Recent legislative initiatives, such as the TRUST in Congress Act (which did not make it to the floor), aim to establish a firewall between Congress members' investment activities and the sensitive information they can access.[14] These legislative efforts come from the concern that the STOCK Act's disclosure requirements do not effectively prevent insider trading; rather, legislators do it more secretively. A more radical solution to curb insider trading on Capitol Hill and restore trust in government would be to prohibit members of Congress from engaging in any stock trading.

This paper addresses key questions central to the ongoing debate over Congressional insider trading. Using the most updated data, our results show that legislators' trades align with market consensus and slightly underperform or at best match the market. These findings do not imply that legislators' stockholdings are inconsequential for governance. Prior work shows that holdings influence roll-call votes (Grose 2013), the governmental contracts firms receive (Tahoun 2014), lobbying intensity (Ridge, Hill, and Ingram 2018), and market returns (Abdurakhmonov et al. 2023).

While the findings suggest that insider trading among Congress members is far from rampant, they do not rule out the possibility that some American politicians engage in rent-seeking financial activities, especially in less regulated areas. Future studies should examine legislators' performance on cryptocurrency and betting markets, as well as study the impact of congressional trades on financial markets.

[14] `https://www.congress.gov/bill/117th-congress/house-bill/336/text`.

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Online Appendix

Intended for online publication only.

Contents

A.1 Impacts of Congressional Insider Trading: Evidence from ETFs

The Subversive Unusual Whales Democratic ETF (NANC) and Subversive Unusual Whales Republican ETF (GOP) are two ETFs that trade by mimicking the financial decisions of U.S. legislators. They have gained increasing popularity and are reported to outperform the market.[15] By March 2026, the Total Assets Under Management (AUM) for NANC and GOP were $232.14 million and $67.42 million, respectively.

Table A.1.1 reports the top ten holdings of each ETF as of March 2026. NANC is heavily concentrated in mega-cap technology stocks: NVIDIA, Alphabet, Microsoft, Amazon, and Apple together account for over 31% of the portfolio. GOP is more diversified across sectors, with its largest position in Comfort Systems USA (7.35%), followed by JPMorgan Chase (4.38%) and Intel (3.48%). The two ETFs share only 18.72% overlap by weight across 40 common holdings, reflecting distinct portfolio strategies that mirror the different trading patterns of Democratic and Republican legislators.

Table A.1.1: **Top Ten Holdings of Congressional Trading ETFs**

GOP (Republican)			NANC (Democrat)		
Ticker	Company	Weight	Ticker	Company	Weight
FIX	Comfort Systems USA	7.35%	NVDA	NVIDIA	10.24%
JPM	JPMorgan Chase	4.38%	GOOG	Alphabet	6.01%
INTC	Intel	3.48%	MSFT	Microsoft	5.95%
IBIT	iShares Bitcoin Trust	3.14%	AMZN	Amazon	4.89%
NVDA	NVIDIA	3.09%	AAPL	Apple	4.23%
ANET	Arista Networks	2.62%	AMAT	Applied Materials	3.66%
T	AT&T	2.56%	NFLX	Netflix	3.44%
UTHR	United Therapeutics	2.45%	PM	Philip Morris Intl	3.19%
CVX	Chevron	2.13%	AXP	American Express	2.92%
FGXXX	First American Govt	2.05%	AORT	Artivion	2.90%

Note: Holdings as of March, 2026.

[15] `https://markets.businessinsider.com/news/etf/congress-democrats-stock-market-trades-nanc-etf-democrats-outperforms-sp500-2024-2`.

A.2 The STOCK Act and Data Collection

The STOCK Act requires members of Congress to disclose their own, spouse's and dependent children's financial transactions within 45 days of the trade date exceeding $1,000. We obtain financial transaction histories of Congress members from the Periodic Transaction Reports on the United States Senate Financial Disclosures website and the Office of the Clerk of the U.S. House of Representatives website.[16] These reports are available as electronic or paper filings in PDF format. Figure A.2.1 shows an example.

Figure A.2.1: **Example Periodic Transaction Report**

This Report Should Be Filed With:
Secretary of the Senate
Office of Public Records
Hart Building, Suite 232
Washington, DC 20510

PERIODIC [illegible] OF FINANCIAL TRANSACTIONS

(Time/Date)

Reporting Individual's Name	☐ Amendment	Senate Office / Agency in Which Employed	Page Number
Burr, Richard M.			1

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.

Identification of Assets		Transaction Type (x): Purchase	Sale	Exchange	Transaction Date (Mo., Day, Yr.)	Amount of Transaction (x): $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	Home Depot Inc. (stock) NYSE		X		8/30/12	X										
2	(S) Home Depot Inc. (stock) NYSE		X		8/30/12		X									
3																
4																
5																

Between January 2012 and December 2020, we hand-collected financial transactions made by senators and House members, recording the transaction date, security involved, nominal value for each trade, as reported in Belmont et al. (2022). These records cover all categories of securities, both public and private, including public equities, options, bonds, private bonds, mutual funds, and hedge funds. While we document all transactions involving publicly listed securities, we exclude those related to private or non-listed securities. We also incorporate stock transactions disclosed in Annual Financial Disclosure Reports that do not appear in the Periodic Transaction Reports. For trades from January 2021 to December 2023, we use web scraping and employ Optical Character Recognition (OCR) and Convolutional Neural Networks (CNNs) to extract entries from Periodic Transaction Reports.[17]

[16] https://efdsearch.senate.gov and https://disclosures-clerk.house.gov/FinancialDisclosure.
[17] We follow the practices in Smith (2007) and Schreiber et al. (2017).

A.3 Data Description

Table A.3.1 displays the summary statistics of our data.

Table A.3.1: **Summary Statistics for Congressional Stock Trades, 2012–2023**

	Overall	Democrats	Republicans
Position			
Buy	36,430 (51%)	17,791 (53%)	18,639 (50%)
Sell	34,903 (49%)	15,913 (47%)	18,990 (50%)
Value Range			
$1,000	52,667 (74%)	26,988 (80%)	25,679 (68%)
$15,000	11,918 (17%)	4,431 (13%)	7,487 (20%)
$50,000	3,012 (4%)	972 (3%)	2,040 (5%)
$100,000	2,268 (3%)	547 (2%)	1,721 (5%)
$250,000	826 (1%)	397 (1%)	429 (1%)
Unreported	642 (1%)	369 (1%)	273 (1%)
Chamber			
House	58,692 (82%)	29,324 (87%)	29,368 (78%)
Senate	12,612 (18%)	4,380 (13%)	8,232 (22%)
Tech Stock	14,817 (21%)	7,364 (22%)	7,453 (20%)
Firm Characteristics			
Book to Market	1.290	1.229	1.345
Price to Book	6.927	8.049	5.842
Price to Sales	4.856	5.754	3.979
Return on Equity	0.254	0.294	0.216
Dividend Yield	0.023	0.022	0.024
N	71,333	33,704	37,629

Note: Percentages are column percentages (within Overall, Democrats, or Republicans). We combine transactions from the same legislator on the same date and in the same security. The nominal value of each trade is reported in 11 overlapping buckets: 1) $1,001 to $15,000; 2) $15,001 to $50,000; 3) $50,001 to $100,000; 4) $100,001 to $250,000; 5) $250,001 to $500,000; 6) $500,001 to $1,000,000; 7) Over $1,000,000; 8) $1,000,001 to $5,000,000; 9) $5,000,001 to $25,000,000; 10) $25,000,001 to $50,000,000; and 11) Over $50,000,000. We then clean these values to five finer "Value Ranges": [$1,000-$15,000), [$15,000-$50,000), [$50,000-$100,000), [$100,000-$250,000), and $250,000 or more. Independent politicians are excluded. Tech stocks are defined using 3-digit SIC codes (283, 357, 367, and 737). Firm characteristics are reported as trade-level means based on the traded firm: Book-to-Market, Price-to-Book, and Price-to-Sales are standard accounting ratios; Return on Equity is net income over book equity; Dividend Yield is cash dividends over price.

We also report the top 15 most-traded tickers by Democrats and Republicans in Table A.3.2.

Table A.3.2: **Top 15 Assets Traded by Members of Congress, by Party**

Democrats			Republicans		
Ticker	Count	Asset Name	Ticker	Count	Asset Name
AAPL	437	Apple Inc.	AAPL	574	Apple Inc.
MSFT	389	Microsoft Corp.	MSFT	483	Microsoft Corp.
AMZN	238	Amazon.com Inc.	AMZN	281	Amazon.com Inc.
DIS	218	Walt Disney Co.	XOM	252	Exxon Mobil Corp.
GOOGL	210	Alphabet Inc.	PCLN	243	Priceline Group Inc.
VZ	205	Verizon Communications Inc.	JNJ	235	Johnson & Johnson
PG	195	Procter & Gamble Co.	GE	225	General Electric Co.
NVDA	189	NVIDIA Corp.	CVX	222	Chevron Corp.
T	188	AT&T Inc.	QCOM	217	Qualcomm Inc.
V	187	Visa Inc.	WFC	211	Wells Fargo & Co.
PFE	184	Pfizer Inc.	T	210	AT&T Inc.
JPM	181	JPMorgan Chase & Co.	JPM	200	JPMorgan Chase & Co.
HD	176	Home Depot Inc.	PG	194	Procter & Gamble Co.
KO	168	Coca-Cola Co.	SBUX	191	Starbucks Corp.
JNJ	163	Johnson & Johnson	INTC	190	Intel Corp.

Note: Table reports the top 15 most commonly traded assets by Democratic and Republican members of Congress.

A.4 Abnormal Returns Details

A.4.1 Abnormal Returns Using Alternative Weighting Strategy

Table A.4.1: **Abnormal Returns of Congressional Trading, Weighted by Value**

	Half Month	One Month	Three Months	Six Months	One Year
All	0.0011	0.0024	0.0006	0.0024	0.0115
	(0.0007)	(0.0010)	(0.0017)	(0.0026)	(0.0047)
Buy	0.0006	0.0031	0.0018	0.0051	0.0192
	(0.0010)	(0.0014)	(0.0022)	(0.0034)	(0.0054)
Sell	0.0014	0.0017	-0.0005	0.0000	0.0048
	(0.0010)	(0.0015)	(0.0024)	(0.0039)	(0.0076)
House	0.0009	0.0030	0.0012	0.0024	0.0081
	(0.0008)	(0.0011)	(0.0018)	(0.0029)	(0.0054)
Senate	0.0014	0.0002	-0.0012	0.0026	0.0220
	(0.0016)	(0.0021)	(0.0037)	(0.0059)	(0.0090)
Democrat	-0.0009	0.0015	-0.0034	-0.0056	-0.0009
	(0.0014)	(0.0019)	(0.0029)	(0.0047)	(0.0074)
Republican	0.0022	0.0029	0.0029	0.0070	0.0186
	(0.0008)	(0.0012)	(0.0020)	(0.0031)	(0.0060)
Frequent Trader	0.0002	0.0011	-0.0024	-0.0051	0.0022
	(0.0008)	(0.0011)	(0.0018)	(0.0028)	(0.0043)
Leader	0.0104	0.0162	0.0265	0.0519	0.0565
	(0.0063)	(0.0076)	(0.0134)	(0.0183)	(0.0340)
Committee Oversight	0.0024	-0.0021	-0.0063	-0.0139	-0.0312
	(0.0022)	(0.0026)	(0.0041)	(0.0061)	(0.0096)

Note: Entries report mean abnormal returns with standard errors in parentheses. Returns are measured from the day of the trade over horizons of half-month, 1-month, 3-months, 6-months, and 12-months while weighting trades by disclosed amount. The first row compares to the CRSP value-weighted benchmark. Subgroup rows are likewise value-weighted and defined as: Buy/Sell = trade position; House/Senate = chamber; Democrat/Republican = party; Frequent Trader = members with $\geq$50 trades/year; Leader = party leaders (majority or minority); Committee Oversight = trades in industries matched to the legislator's committee(s) based on 4-digit SIC codes.

A.4.2 Abnormal Returns Using Industry-size Benchmark

Table A.4.2: **Abnormal Returns of Congressional Trading (Industry-size Matched)**

	Half Month	One Month	Three Months	Six Months	One Year
All	-0.0004	-0.0004	-0.0001	0.0014	0.0026
	(0.0002)	(0.0002)	(0.0004)	(0.0006)	(0.0010)
Buy	-0.0007	-0.0004	0.0000	0.0016	0.0032
	(0.0002)	(0.0003)	(0.0006)	(0.0009)	(0.0013)
Sell	-0.0000	-0.0004	-0.0001	0.0012	0.0021
	(0.0003)	(0.0004)	(0.0006)	(0.0009)	(0.0014)
House	-0.0004	-0.0003	0.0003	0.0019	0.0027
	(0.0002)	(0.0003)	(0.0005)	(0.0007)	(0.0011)
Senate	-0.0002	-0.0007	-0.0017	-0.0010	0.0024
	(0.0004)	(0.0005)	(0.0010)	(0.0014)	(0.0023)
Democrat	-0.0005	0.0002	0.0022	0.0040	0.0081
	(0.0003)	(0.0004)	(0.0007)	(0.0010)	(0.0016)
Republican	-0.0003	-0.0010	-0.0021	-0.0009	-0.0023
	(0.0002)	(0.0003)	(0.0005)	(0.0008)	(0.0012)
Frequent Trader	-0.0004	-0.0003	-0.0002	0.0007	0.0010
	(0.0002)	(0.0003)	(0.0005)	(0.0007)	(0.0010)
Leader	0.0007	-0.0019	-0.0016	0.0004	-0.0033
	(0.0018)	(0.0023)	(0.0044)	(0.0062)	(0.0096)
Committee Oversight	-0.0002	-0.0006	-0.0001	-0.0007	0.0004
	(0.0005)	(0.0007)	(0.0014)	(0.0017)	(0.0027)

Note: Entries report mean abnormal returns with standard errors in parentheses. Returns are measured from the day of the trade over half-month, 1-month, 3-month, 6-month, and 12-month horizons and are benchmarked to portfolios matched by 4-digit SIC and size quintile. Subgroups: Buy/Sell = trade position; House/Senate = chamber; Democrat/Republican = party; Frequent Trader = members with ≥50 trades per year; Leader = party leaders (majority or minority); Committee Oversight = trades in industries matched to the legislator's committee(s) based on 4-digit SIC codes.

A.4.3 Abnormal Returns Using DGTW Benchmark

Table A.4.3: **Abnormal Returns of Congressional Trading (DGTW)**

	Half Month	One Month	Three Months	Six Months	One Year
All	-0.0001	0.0002	0.0014	0.0055	0.0184
	(0.0002)	(0.0003)	(0.0005)	(0.0008)	(0.0020)
Buy	-0.0007	-0.0005	0.0008	0.0040	0.0131
	(0.0003)	(0.0004)	(0.0007)	(0.0011)	(0.0017)
Sell	0.0007	0.0009	0.0021	0.0071	0.0240
	(0.0003)	(0.0004)	(0.0008)	(0.0012)	(0.0036)
House	-0.0002	0.0002	0.0020	0.0065	0.0203
	(0.0002)	(0.0003)	(0.0006)	(0.0009)	(0.0023)
Senate	0.0006	-0.0000	-0.0012	0.0012	0.0098
	(0.0005)	(0.0007)	(0.0012)	(0.0018)	(0.0029)
Democrat	-0.0002	0.0006	0.0034	0.0072	0.0168
	(0.0003)	(0.0005)	(0.0008)	(0.0012)	(0.0019)
Republican	0.0001	-0.0002	-0.0003	0.0040	0.0199
	(0.0003)	(0.0004)	(0.0007)	(0.0011)	(0.0033)
Frequent Trader	0.0001	0.0004	0.0012	0.0045	0.0129
	(0.0002)	(0.0003)	(0.0006)	(0.0009)	(0.0013)
Leader	0.0010	-0.0023	-0.0052	-0.0041	-0.0255
	(0.0023)	(0.0029)	(0.0052)	(0.0076)	(0.0120)
Committee Oversight	-0.0008	-0.0021	-0.0036	-0.0061	-0.0058
	(0.0007)	(0.0009)	(0.0016)	(0.0021)	(0.0034)

Note: Entries report mean abnormal returns with standard errors in parentheses. Returns are measured from the day of the trade over horizons of half-month, 1-month, 3-months, 6-months, and 12-months. This table uses the DGTW (Daniel–Grinblatt–Titman–Wermers) benchmark, which is commonly used to measure the performance of institutional investors. Subgroups: Buy/Sell = trade position; House/Senate = chamber; Democrat/Republican = party; Frequent Trader = having ≥50 trades/year; Leader = party leaders (majority or minority); Committee Oversight = trades in industries matched to the legislator's committee(s) based on 4-digit SIC codes.

A.4.4 Abnormal Returns Using Factor Models

Following conventions in financial studies, we also compute buy-and-hold abnormal returns using factor-model expected returns from Fama and French (1993)'s three-factor model and Carhart (1997)'s four-factor model. The factor models are:

$$\begin{aligned} R_{it} - R_t^F &= \alpha + \beta_1(R_t^M - R_t^F) + \beta_2 SMB_t + \beta_3 HML_t + \epsilon_{it} \\ R_{it} - R_t^F &= \alpha + \beta_1(R_t^M - R_t^F) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \epsilon_{it} \end{aligned} \tag{1}$$

Here R_{it} is the return of the portfolio of member i at time t, R_t^F is the risk-free rate at time t, and R_t^M is the return of the market benchmark at time t. As for factors, SMB_t is the average return on small minus big portfolios (size effect), HML_t is the average return on high minus low portfolios (value effect), and MOM_t is the momentum. For each trade, we estimate the factor loadings over a pre-trade estimation window, compute the expected return for each holding period using the estimated betas, and report the cumulative buy-and-hold abnormal return (the difference between the realized return and the factor-model expected return) in the tables below.

Table A.4.4: **Abnormal Returns of Congressional Trading (Fama French)**

	Half Month	One Month	Three Months	Six Months	One Year
All	-0.0005	-0.0010	-0.0016	-0.0035	-0.0029
	(0.0002)	(0.0003)	(0.0005)	(0.0008)	(0.0017)
Buy	-0.0015	-0.0018	-0.0022	-0.0042	-0.0063
	(0.0003)	(0.0004)	(0.0007)	(0.0011)	(0.0015)
Sell	0.0006	-0.0002	-0.0010	-0.0028	0.0007
	(0.0003)	(0.0005)	(0.0008)	(0.0012)	(0.0031)
House	-0.0006	-0.0010	-0.0015	-0.0032	-0.0023
	(0.0002)	(0.0003)	(0.0006)	(0.0009)	(0.0020)
Senate	0.0002	-0.0014	-0.0019	-0.0053	-0.0054
	(0.0005)	(0.0007)	(0.0013)	(0.0017)	(0.0025)
Democrat	-0.0008	-0.0011	-0.0008	-0.0047	-0.0089
	(0.0003)	(0.0005)	(0.0008)	(0.0012)	(0.0017)
Republican	-0.0001	-0.0010	-0.0023	-0.0025	0.0025
	(0.0003)	(0.0004)	(0.0007)	(0.0011)	(0.0028)
Frequent Trader	-0.0003	-0.0008	-0.0016	-0.0043	-0.0071
	(0.0002)	(0.0003)	(0.0006)	(0.0008)	(0.0012)
Leader	-0.0003	0.0001	-0.0035	-0.0104	-0.0389
	(0.0024)	(0.0029)	(0.0052)	(0.0073)	(0.0106)
Committee Oversight	-0.0013	-0.0027	-0.0059	-0.0151	-0.0251
	(0.0007)	(0.0010)	(0.0017)	(0.0021)	(0.0031)

Note: Entries report mean abnormal returns with standard errors in parentheses. Returns are measured from the day of the trade over horizons of half-month, 1-month, 3-months, 6-months, and 12-months. This table uses the Fama French factor model. Subgroups: Buy/Sell = trade position; House/Senate = chamber; Democrat/Republican = party; Frequent Trader = having $\geq$50 trades/year; Leader = party leaders (majority or minority); Committee Oversight = trades in industries matched to the legislator's committee(s) based on 4-digit SIC codes.

Table A.4.5: **Abnormal Returns of Congressional Trading (Carhart)**

	Half Month	One Month	Three Months	Six Months	One Year
All	-0.0016	-0.0032	-0.0061	-0.0014	0.0526
	(0.0002)	(0.0003)	(0.0006)	(0.0012)	(0.0052)
Buy	-0.0028	-0.0044	-0.0088	-0.0065	0.0331
	(0.0003)	(0.0004)	(0.0008)	(0.0015)	(0.0033)
Sell	-0.0003	-0.0019	-0.0033	0.0040	0.0729
	(0.0003)	(0.0005)	(0.0009)	(0.0019)	(0.0102)
House	-0.0019	-0.0035	-0.0069	-0.0027	0.0518
	(0.0002)	(0.0004)	(0.0007)	(0.0014)	(0.0062)
Senate	-0.0001	-0.0017	-0.0023	0.0047	0.0562
	(0.0005)	(0.0008)	(0.0015)	(0.0025)	(0.0059)
Democrat	-0.0019	-0.0035	-0.0069	-0.0067	0.0297
	(0.0003)	(0.0005)	(0.0009)	(0.0016)	(0.0032)
Republican	-0.0013	-0.0029	-0.0054	0.0034	0.0732
	(0.0003)	(0.0004)	(0.0008)	(0.0018)	(0.0095)
Frequent Trader	-0.0015	-0.0033	-0.0070	-0.0043	0.0342
	(0.0002)	(0.0004)	(0.0007)	(0.0012)	(0.0025)
Leader	-0.0019	-0.0016	-0.0079	-0.0023	0.0165
	(0.0025)	(0.0034)	(0.0067)	(0.0120)	(0.0242)
Committee Oversight	-0.0020	-0.0045	-0.0070	-0.0079	0.0103
	(0.0007)	(0.0010)	(0.0018)	(0.0028)	(0.0055)

Note: Entries report mean abnormal returns with standard errors in parentheses. Returns are measured from the day of the trade over horizons of half-month, 1-month, 3-months, 6-months, and 12-months. This table uses the Carhart four-factor model (Fama French factors plus momentum). Subgroups: Buy/Sell = trade position; House/Senate = chamber; Democrat/Republican = party; Frequent Trader = having $\geq$50 trades/year; Leader = party leaders (majority or minority); Committee Oversight = trades in industries matched to the legislator's committee(s) based on 4-digit SIC codes.

A.4.5 Abnormal Returns: Member-Equal Weights and Excluding Top Traders

Table A.4.6: **Abnormal Returns: Member-Equal Weights and Excluding Top Traders**

	Half Month	One Month	Three Months	Six Months	One Year
Panel A: Member-Equal Weighted					
CRSP Benchmark	0.0008	-0.0036	-0.0036	-0.0032	-0.0018
	(0.0015)	(0.0021)	(0.0032)	(0.0079)	(0.0134)
Industry-size	-0.0004	-0.0052	-0.0003	0.0072	0.0125
	(0.0010)	(0.0035)	(0.0036)	(0.0066)	(0.0080)
Fama French	0.0008	-0.0037	-0.0037	-0.0034	-0.0029
	(0.0015)	(0.0021)	(0.0031)	(0.0069)	(0.0111)
Panel B: Excluding Khanna and McCaul					
CRSP Benchmark	-0.0004	-0.0009	-0.0012	-0.0032	0.0011
	(0.0003)	(0.0004)	(0.0006)	(0.0010)	(0.0025)
Industry-size	-0.0003	-0.0001	0.0001	0.0011	0.0020
	(0.0002)	(0.0003)	(0.0005)	(0.0007)	(0.0011)
Fama French	-0.0004	-0.0010	-0.0014	-0.0031	-0.0007
	(0.0003)	(0.0004)	(0.0006)	(0.0009)	(0.0021)

Note: Panel A reports member-equal weighted abnormal returns: we first average BHARs within each legislator and then compute the mean and standard error across legislators (N = number of legislators). Panel B excludes the two highest-volume traders, Representatives Rohit Khanna and Michael McCaul. Standard errors in parentheses.

A.4.6 Abnormal Returns During the COVID-19 Pandemic

Table A.4.7: **Abnormal Returns of Congressional Trading, during COVID-19**

	Half Month	One Month	Three Months	Six Months	One Year
All	-0.0005	-0.0025	0.0088	0.0201	0.0744
	(0.0013)	(0.0018)	(0.0034)	(0.0054)	(0.0077)
All (Weighted)	0.0047	0.0060	0.0234	0.0654	0.1104
	(0.0034)	(0.0048)	(0.0091)	(0.0154)	(0.0205)
Buy	-0.0046	-0.0061	0.0014	0.0135	0.0751
	(0.0017)	(0.0024)	(0.0045)	(0.0077)	(0.0110)
Sell	0.0037	0.0011	0.0164	0.0268	0.0736
	(0.0019)	(0.0027)	(0.0050)	(0.0076)	(0.0107)
House	-0.0017	-0.0021	0.0119	0.0305	0.0804
	(0.0014)	(0.0020)	(0.0038)	(0.0064)	(0.0088)
Senate	0.0041	-0.0043	-0.0034	-0.0209	0.0506
	(0.0028)	(0.0042)	(0.0074)	(0.0091)	(0.0157)
Democrat	0.0026	0.0062	0.0238	0.0311	0.0863
	(0.0016)	(0.0024)	(0.0045)	(0.0072)	(0.0106)
Republican	-0.0050	-0.0151	-0.0128	0.0042	0.0571
	(0.0020)	(0.0028)	(0.0050)	(0.0081)	(0.0110)
Frequent Trader	0.0000	-0.0022	0.0110	0.0200	0.0819
	(0.0014)	(0.0020)	(0.0037)	(0.0057)	(0.0087)
Leader	-0.0097	-0.0110	0.0272	0.0405	0.1003
	(0.0107)	(0.0110)	(0.0249)	(0.0360)	(0.0501)

Note: Entries report mean abnormal returns with standard errors in parentheses, restricted to trades during the COVID-19 period (January 1, 2020 to December 11, 2020). Returns are measured from the day of the trade over horizons of half-month, 1-month, 3-months, 6-months, and 12-months. The first row compares to the CRSP value-weighted benchmark. The Value Weighted row weights by trade amount. Subgroups: Buy/Sell = trade position; House/Senate = chamber; Democrat/Republican = party; Frequent Trader = having ≥50 trades/year; Leader = party leaders (majority or minority).

A.5 Abnormal Returns and Politicians' Characteristics

In Table A.5.1, we regress one-month buy-and-hold abnormal returns (relative to the CRSP value-weighted benchmark) on legislator characteristics to test whether any observable traits predict trading performance. Column 1 reports the baseline estimate for party affiliation. Republicans earn 0.1 percentage points higher abnormal returns than Democrats (SE = 0.08). Columns 2–7 progressively add controls for party *leadership*, *seniority*, *committee oversight* (an indicator for trades in industries likely overseen by the legislator's committee(s)), and chamber and year fixed effects. Party leaders earn 0.14–0.19 percentage points more than backbenchers (SE = 0.18), while this difference is small and not statistically significant. In our fullest specification (Column 7), committee-oversight trades earn -0.2 percentage points lower abnormal returns (SE = 0.07). The pattern is inconsistent with legislators exploiting committee-specific information; instead, it suggests that even trades with the greatest potential for informed trading generate no abnormal returns.

Table A.5.1: **Unpacking the Relationship Between Abnormal Returns and Politicians' Characteristics**

	One-month Abnormal Return						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Republican	0.0011	0.0013	0.0011	0.0013	0.0011	0.0014	0.0011
	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0010)
Leader		0.0015	0.0014	0.0014	0.0014	0.0014	0.0019
		(0.0018)	(0.0018)	(0.0018)	(0.0019)	(0.0019)	(0.0018)
Senior			0.0003	0.0004	0.0003	0.0004	0.0002
			(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Committee Oversight					-0.0019	-0.0018	-0.0019
					(0.0008)	(0.0008)	(0.0007)
N	61,370	61,370	61,370	61,370	61,370	61,370	61,370
Chamber FEs		✓		✓		✓	✓
Year FEs							✓

Note: Standard errors clustered by legislator are reported in parentheses. The outcome variable is the one-month buy-and-hold abnormal return relative to the CRSP value-weighted benchmark. Observations with Cook's Distance greater than $4/n$ are excluded. Leader is an indicator for whether the member is a majority or minority party leader. Senior equals one if the member's tenure is above the median. Committee Oversight equals one for trades in industries matched to the legislator's committee(s) based on 4-digit SIC codes. Chamber FEs and Year FEs denote the inclusion of chamber and year fixed effects, respectively.

Table A.5.2 lists the ten best- and worst-timed traders by mean one-year buy-and-hold abnormal returns (relative to the CRSP value-weighted benchmark), among the members with at least 10 trades in our sample. The extreme outlier is Rep. Austin Scott (R-GA). His extreme negative mean is driven by 15 Plug Power sells between February and September 2013, when the stock traded between $0.12 and $0.57 per share. Plug Power then rallied to $10.31 by March 2014. These poorly timed sells of a single penny stock dominate his average; excluding Plug Power, his mean adjusted BHAR falls near zero.

Table A.5.2: **Top and Bottom Ten Legislators by One-Year Abnormal Returns**

Name	Party	Buys	Sells	Mean BHAR
Panel A: Best-Timed Traders				
Bryan Steil	R	0	14	0.2161
Richard Blumenthal	D	12	37	0.1883
John Ricketts	R	0	23	0.1648
David Rouzer	R	9	10	0.1508
Michael Gallagher	R	0	37	0.1481
Steve Stivers	R	1	22	0.1384
Daniel Crenshaw	R	8	8	0.1322
Joseph Hollingsworth	R	62	10	0.1320
Mark Green	R	191	96	0.1183
Daniel Sullivan	R	19	70	0.1058
Panel B: Worst-Timed Traders				
Austin Scott	R	41	89	-3.0748
Daniel Meuser	R	0	12	-0.4230
Lloyd Smucker	R	0	22	-0.3004
Kimberly Schrier	D	2	32	-0.2002
Shri Thanedar	D	0	16	-0.1981
Ted Cruz	R	8	4	-0.1758
Cory Booker	D	0	12	-0.1752
John Duncan	R	0	11	-0.1604
Roger Williams	R	7	6	-0.1377
Beto O'Rourke	D	6	5	-0.1292

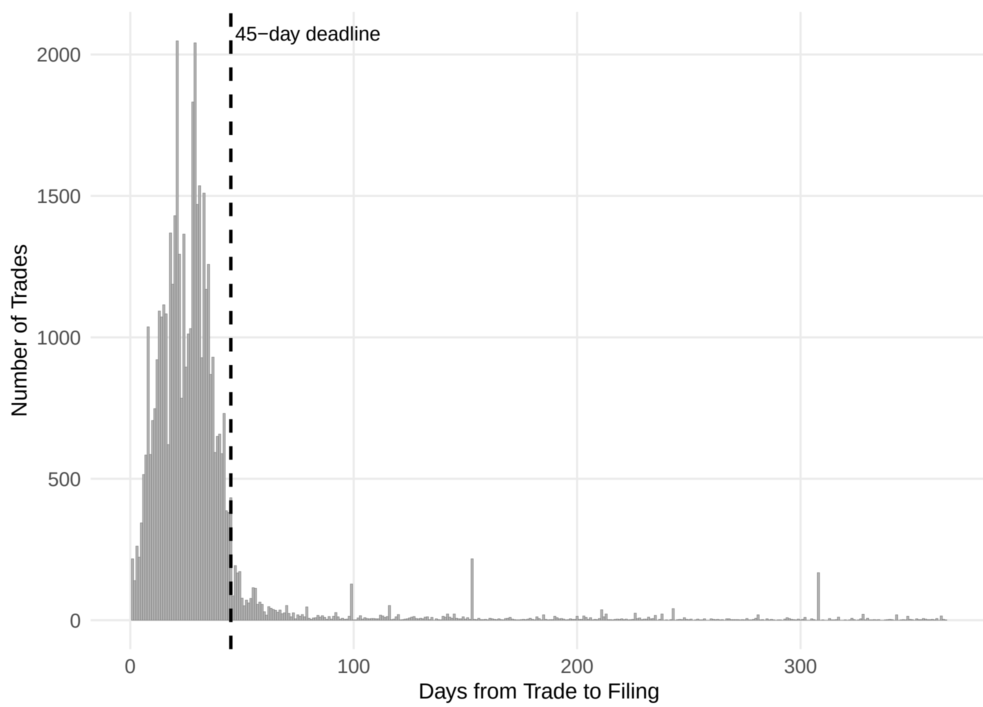
Note: Table reports the ten legislators with the highest and lowest mean one-year buy-and-hold abnormal returns relative to the CRSP value-weighted benchmark, among legislators with at least 10 trades. Following the insider trading literature, BHARs for sell trades are negated so that positive values indicate good timing for both purchases and sales.

A.6 When Legislators Break the 45-day Disclosure Rule

Although the STOCK Act mandates that trades must be reported within 45 days, enforcement of this disclosure requirement is currently minimal.[18] Might legislators exploit this legal loophole by delaying the reporting of actual insider trades?

Figure A.6.1 first plots the distribution of filing gaps (mean = 33.1 days) for all congressional trades filed within one year. The distribution is right-skewed, with the majority of trades filed before the 45-day deadline but a substantial tail of late filings extending beyond 100 days.

Figure A.6.1: **Filing Gaps**



[18] https://www.businessinsider.com/congress-stock-act-violations-penalties-consequences-2021-12.

Figure A.6.2 examines whether trades disclosed more than 45 days after the trade yield systematically higher abnormal returns compared to trades disclosed on time. Each point shows the mean BHAR with 95% confidence intervals. The horizontal dashed line at zero marks the benchmark of no abnormal returns. Neither on-time nor late filers earn statistically significant abnormal returns, with both confidence intervals spanning zero. If legislators possessed private information, we might expect late filers to earn higher returns. Instead, the figure shows no meaningful difference between the two groups, providing no evidence that delayed disclosure is associated with informed trading.

Figure A.6.2: **Abnormal Returns by Disclosure Days**

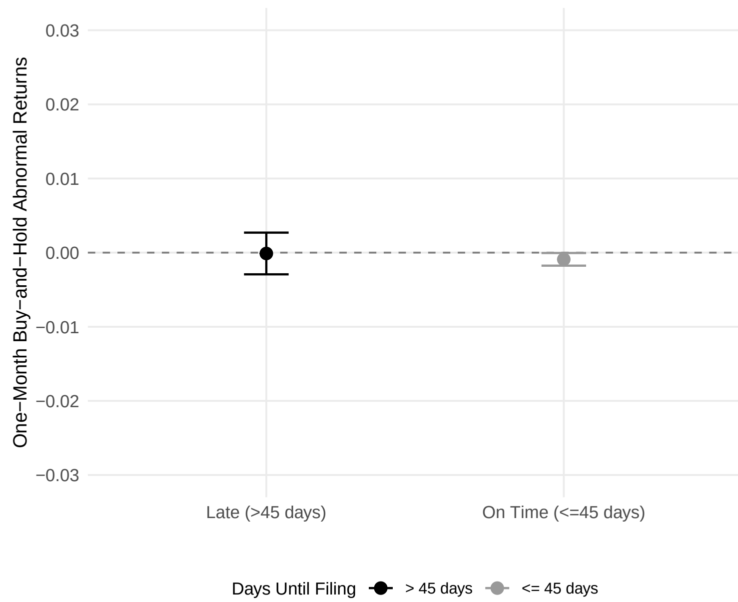
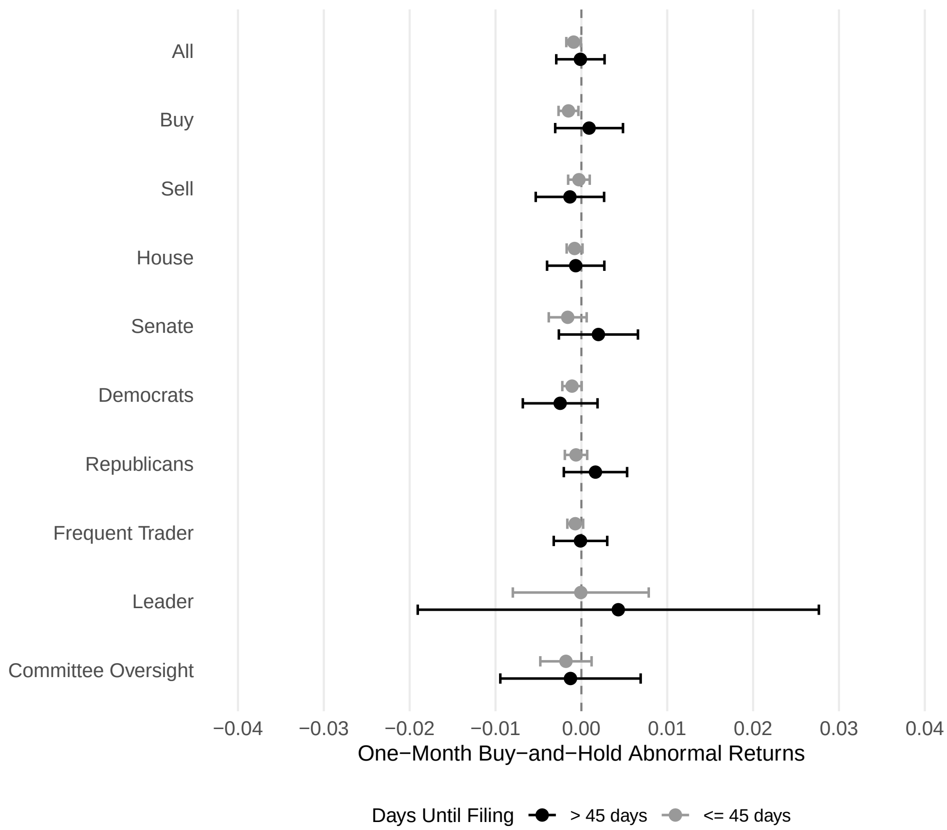


Figure A.6.3 extends the comparison in Figure A.6.2 to several subgroups: purchases, sales, by House members, by senators, by democrats, by republicans, by frequent traders, by party leaders, and legislators who trade in industries their committee(s) might oversee. For each subgroup, we plot mean one-month BHAR separately for on-time filers (gray) and late filers (black), with 95% confidence intervals. The vertical dashed line at zero marks the benchmark. Across all subgroups, confidence intervals for both on-time and late filers overlap with zero and with each other. The pattern is consistent across chambers, parties, trade directions, and even among legislators with potential access to private information. This reinforces the conclusion that filing delays are not associated with superior trading performance.

Figure A.6.3: **Abnormal Returns by Disclosure Days**



A.7 Legislators' Trades Follow Analysts' Recommendations

A.7.1 Legislators Who Have More Information

Table A.7.1: **Legislators Follow Analysts: Frequent Traders**

	Buy (=1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg Rec	-0.0472	-0.0530				
	(0.0145)	(0.0090)				
Upgrade			0.0264	0.0193	0.0195	0.0203
			(0.0133)	(0.0121)	(0.0092)	(0.0092)
Downgrade			-0.0389	-0.0429	-0.0452	-0.0457
			(0.0116)	(0.0102)	(0.0103)	(0.0095)
Momentum						-0.0533
						(0.0411)
Log(Market Cap)						-0.0136
						(0.0027)
Log(Analyst Coverage)						0.0175
						(0.0080)
Observations	38,452	38,452	38,452	38,452	38,452	38,452
Outcome Mean	0.516	0.516	0.516	0.516	0.516	0.516
Legislator FE	No	Yes	No	Yes	Yes	Yes
Date FE	No	Yes	No	No	Yes	Yes
Stock Controls	No	No	No	No	No	Yes

Note: Robust standard errors clustered by legislator in parentheses. The dependent variable equals one if the trade is a buy, zero if a sell. *Avg Rec* is the mean analyst recommendation (1=strong buy to 5=strong sell). *Upgrade* equals one if net analyst recommendation changes in the 30 days before the trade is positive. *Downgrade* equals one if the net change is negative. Stock Controls include Momentum (6-month stock return), Log(Market Cap) (market capitalization), and Log(Analyst Coverage) (number of analysts covering the stock). Legislator FE controls for time-invariant legislator characteristics. Date FE absorbs market-wide conditions on each trading day. Sample restricted to frequent traders (having $\geq$50 trades per year).

Table A.7.2: **Legislators Follow Analysts: Legislative Leaders**

	Buy (=1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg Rec	-0.0494	-0.1501				
	(0.0698)	(0.1687)				
Upgrade			-0.0107	-0.0060	0.0314	0.0369
			(0.0659)	(0.0346)	(0.0835)	(0.0815)
Downgrade			0.0085	0.0281	-0.0386	-0.0350
			(0.0617)	(0.0552)	(0.1134)	(0.1115)
Momentum						0.1071
						(0.1462)
Log(Market Cap)						0.0028
						(0.0160)
Log(Analyst Coverage)						-0.0034
						(0.0209)
Observations	545	545	545	545	545	545
Outcome Mean	0.473	0.473	0.473	0.473	0.473	0.473
Legislator FE	No	Yes	No	Yes	Yes	Yes
Date FE	No	Yes	No	No	Yes	Yes
Stock Controls	No	No	No	No	No	Yes

Note: Robust standard errors clustered by legislator in parentheses. The dependent variable equals one if the trade is a buy, zero if a sell. *Avg Rec* is the mean analyst recommendation (1=strong buy to 5=strong sell). *Upgrade* equals one if net analyst recommendation changes in the 30 days before the trade is positive. *Downgrade* equals one if the net change is negative. Stock Controls include Momentum (6-month stock return), Log(Market Cap) (market capitalization), and Log(Analyst Coverage) (number of analysts covering the stock). Legislator FE controls for time-invariant legislator characteristics. Date FE absorbs market-wide conditions on each trading day. Sample restricted to party leaders (majority or minority).

Table A.7.3: **Legislators Follow Analysts: Committee Sector Match**

	Buy (=1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg Rec	-0.0778	-0.0701				
	(0.0279)	(0.0212)				
Upgrade			0.0193	0.0070	0.0545	0.0573
			(0.0241)	(0.0236)	(0.0231)	(0.0242)
Downgrade			-0.0300	-0.0315	-0.0407	-0.0394
			(0.0243)	(0.0236)	(0.0261)	(0.0260)
Momentum						-0.0203
						(0.0798)
Log(Market Cap)						0.0022
						(0.0110)
Log(Analyst Coverage)						-0.0161
						(0.0207)
Observations	5,028	5,028	5,028	5,028	5,028	5,028
Outcome Mean	0.479	0.479	0.479	0.479	0.479	0.479
Legislator FE	No	Yes	No	Yes	Yes	Yes
Date FE	No	Yes	No	No	Yes	Yes
Stock Controls	No	No	No	No	No	Yes

Note: Robust standard errors clustered by legislator in parentheses. The dependent variable equals one if the trade is a buy, zero if a sell. *Avg Rec* is the mean analyst recommendation (1=strong buy to 5=strong sell). *Upgrade* equals one if net analyst recommendation changes in the 30 days before the trade is positive. *Downgrade* equals one if the net change is negative. Stock Controls include Momentum (6-month stock return), Log(Market Cap) (market capitalization), and Log(Analyst Coverage) (number of analysts covering the stock). Legislator FE controls for time-invariant legislator characteristics. Date FE absorbs market-wide conditions on each trading day. Sample restricted to trades where the legislator sits on a committee matched to the firm's industry based on 4-digit SIC codes.

A.7.2 Additional Robustness Checks

Table A.7.4: **Legislators Follow Analysts: 60-Day Window**

	Buy (=1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg Rec	-0.0392	-0.0468				
	(0.0121)	(0.0072)				
Upgrade			0.0207	0.0182	0.0206	0.0201
			(0.0066)	(0.0067)	(0.0052)	(0.0045)
Downgrade			-0.0269	-0.0294	-0.0250	-0.0265
			(0.0086)	(0.0073)	(0.0073)	(0.0067)
Momentum						-0.0285
						(0.0309)
Log(Market Cap)						-0.0086
						(0.0032)
Log(Analyst Coverage)						0.0176
						(0.0054)
Observations	68,163	68,163	68,163	68,163	68,163	68,163
Outcome Mean	0.508	0.508	0.508	0.508	0.508	0.508
Legislator FE	No	Yes	No	Yes	Yes	Yes
Date FE	No	Yes	No	No	Yes	Yes
Stock Controls	No	No	No	No	No	Yes

Note: Robust standard errors clustered by legislator in parentheses. The dependent variable equals one if the trade is a buy, zero if a sell. *Avg Rec* is the mean analyst recommendation (1=strong buy to 5=strong sell). *Upgrade* equals one if net analyst recommendation changes in the 60 days before the trade is positive. *Downgrade* equals one if the net change is negative. Stock Controls include Momentum (6-month stock return), Log(Market Cap) (market capitalization), and Log(Analyst Coverage) (number of analysts covering the stock). Legislator FE controls for time-invariant legislator characteristics. Date FE absorbs market-wide conditions on each trading day.

A remaining identification concern is whether the correlation between analyst recommendations and trades reflects legislators *following* analysts, or whether both respond to the same underlying information shock. If the latter, we would expect trades to predict future analyst changes as well as past ones. We address this concern using a lead-lag test. While lead upgrades are insignificant across all specifications, the lead downgrade coefficient is marginally significant (Column 4: -0.0125, SE $= 0.0059$), suggesting that legislators may be slightly less likely to buy stocks that will subsequently be downgraded. However, this coefficient is substantially smaller than the lagged downgrade effect (-0.0338), and the weekly event study (Figure A.7.1) shows no systematic pre-trend in trade direction before analyst revisions.

Table A.7.5: **Legislators Follow Analysts: Timing Test**

	Buy (=1)			
	(1)	(2)	(3)	(4)
Upgrade	0.0185		0.0188	0.0179
	(0.0069)		(0.0070)	(0.0068)
Downgrade	-0.0325		-0.0319	-0.0338
	(0.0066)		(0.0065)	(0.0063)
Upgrade (Lead)		-0.0024	-0.0029	-0.0039
		(0.0054)	(0.0055)	(0.0054)
Downgrade (Lead)		-0.0123	-0.0110	-0.0125
		(0.0060)	(0.0059)	(0.0059)
Momentum				-0.0276
				(0.0311)
Log(Market Cap)				-0.0087
				(0.0032)
Log(Analyst Coverage)				0.0196
				(0.0052)
Observations	68,163	68,163	68,163	68,163
Outcome Mean	0.508	0.508	0.508	0.508
Legislator FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Stock Controls	No	No	No	Yes

Note: Robust standard errors clustered by legislator in parentheses. This table tests the timing of the relationship between analyst recommendations and legislator trades. *Upgrade* and *Downgrade* measure net recommendation changes in the 30 days *before* the trade. *Upgrade (Lead)* and *Downgrade (Lead)* measure changes in the 30 days *after* the trade. Stock Controls include Momentum (6-month stock return), Log(Market Cap) (market capitalization), and Log(Analyst Coverage) (number of analysts covering the stock). If legislators follow analysts, lagged variables should predict trades while lead variables should not. The lead upgrade coefficients are insignificant; the lead downgrade coefficient is marginally significant but substantially smaller than the lagged effect, suggesting legislators primarily respond to past analyst signals.

We complement the lead-lag test with an event-study design centered on analyst revision weeks. For each congressional trade, we link the trade to the closest analyst upgrade (or downgrade) week within a ± 4 week window, and then trace buy-sell decisions in the weeks leading up to and following that revision week. Consistent with no anticipatory trading, the estimates show no systematic shift toward buying in the weeks before upgrades or toward selling in the weeks before downgrades.

Figure A.7.1: **Congressional Trades Around Analyst Revisions**

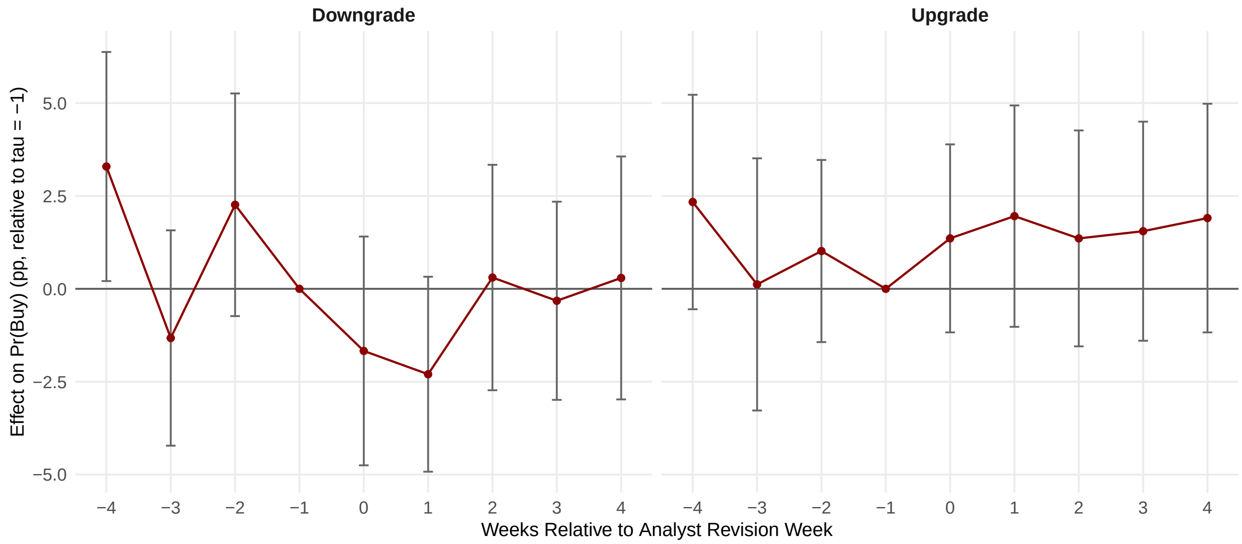
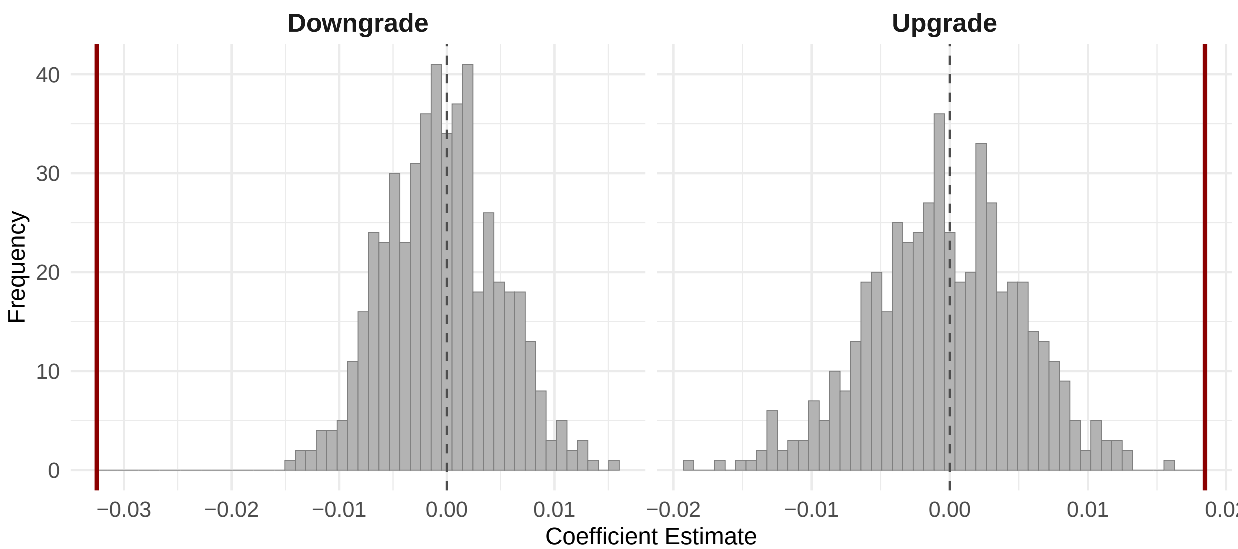


Figure A.7.2 presents a permutation-based placebo test for our main analyst recommendation results. We construct a three-level categorical variable (Upgrade, Downgrade, or None) to preserve the mutually exclusive structure of the indicators, then randomly permute this category within trading days to preserve time-varying frequencies. We repeat this procedure 500 times, re-estimating our preferred specification (with legislator and date fixed effects) for each permutation. The figure shows histograms of the resulting placebo coefficients, with vertical dark red lines marking the actual estimates from Table 2 (Upgrade = 1.85 pp; Downgrade = −3.25 pp) and dashed vertical lines at zero. The actual estimates lie far in the tails of the placebo distributions, confirming that the relationship between analyst recommendations and legislator trades is unlikely to arise by chance.

Figure A.7.2: **Placebo Tests**



Note: Histograms show distribution of coefficients from 500 permutations.
Vertical dark red lines show actual estimates.

A.8 Legislators' Trades Follow Market Sentiments

A.8.1 StockTwits Attention

Figure A.8.1 presents example tweets from StockTwits on SanDisk Corp ($SNDK). It is the largest social media platform for traders and investors, with over 10 million registered users.

Figure A.8.1: **Example StockTwits Posts**

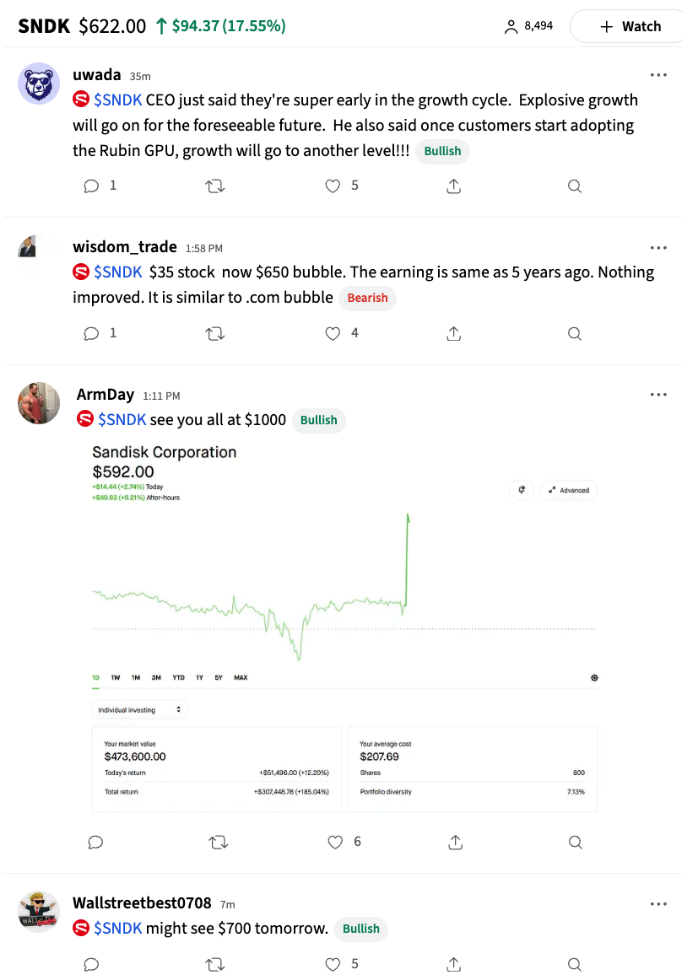


Table A.8.1 tests whether the attention spike at $\tau = 0$ survives alternative specifications. The baseline estimate (Column 1) is 0.026 (SE = 0.003). We consider two potential concerns. First, attention may be serially correlated: if a stock attracted attention last week, it likely attracts attention this week. The spike at $\tau = 0$ could simply reflect momentum rather than a discrete event. Column 2 addresses this by controlling for lagged attention. The coefficient falls to 0.020 (SE = 0.004)—smaller, but still positive and significant. The attention spike is not just a continuation of prior trends; it represents an incremental jump during the trade week. Second, legislators may systematically trade high-profile stocks that always receive more attention. Column 3 adds stock fixed effects, which absorb permanent differences across tickers. The estimate remains 0.026, unchanged from the baseline. This rules out the concern that results are driven by selection into attention-grabbing stocks. Column 4 combines both controls; the estimate is 0.020 (SE = 0.004).

Table A.8.1: **Event-Study Estimates: Abnormal Attention Around Trade Dates**

	(1)	(2)	(3)	(4)
$\tau = -2$	−0.024	−0.023	−0.024	−0.023
	(0.003)	(0.004)	(0.003)	(0.004)
$\tau = 0$	0.026	0.020	0.026	0.020
	(0.003)	(0.004)	(0.003)	(0.004)
$\tau = +1$	−0.031	−0.044	−0.031	−0.044
	(0.004)	(0.004)	(0.004)	(0.004)
$\tau = +2$	−0.042	−0.040	−0.042	−0.040
	(0.004)	(0.004)	(0.004)	(0.004)
Lagged $AVolume_{i,w-1}$		0.261		0.251
		(0.005)		(0.005)
Observations	585,699	585,699	585,699	585,699
Ticker-week events	53,738	53,738	53,738	53,738
Unique tickers	3,210	3,210	3,210	3,210
Outcome mean	0.054	0.054	0.054	0.054
Week FE	Yes	Yes	Yes	Yes
Ticker FE	No	No	Yes	Yes

Note: Robust standard errors clustered by ticker in parentheses. The dependent variable $AVolume_{i,w}$ is abnormal StockTwits attention for stock i in week w, defined as log posting activity minus log median posting activity over the prior eight weeks. τ denotes event time in weeks relative to the trade date, with $\tau = -1$ (one week before the trade) as the omitted reference period; $\tau = 0$ is the trade week. Lagged $AVolume_{i,w-1}$ controls for persistence in attention. Week FE absorbs market-wide variation in StockTwits activity. Ticker FE absorbs time-invariant stock-level differences in attention.

Table A.8.2 asks whether results depend on how we define “recent.” The main specification uses an 8-week window; here we compare 4-week, 8-week, and 12-week alternatives. The results are stable.

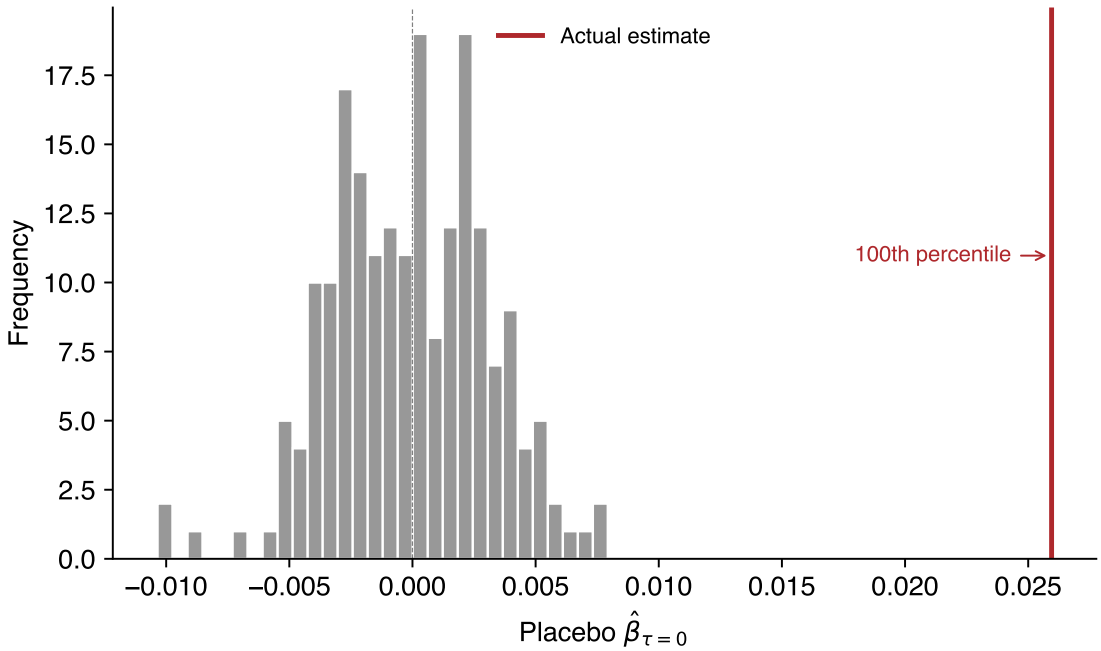
Table A.8.2: **Event-Study Estimates: Varying Baseline Windows**

	(1) 4-week	(2) 8-week	(3) 12-week
$\tau = -2$	-0.021	-0.024	-0.025
	(0.004)	(0.003)	(0.003)
$\tau = 0$	0.020	0.026	0.028
	(0.004)	(0.003)	(0.003)
$\tau = +1$	-0.044	-0.031	-0.026
	(0.004)	(0.004)	(0.004)
$\tau = +2$	-0.057	-0.042	-0.035
	(0.005)	(0.004)	(0.004)
Observations	585,699	585,699	585,699
Ticker-week events	53,738	53,738	53,738
Unique tickers	3,210	3,210	3,210
Outcome mean	0.013	0.054	0.070
Week FE	Yes	Yes	Yes

Note: Robust standard errors clustered by ticker in parentheses. The dependent variable $AVolume_{i,w}$ is abnormal StockTwits attention, defined as log posting activity minus log median posting activity over a rolling baseline window. Columns vary the baseline window: 4 weeks (column 1), 8 weeks (column 2, main specification), or 12 weeks (column 3). τ denotes event time in weeks relative to the trade date, with $\tau = -1$ (one week before the trade) as the omitted reference period; $\tau = 0$ is the trade week. Week FE absorbs market-wide variation in StockTwits activity.

Could the attention spike arise by chance? Figure A.8.2 reports placebo estimates under the null hypothesis that trade timing is unrelated to attention. The gray histogram displays the placebo distribution. It centers tightly on zero (mean = −0.0001, SD = 0.003). This is exactly what we would expect if trade dates were arbitrary. The dark red vertical line marks the actual estimate of 0.026 — far to the right of the histogram.

Figure A.8.2: **Placebo Tests**



A.8.2 Social Media Sentiments

Table A.8.3: **Legislators Follow Sentiment: Alternative Threshold**

	Buy (=1)					
	(1)	(2)	(3)	(4)	(5)	(6)
S-Score	0.0131	0.0183				
	(0.0054)	(0.0052)				
High Sentiment			-0.0117	-0.0071	0.0204	0.0107
			(0.0446)	(0.0412)	(0.0358)	(0.0331)
Low Sentiment			0.0198	0.0301	0.0206	0.0071
			(0.0680)	(0.0703)	(0.0628)	(0.0662)
Momentum						-0.0103
						(0.0327)
Log(Market Cap)						-0.0056
						(0.0046)
Log(Tweet Volume)						-0.0012
						(0.0050)
Observations	45,386	45,386	45,386	45,386	45,386	45,386
Outcome Mean	0.516	0.516	0.516	0.516	0.516	0.516
Legislator FE	No	Yes	No	Yes	Yes	Yes
Date FE	No	Yes	No	No	Yes	Yes
Stock Controls	No	No	No	No	No	Yes

Note: Robust standard errors clustered by legislator in parentheses. The dependent variable equals one if the trade is a buy, zero if a sell. *S-Score* is the average normalized Twitter sentiment over the 7 days before the trade. *High Sentiment* equals one if S-Score > 2 (two standard deviations above, i.e., statistically significant bullish sentiment). *Low Sentiment* equals one if S-Score < -2 (statistically significant bearish sentiment). Stock Controls include Momentum, Log(Market Cap), and Log(Tweet Volume). Sample restricted to stock-days with at least 3 tweets per day on average.

As a placebo test, we ask whether *future* sentiment predicts current trade direction. If it does not, this supports the interpretation that legislators respond to contemporaneous signals rather than anticipating sentiment shifts. Table A.8.4 reports the results. The lead S-Score coefficient is small and insignificant across all specifications (e.g., Column 3: -0.0053, SE = 0.0041), while the current S-Score coefficient remains stable. Future sentiment has no predictive power for current trade direction, consistent with signal-following rather than anticipation.

Table A.8.4: **Sentiment and Trade Direction: Timing Test**

	Buy (=1)			
	(1)	(2)	(3)	(4)
S-Score	0.0185		0.0181	0.0183
	(0.0052)		(0.0051)	(0.0053)
S-Score (Lead)		-0.0071	-0.0053	-0.0048
		(0.0042)	(0.0041)	(0.0042)
Momentum				-0.0115
				(0.0328)
Log(Market Cap)				-0.0049
				(0.0048)
Log(Tweet Volume)				-0.0026
				(0.0051)
Observations	45,321	45,321	45,321	45,321
Outcome Mean	0.516	0.516	0.516	0.516
Legislator FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Stock Controls	No	No	No	Yes

Note: Robust standard errors clustered by legislator in parentheses. This table tests whether future sentiment predicts current trade direction. *S-Score* is the average normalized Twitter sentiment over the 7 days *before* the trade. *S-Score (Lead)* measures sentiment over the 7 days *after* the trade. If legislators follow public sentiment, current sentiment should predict trade direction while future sentiment should not. Stock Controls include Momentum, Log(Market Cap), and Log(Tweet Volume). Sample restricted to stock-days with at least 3 tweets per day on average.

A.9 When Legislators Trade Connected Firms

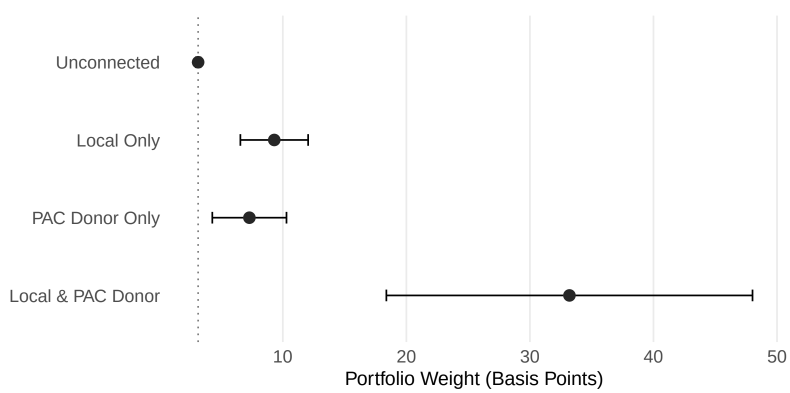
We construct two measures of political connection between legislators and the firms they trade. *Local* equals one if the firm's headquarters state (from Compustat) matches the legislator's home state. *Donated* equals one if the firm's corporate PAC made a contribution to the legislator at any point during the 2012–2024 period, reflecting a persistent relationship. We identify corporate PACs using the FEC data, and match these organization names to Compustat firms through string matching and manual corrections for firms whose PAC names changed over time (e.g., XTO Energy to Exxon Mobil). We then link PAC contributions to legislators via the FEC PAC-to-candidate transaction files. Of the 71,304 trades with valid party and position data, 5,542 (7.77%) involve local firms and 8,914 (12.50%) involve firms whose PAC ever donated to the trading legislator.

To test whether legislators tilt their trading toward connected firms, we adapt the portfolio-weight regression from Eggers and Hainmueller (2014). For each legislator i, the *portfolio weight* of firm j is the share of legislator i's total trades allocated to firm j, scaled to basis points. We construct a panel of all legislator–firm pairs and estimate:

$$w_{ij} = \alpha + \beta_1 Local_{ij} + \beta_2 Donated_{ij} + \theta_i + \theta_j + \varepsilon_{ij},$$

where w_{ij} is the portfolio weight in basis points, $Local_{ij}$ equals one if firm j is headquartered in legislator i's home state, and $Donated_{ij}$ equals one if firm j's corporate PAC contributed to legislator i during the 2012–2024 election cycles. The member and firm fixed effects (θ_i, θ_j) absorb all unobserved heterogeneity that varies across legislators or across firms, so that the β coefficients capture only the within-member, within-firm portfolio tilt toward connected stocks. Standard errors are clustered by member. In this model, $\hat{\beta}_1 = 8.51$ (SE = 1.55) and $\hat{\beta}_2 = 5.93$ (SE = 1.49). Figure A.9.1 visualizes a categorical specification that replaces the two separate indicators with a four-level factor variable (Unconnected, Local Only, PAC Donor Only, and Local & PAC Donor), with unconnected firms as the reference category. Each point reports the adjusted mean portfolio weight with 95% confidence intervals; the vertical dotted line marks the unconnected baseline.

Figure A.9.1: **Portfolio Weights by Political Connection**



The results are qualitatively consistent with the overweighting pattern documented in Eggers and Hainmueller (2014) for the 2004–2008 period. Unconnected firms receive an average portfolio weight of 3.15 basis points. Local firms receive roughly three times as much weight (9.31 bp), PAC-donating firms receive more than twice the baseline (7.29 bp), and firms with both connections receive approximately ten times the baseline weight (33.20 bp).

Table A.9.1 then reports mean buy-and-hold abnormal returns for trades in politically connected firms. If legislators exploit private information gained through political relationships, we would expect connected trades to earn positive abnormal returns. In Panel A, trades in local firms *underperform*, losing 45 basis points at one month (SE = 13 bps) and 89 basis points at one year (SE = 54 bps) — this is the opposite of a "hometown information advantage." In Panel B, trades in donating firms earn returns indistinguishable from zero across all horizons: −1 basis point at one month (SE = 7 bps) and 83 basis points at one year (SE = 28 bps).

Table A.9.1: **Abnormal Returns When Legislators Trade Connected Firms**

	Half Month	One Month	Three Months	Six Months	One Year
Panel A: Local Firms (HQ in Legislator's State)					
Local	-0.0018	-0.0045	-0.0065	-0.0122	-0.0089
	(0.0010)	(0.0013)	(0.0023)	(0.0037)	(0.0054)
N	5,542	5,542	5,542	5,542	5,542
Panel B: Firms That Donated to Legislator					
Donated	0.0002	-0.0001	0.0014	0.0012	0.0083
	(0.0005)	(0.0007)	(0.0011)	(0.0017)	(0.0028)
N	8,914	8,914	8,914	8,914	8,914

Note: Entries report mean buy-and-hold abnormal returns (relative to the CRSP value-weighted benchmark) with standard errors in parentheses. Returns are measured from the trade date over horizons of half-month, 1-month, 3-months, 6-months, and 12-months. *Local* equals one if the traded firm's headquarters (from Compustat) is in the same state as the legislator. *Donated* equals one if the firm's corporate PAC contributed to the legislator during the 2012–2024 period (FEC data).

Comparing to the first row of Table 1, trades in local firms perform substantially worse. Trades in PAC-donating firms, by contrast, earn returns close to zero and slightly above the full-sample average (−1 versus −10 basis points at one month). While legislators do overweight both local and PAC-donating firms, this overweighting produces no financial payoff, which may suggest that legislators' preference for connected firms reflects familiarity rather than an information advantage.

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