Unreadable Political Trades*

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Abstract

Legislators can disclose their stock trading transactions through either typed electronic filings (machine-readable) or handwritten-then-scanned filings (largely "unreadable"), in the latter of which information is more difficult to disseminate and less readily accessible. Using a novel dataset of congressional trading from 2014 to 2022, we show that compared to trades reported in readable filings, trades from unreadable filings are more profitable, involve a larger number of stocks and greater trading volume, are more likely to be executed through a legislator's spouse or children, and are filed less promptly. Prior to economically sizable legislative events, trades extracted from any two politicians' unreadable filings exhibit significant similarity. Individuals with highly "unreadable" political connections are also more likely to co-sponsor a bill in the near future. Our findings highlight the role of strategic disclosure in legislative trades and identify political networks embedded in unreadable filings that remain undetectable through readable filings or known political connections.

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1 Introduction

Legislators can disclose their stock transactions through either electronically typed, machine-readable filings or handwritten-then-scanned "unreadable" filings, which are substantially harder for the public and researchers to process. Using this institutional contrast, we first show that unreadable disclosure files systematically concentrate economically important trading. Relative to readable filings, trades reported in unreadable files earn higher subsequent abnormal returns, involve larger dollar amounts and more stocks, are more likely to be executed through family member accounts, and are disclosed closer to the statutory reporting deadline. Moreover, these opaque filings encode a latent trading network: prior to major fiscal legislation, legislators connected through unreadable filings trade unusually similar portfolios, and these same connections predict future bill co-sponsorship. Together, our results indicate that unreadable disclosure formats are not random reporting artifacts but instead serve as a strategic channel through which profitable and politically connected trading is both conducted and concealed.

Our analysis uses a newly constructed dataset of congressional stock trades from 2014 to 2022. We collect all periodic transaction reports filed by members of the U.S. House of Representatives and classify each of the 5,113 disclosure files into readable electronic filings (3,532 files) and unreadable scanned filings (1,581 files). The sample includes 276 legislators (123 Democrats and 151 Republicans) and 4,492 distinct stocks. We merge transaction-level data to daily stock returns from CRSP to compute direction-adjusted cumulative abnormal returns and dollar profits over horizons of 22, 30, 35, and 40 trading days. We further combine these data with committee assignments, bill sponsorship records from Congress.gov, and macroeconomic announcement surprises from Bloomberg to construct a comprehensive panel of trading, political, and information environments.

Our first result shows that unreadable filings systematically concentrate higher-value trading. At the transaction level, purchase trades disclosed in unreadable files earn 33 to 41 basis points higher abnormal returns over the following one to two months than comparable trades disclosed in readable files, even after controlling for stock fixed effects, year–month fixed effects, FOMC windows, and macroeconomic announcements. These performance differences are not confined to returns alone. Unreadable filings also involve much larger dollar volumes and broader portfolios: at the person–day level, trading volume is roughly 68% higher in unreadable files, and at the file level these filings contain more than 30 additional transactions on average. Thus, unreadable files concentrate both profitability and trading intensity.

Unreadable disclosure formats are also closely linked to concealment along two additional margins. First, trades reported in unreadable files are far more likely to be executed through family members: the probability that a transaction is owned by a spouse or child is 16–23 percentage points higher in unreadable filings. Moreover, family-member trades reported through unreadable files are economically dominant, involving 64% higher trading volume and generating \$11,000–\$13,000 more in monthly dollar profits, even though percentage abnormal returns are similar. Second, unreadable filings are strategically delayed. Transactions reported in unreadable files are about four percentage points more likely to be disclosed exactly at the statutory 28–31 day deadline, keeping economically important trades out of public view for as long as legally permissible.

To study the implications, we further examine and show that unreadable filings reveal a distinct network of politically-relevant trading connections. Focusing on twelve major fiscal acts between 2014 and 2022, we examine whether legislators trade the same stocks in the months preceding each act's passage. Dyads of legislators drawn from unreadable filings are 8–12 percentage points more likely to share at least one traded stock in the 60-, 90-, and 180-day windows before enactment, even after controlling for committee overlap, state representation, and total trading activity. These effects are strongest closest to the passage date, consistent with coordination around evolving legislative information.

These trading links have real political consequences. Legislator pairs that share stocks through unreadable filings are over six percentage points more likely to co-sponsor bills in the 180 days following a major fiscal act, whereas trading overlap in readable files has little predictive power. Network visualizations further show that unreadable filings generate a dense, cross-partisan web of trading connections, while the same legislators' readable filings display no comparable structure. Taken together, unreadable disclosure files do not merely hide isolated profitable trades; they encode an economically and politically meaningful network of legislators who trade together on forthcoming fiscal legislation and subsequently coordinate in the law-making process.

We contribute to the ongoing debate regarding the informational advantage and trading performance of congressional members. Some studies document that members of Congress earn abnormal returns on their stock trades, and that their trades trigger stock market reactions and predict the passage of economically relevant bills, suggesting that politicians profit from their private information (e.g., Ziobrowski, Cheng, Boyd, and Ziobrowski, 2004; Ziobrowski, Boyd, Cheng, and Ziobrowski, 2011; Dong and Xu, 2025). Others find these politicians do not outperform the market, particularly following the passage of the STOCK Act, or that any outperformance is limited to specific circumstances, such as periods preceding major legislative actions or moments when politicians assume greater authority (e.g., Eggers and Hainmueller, 2013; Stephan, Walther, and Wellman, 2021; Belmont, Sacerdote, Sehgal, and Hoek, 2022; Huang and Xuan, 2023; Wei and Zhou, 2025; Li, Michelson, Mollica, and Zhou, 2025). We show that strategic disclosure not only masks profitable trades by congressional members, including those executed after the STOCK Act, but also reveals political networks that remain undetectable through traditional measures of political connections.

Our paper also adds to the literature on identifying connected politicians. For example, social interactions, measured through seating assignments, alumni networks, or other interpersonal ties, shape voting alignment and patterns of bill co-sponsorship (e.g., Masket, 2008; Kirkland, 2011; Battaglini and Patacchini, 2018; Battaglini, Sciabolazza, and Patacchini, 2020; Harmon, Fisman, and Kamenica, 2019). Instead, we show that connected trades reported in unreadable filings reveal political networks that are not captured by existing traditional, observable metrics. Rather than stemming from social or personal relationships, the connections we identify arise from profitable trades that directly convey material gains.

2 Institutional Background and Data

2.1 Institutional Background

In this section, we summarize the institutional setting for congressional financial disclosures and provide the foundation for our empirical design. The key legislative foundation of our study is the Stop Trading on Congressional Knowledge (STOCK) Act of 2012 (https://www.congress.gov/bill/112th-congress/senate-bill/2038), which responded to concerns about potential insider trading by members of Congress and explicitly affirmed that they may not use nonpublic information obtained through their official duties for personal financial gain. The Act amended the Ethics in Government Act to require relatively prompt reporting of securities transactions: trades exceeding $1,000 must be disclosed within 30 days of receiving notice and no later than 45 days after the transaction date, subject to several asset-class exemptions.[1] A 2013 amendment (https://www.congress.gov/bill/113th-congress/senate-bill/716) subsequently modified the STOCK Act's transparency provisions by narrowing the scope of mandatory online posting and relaxing the requirement that all covered reports be provided in a fully searchable, downloadable public database, while retaining the obligation to maintain electronic filing systems. In practice, the post-2013 framework does not prescribe a single filing format: in the U.S. House of Representatives, for example, filers may submit their disclosures either through the electronic system or on paper forms, which are then made publicly available as scanned PDF documents. This institutional environment motivates our sample period and, crucially, allows us to distinguish between born-digital electronic files and scanned documents in the analysis that follows.

[1]The extensive list exempts members, if they choose, from reporting certain transactions involving mutual funds, exchange-traded funds, or any other asset that is an excepted investment fund (EIF) (see the financial disclosure report instructions for the definition of an EIF); holdings in a blind trust; real property; cash accounts (e.g., checking, savings, and money markets); U.S. Treasury bonds, bills, and notes; pensions; and any asset that is solely incidental to the trade or business of an entity.

Building on this institutional background, unreadable files in this paper are defined as PDF documents produced by scanning handwritten or printed pages, whereas readable files are born-digital PDF files generated directly from electronically typed text. Overall, during our sample period from 2014 to 2022[2], we obtain a total of 5,113 files from raw resources, among which 3,532 are classified as readable and 1,581 are classified as unreadable. The classification is quite trivial. Appendix A.2 offers a few demonstrations on readable versus unreadable files. We focus on the House of Representatives only in the present research, considering data volume (i.e. more individuals in the House Chamber than the Senate Chamber) and manual work capacity that we have.

2.2 Data

We use a wide spectrum of datasets for our analyses.

Trading data. Our whole sample consists of 92,713 transaction records reported by 276 members of the House of Representatives (123 Democrats and 151 Republicans). These records cover 4,492 unique tickers. Among all transactions, 61,171 are drawn from unreadable trading disclosure files and 31,542 from readable trading disclosure files. The unreadable files involve 2,843 unique tickers, whereas the readable files contain 3,196 unique tickers.

In our empirical framework, we systematically exclude the year 2020 from the whole sample. The COVID-19 outbreak induced a highly unusual market environment characterized by unprecedented volatility, emergency monetary interventions, and elevated trading activity among investors. These conditions pose substantial challenges for interpreting legislators' trading behavior in a manner comparable to other years, as macroeconomic shocks rather than information effects may dominate observed asset returns and trading patterns. Accordingly, our main analysis focuses on a sample period that omits 2020 and reflects a more stable economic environment, thereby enhancing the interpretability of

[2] The sample period from 2014 to 2022 is defined with respect to the disclosure dates of the transaction reports. As a result, the actual trade dates for some stocks in our sample occurred in 2013.

the results.

Stock market data. The stock return data and market return data are obtained from CRSP. We merge CRSP daily returns to our transaction records using the ticker identifier and the actual trading date. Our market return measure is the CRSP value-weighted market index return inclusive of distributions (VWRETD). Following Ravina and Sapienza (2010), we construct direction-adjusted cumulative abnormal returns (CARs) over a variety of horizons. Specifically, we capture a buy-and-hold return from an executed trade over the following $h \in \{22, 30, 35, 40\}$ trading days as

$$\mathrm{CAR}_{i,t}^{(h,m)} = D_{i,t} \times \left[\prod_{n=1}^{h} (1 + r_{i,t+n}) - \prod_{n=1}^{h} (1 + r_{t+n}^{(m)}) \right],$$
$$D_{i,t} \in \{+1, -1\}, \quad h \in \{22, 30, 35, 40\},$$

where $r_{i,t+n}$ denotes the daily return of ticker i on trading day $t+n$, and $r_{t+n}^{(m)}$ denotes the market return on the same day. $D_{i,t} = +1$ for purchases and $D_{i,t} = -1$ for sales, so that the sign of the return measure is aligned with the trade direction. In Table 1 and Appendix Table A1, we restrict the analysis to transactions classified as purchases, and compute cumulative abnormal returns for these purchase transactions as defined in the equation above. We follow the literature to winsorize CARs at the 1% and 99% levels in our main analysis,

Bill sponsoring data. Bill sponsoring data are obtained from the official Congress website (`https://www.congress.gov`), which provides detailed bill information, including the introduction date and the full list of sponsor and co-sponsors for each bill.

Other. House of Representatives committee assignments for each legislative member in our sample are obtained from the Congressional Directory (CDIR), available via the govinfo website at `https://www.govinfo.gov/app/collection/CDIR`.

Macro control variables are constructed from Bloomberg's Macroeconomic Announcements dataset and consist of normalized macroeconomic surprise measures. We follow Bianchi, Gómez-Cram, and Kung (2024) and consider the list of macro variables, which we also describe in Appendix Section A.3. For each announcement j on date t, the dataset reports the realized value ($AC_{j,t}$) and the survey median forecast ($SUM_{j,t}$), which captures the market consensus expectation compiled by Bloomberg prior to the release. We then select the 50 announcements with the highest relevance scores provided by Bloomberg; accordingly, the final sample includes 50 macroeconomic announcements. For each selected macroeconomic event p (identified by its ticker symbol), we compute the normalized macroeconomic surprise as: $\text{macro\_control}_{p,t} = \frac{AC_{p,t} - SUM_{p,t}}{\sigma_p}$, where $AC_{p,t}$ denotes the realized value and $SUM_{p,t}$ denotes the survey median forecast. The term σ_p is the standard deviation of the forecast error $AC_{p,t} - SUM_{p,t}$ for event p over the sample period.

3 Evidence of Strategic Behaviors

In this section, we document systematic differences between trades reported in unreadable and readable disclosure files over the 2014–2022 period. We show that unreadable filings are associated with four distinct patterns: higher subsequent trading profitability, larger trading scale and broader portfolio scope (Section 3.1), greater reliance on family member accounts (Section 3.2), and longer delays between transaction dates and public disclosure dates (Section 3.3).

3.1 Profitability, amounts, and numbers of tickers

Table 1 presents the first set of main trading patterns.

Trading profitability. Panel A shows that purchase trades disclosed through unreadable files earn significantly higher subsequent abnormal returns than those disclosed through readable filings. To be more specific, the specification is at the file-ticker level, and file carries a dimension of person-time. To concentrate on information-driven trading activities that are less likely to follow mechanically from diversification motives or portfolio re-balancing after stock grants or option exercises, we focus on share purchase records rather than sales transactions (e.g., Seyhun, 1986, 1992). As a result, this dependent variable captures the abnormal returns over four various horizons given purchase records at file-ticker level (see Section 2.2 for more details on the construction of each ticker's abnormal returns).

Across all four return horizons ({22, 30, 35, 40} trading days after the actual purchase transaction), the coefficient on Unreadable is positive and statistically significant. The magnitudes are economically meaningful: transactions reported in unreadable formats outperform comparable readable-file trades by roughly 33 to 41 basis points over the following one to two months. These results are obtained after controlling for stock fixed effects, year–month fixed effects, controls for trading around FOMC meetings, and a rich set of macroeconomic surprise controls (see the full list in Appendix Section A.3), implying that the performance gap is not driven by systematic exposure to market-wide, macroeconomic, monetary policy events or firm-specific news. Economic magnitudes remain stable across horizons, with statistical significance tapering modestly at longer windows, which is interesting as it appears to suggest that legislators either have information about stock prices in the recent future or have the ability to influence. Panel A of Table 1 is the first empirical indication that unreadable trades could be intended to hide higher profitability.

[Insert Table 1 here]

We explore an important – and quite experimental – robustness setting where we create an alternative "unreadable" variable with some variation. We construct an intensive-margin unreadability measure using the AI-generated readability score (0–10, 10 strictly being electronic and machine-readable filings) assigned to each disclosure PDF based on visual legibility, where lower values reflect greater blur, distortion, or handwritten interference that reduces extraction certainty. Unreadability is hence defined as the inverse (or negative) of this score, so that higher values correspond to more severely degraded and harder-to-read filings, rather than a simple binary flag. We use Gemini 3 Pro in this process, and we carefully verify the entire work with manual examinations, for instance, to capture certain obvious mistakes. Appendix A.1 provides more technical details on how we use Gemini Pro to produce (un)readability scores for each file. Appendix Table A1 replicates Panel A of Table 1 using our continuous unreadability measure. There are two main observations. First, the overeall pattern appears quite intact, with a decaying effect as we increase the return horizons of interest. Second, statistical significances become smaller, which could be due to empirical noise that AI-calculation introduces or the fact that intensive margin indeed is not meaningful in our empirical question. As a result, in the rest of the paper, we focus on the simple binary variable (as presented in Table 1) as our unreadability measure of interest, for which the classification is extremely straightforward and replicable (see examples in Appendix Section A.2).

Trading scale and scope. Panels B and C of Table 1 examine whether disclosure-file unreadability is associated with differences in the scale (volume) and scope (number of tickers) of trading activity. Panel B uses Log Trading Amount as the dependent variable, constructed as the natural logarithm of the total dollar amount traded, measured using the midpoints of the transaction amount ranges.[3] Panel C uses Trading Number, defined as the number of transaction records. Both dependent variables are constructed and examined at four levels of aggregation: the person-trading date level, the person-ticker-trading date level, the person-trading date (average) level, and the disclosure-file level. Time fixed effects, stock fixed effects, FOMC-window indicators, and macroeconomic surprise controls are included where applicable.

Panels B and C show that unreadable disclosure files are systematically associated with larger and more extensive trading activity. In Panel B, the coefficient on Unreadable is positive and statistically significant across all four data constructions, indicating that trades reported in unreadable files involve substantially larger dollar amounts. At the person-date level in Columns (1) and (2), trading dollar volume is about 68% higher

[3]The STOCK Act of 2013 does not require legislators to disclose exact amount; instead, they can select appropriate dollar ranges.

for trades submitted through unreadable formats than those submitted through readable formats. Column (3) considers average trading volume, whereas Column (4) considers directly the person-ticker-date level. Both coefficient estimates have similar sizes as expected at this much granular dimension: unreadable trades are associated with about 21-27% higher dollar volume. Column (5) aggregates the dollar volume at the file level and the unreadable coefficient remains statistically significant.

Panel C uses similar empirical constructs and reveals a similar pattern for trading breadth. Transactions reported in unreadable files involve significantly more trades and a greater number of distinct tickers. Columns (1) and (5) present easier-to-interpret economic magnitudes. At the person-trading date level, unreadable filings are associated with more than four additional trades per day, and at the disclosure-file level they contain over 30 more transactions on average. Taken together, Panels B and C indicate that unreadable files concentrate not only more profitable trades, but also trades that are larger in scale and broader in portfolio scope.

3.2 Spouse trades

Under the hypothesis that legislators are strategically hiding trades that achieve higher monetary gains in unreadable files, one might also expect such trades to be further reported through their family members' account rather than self portfolios; both family members and self accounts need to be reported via the same periodic disclosure files. More specifically, Table 2 examines whether unreadable disclosure files are systematically associated with the use of family member accounts, and whether such trades exhibit higher monetary importance (scope, scale, profitability).

Panel A: Transaction ownership. Panel A tests whether unreadable files contain more trades submitted through family members accounts than readable files. The unit of observation is at the transaction (trade)-file level. The dependent variables indicate whether a transaction is owned by any family member, by children, or by the spouse. In particular, "Family Member" in Column (1) equals one if the transaction is owned by the legislative member's spouse, child(ren), or a joint account held by the legislative member and a family member.

Across all three columns, unreadable filings are strongly and significantly associated with family-based trading. There is a 16.5% higher chance that a family member trade is reported through unreadable files than through readable files. Breaking it down, there is a 20.8% (22.7%) higher chance for a children (spouse) trade to appear in unreadable files. All coefficients statistically significant at the 1% level. These magnitudes are economically sizable, indicating that unreadable disclosure formats are disproportionately preferred when legislators report family members accounts.

Panel B then directly tests whether family-member trades reported in unreadable files are economically different from other trades. For each year-month and each person, we construct log trading amount, numbers of tickers, trading dollar profits across various return horizons. For each person-time, we can also construct four buckets based on Unreadable and Family Member indicators. The key coefficient of interest is the interaction term Unreadable × Family Member, which captures how trading outcomes differ for family-owned transactions when they are reported in unreadable filings.

The interaction term is large and highly significant for both trading scale (Column (1)), scope (Column (2)) and dollar profits (Columns (3)-(6)). Unreadable family-member trades involve 64.5% higher trading volume and approximately 31 additional trades per month relative to other transactions. These trades also generate substantially higher dollar profits: across horizons from 22 to 40 trading days, the interaction coefficients imply an additional $11,250 to $13,220 in monthly profits (measured in units of $10,000).

By contrast, the interaction term is not statistically significant for abnormal returns. This indicates that family-member trades in unreadable files do not earn higher percentage returns, but instead generate higher economic gains because they are executed at much larger scale. Taken together, Panels A and B show that legislators strategically combine unreadable disclosure formats with family-member accounts to concentrate economically meaningful trades in settings that are less transparent and more difficult to monitor.

[Insert Table 2 here]

3.3 Reporting delays

Table 3 examines whether unreadable disclosures are associated with systematic delays in reporting trades. The sample is at the person-ticker-actual trading date level (or equivalently speaking, at the transaction-file level). The dependent variable is an indicator equal to one if the difference between the actual trading date and the disclosure date falls within $\{28, 29, 30, 31\}$ calendar days, which corresponds to the statutory filing deadline window under the STOCK Act. As an empirical validation, Figure 1 demonstrates that submissions are indeed more likely to appear around the deadline days. The key explanatory variable is Unreadable, which equals one if the transaction is reported in an unreadable disclosure file. All specifications control for trading around FOMC meetings, macroeconomic announcement surprises, transaction amounts, stock fixed effects, and year-month fixed effects.

[Insert Figure 1 here]

Across both columns, unreadable filings are significantly more likely to cluster at the statutory reporting deadline. The coefficient on Unreadable implies that transactions reported through unreadable files are about 3.8 to 4.3 percentage points more likely to be disclosed exactly at the deadline window than transactions reported through readable filings.

The pattern documented in Table 3 is particularly consistent with strategic delay: legislators appear to use unreadable formats to keep high-stakes trades out of the public domain for as long as legally permissible, further increasing the informational opacity surrounding these transactions. These results indicate that unreadable files are not only used to hide economically important trades and to route them through family-member accounts, but are also associated with systematically slower disclosure.

[Insert Table 3 here]

4 Network Implications

In this section, we examine one testable implication revealed by unreadable trades – trading and political networks. That is, we test whether unreadable files could help reveal some networks among politicians that cannot be revealed from readable files or traditional party lines.

To achieve this, we focus on a subsample around major economic acts during our sample period, given that that is where both political and monetary stakes are expected to remain the highest, and fiscal decisions are being highly attended. We identify major economic acts by intersecting enacted federal legislation with (i) bill-level lobbying and spending intensity, (ii) public attention. We start from the set of bills that become law and record their congressional passage dates. We then merge these bills to our lobbying measure, retain bills with lobbying amounts of at least 10^8 dollars, and rank candidates within each year in each congress. To preserve clean identification of discrete information shocks, we impose a non-overlap rule on event windows: if two high-lobby bills pass close in time, we keep the bill with clearer policy relevance or greater salience. Finally, we validate that the public attention of selected bills is significantly high comparing with other large acts passed in that year, reported in Figure 2.

[Insert Figure 2 here]

This procedure yields the 12 acts, as displayed in Appendix Section A.4, which are major fiscal legislation, including appropriations and budget measures, emergency relief packages, and defense authorizations. What is relevant to our research is that these high—stake fiscal bills – how the Congress should spend money – are likely to trigger pre- or post-enactment actions. We further hypothesize that such actions may appear more likely through unreadable files.

[Insert Figure 2 here]

Section 4.1 tests whether pre-enactment trading network is more likely to be revealed through unreadable files. Section 4.2 examines whether legislators who trade together prior to enactment – revealed from their unreadable files – indeed exhibit tighter political ties with real and measurable consequences, such as an increased likelihood of co-sponsoring legislation.

4.1 Pre-enactment trading network

In our first implication analysis, we test whether unreadable disclosure files reveal coordinated trading behavior among legislators prior to the passage of major fiscal legislation. If unreadable filings are used to conceal economically important and time-sensitive trades, then transactions reported through these files should exhibit stronger cross-legislator similarity when information about upcoming legislation is most valuable.

We focus on the twelve major fiscal acts described at the opening of Section 4 and Appendix Section A.4. For each act, we construct dyadic (member pair) samples of legislators based on their trading activity within 60-, 90-, and 180-day windows prior to the act's final passage date. For each legislator pair (i, j), we define the indicator $\text{ShareAnyTicker}_{ij,a}$, which equals one if both legislators purchased at least one common stock during the pre-passage window for act a. We estimate regressions of the form

$$\text{ShareAnyTicker}_{ij,a} = \beta \cdot \text{Unreadable}_{ij,a} + \Gamma X_{ij,a} + \alpha_a + \varepsilon_{ij,a},$$

where $\text{Unreadable}_{ij,a}$ equals one if the dyadic trading data are drawn from unreadable disclosure files, $X_{ij,a}$ includes controls for committee overlap, same-state affiliation, and total trading intensity for each legislator in the dyad, and α_a denotes act fixed effects. Standard errors are double-clustered by dyad and act.

Panel A of Table 4 reports results of all coefficient estimates for the 60-day window prior to each act. Across all specifications, unreadable trading files are associated with substantially higher cross-legislator trading similarity. In the baseline specification, dyads drawn from unreadable filings are 10.3 percentage points more likely to share at least one traded stock than dyads drawn from readable filings. The magnitude is economically large relative to the unconditional mean of the dependent variable and is highly statistically significant.

The effect remains stable as additional controls are introduced. Controlling for shared committee memberships, common state representation, and total trading amounts for each legislator leaves the coefficient on Unreadable largely unchanged. In the most conservative specification with all controls and act fixed effects, unreadable dyads are still 7.9 percentage points more likely to overlap in their stock holdings in the pre-passage window.

Panel B extends the analysis to 90-day and 180-day windows, and to conserve space, we only report the main coefficient of interest. The results remain strong and persistent at the 1% significance level. Over the 90-day window, unreadable dyads are approximately 12 percentage points more likely to share a traded stock in baseline specifications and 8.8 percentage points more likely in the fully controlled model. Over the 180-day window, the effect remains economically and statistically meaningful, with unreadable dyads being 6.0 to 9.4 percentage points more likely to exhibit overlapping portfolios.

Taken together, these results show that unreadable disclosure files reveal a trading network that is largely "hidden" in readable filings. Legislators show particularly stronger trade connections in narrow, well-identified pre-enactment windows. It is worth emphasizing that the results hold even after controlling for political proximity and trading intensity, consistent with a distinct form of information-driven coordination embedded in opaque disclosure formats. As an important robustness test, we conduct jackknife exercise by dropping one act at a time from the analysis and re-estimate the specification; Appendix Table A2 show that our results remain significant, both statistically and economically.

[Insert Table 4 here]

4.2 Post-enactment political network

We next test whether the trading network identified in Section 4.1 are related to subsequent actual legislative coordination. This is a meaningful test as it potentially indicates that such "unreadable" trading network among politicians have real effects.

To test this hypothesis, we focus on bill co-sponsorship behavior following each of the major fiscal acts. For each act a, we construct dyads of legislators (i, j) and define the indicator $\text{CoSponsor}_{ij,a}$, which equals one if legislator i and legislator j jointly co-sponsor at least one bill within 180 days after the act's passage. We then estimate

$$\begin{aligned}\text{CoSponsor}_{ij,a} = \beta_1 \text{Unreadable} \cdot \text{Share\_Any\_Ticker}_{ij,a} + \beta_2 \cdot \text{Unreadable} \\ + \beta_3 \cdot \text{Share\_Any\_Ticker}_{ij,a} + \Gamma X_{ij,a} + \alpha_a + \varepsilon_{ij,a},\end{aligned}$$

where $\text{Share\_Any\_Ticker}_{ij,a}$ is an indicator for whether the two legislators traded at least one common stock in the pre-passage window, and where the regressions include the same controls for committee overlap, state affiliation, and trading intensity as in Section 4.1, along with act fixed effects. β_1 is the coefficient of interest.

Column (1) of Table 5 reports the baseline results. Trading links revealed through unreadable disclosure files strongly predict future political coordination. Dyads that share at least one traded stock through unreadable filings are 6.4 percentage points more likely to co-sponsor a bill following the act, relative to dyads with no trading overlap. All estimates are statistically significant at the 5% level. The rest of the columns further demonstrate that this relationship is driven by economically important trading links. As before, Appendix Table A3 shows jackknife exercise dropping one act at a time.

[Insert Table 5 here]

Taken together, the results from Section 3 show that unreadable filings contain trades that earn higher economic gains than readable filings. Moreover, this section further demonstrates that such trades plausibly encode a latent network of legislators who trade together and coordinate in the legislative process, consistent with the existence of private, information-based political trading networks operating through opaque disclosure channels.

4.3 Network illustration

To illustrate such an "unreadable" network, we identify politician connections between two legislators from two different parties, who exhibit very similar stock portfolios according to their unreadable files and cosponsor bills in a future recent period. Figures 3 and 4 provide a visual representation of this result. Using the full sample of unreadable trading disclosures, we first partition each calendar year into six consecutive trading windows. The first five windows contain 60 days each, and the sixth covers the remaining days of the year. Within each window, we compute trading similarity for every pair of legislators, defined as the number of stock–direction pairs (stock, buy or sell) they share divided by the total number of distinct stock–direction pairs traded by either legislator in that window. We then consider the 180-day forward period following the end of each window and keep cross-party legislator pairs that have positive trading similarity and cosponsor at least one bill in this forward period. The list of legislators in our final figures consists of all legislators who appear in at least one such pair. Additionally, our figures represent two aspects of cross-party interaction: the intensity of each legislator's participation and the strength of connections between legislator pairs. Legislators with larger displayed labels participated in more of these qualifying cross-party pairs. Additionally, thicker lines indicate stronger connections between two legislators. We measure the strength of legislators' connections as follows. For each pair, we use the trading similarity defined above and a measure of joint cosponsorship intensity, defined as the natural logarithm of one plus the number of bills they cosponsor in the corresponding 180-day forward period. We then normalize both measures to the $[0, 1]$ range within each window and define the edge weight as the average of these two normalized measures. Larger edge weights correspond to stronger connections between legislators, so in our figures we visualize this by drawing edges with larger weights as thicker lines. All legislators' identifying information has been anonymized and is not recoverable from the figure; all displayed labels are randomly generated placeholders with no real-world meaning. Figure 3, using unreadable filings, presents a trading network that is dense and cross-partisan, with several legislators acting as hubs that connect otherwise distant parts of the political landscape. Figure 4 plots the same legislators using their readable-file data and displays no comparable structure. There, links are sparse and no legislator emerges as a central connector. This contrast indicates that the network structure is not an artifact of who trades frequently, but rather a feature of how and where economically important trades are disclosed.

[Insert Figure 3 here]

[Insert Figure 4 here]

5 Conclusion

Legislators can disclose their stock trading transactions through either typed electronic filings (machine-readable) or handwritten-then-scanned filings (largely "unreadable"), in the latter of which information is more difficult to disseminate and less readily accessible. Using a novel dataset of congressional trading from 2014 to 2022, we show that compared to trades reported in readable filings, trades from unreadable filings are more profitable, involve a larger number of stocks and greater trading volume, are more likely to be executed through a legislator's spouse or children, and are filed less promptly. Prior to economically sizable legislative events, trades extracted from any two politicians' unreadable filings exhibit significant similarity. Individuals with highly "unreadable" political connections are also more likely to co-sponsor a bill in the near future. Our findings highlight the role of strategic disclosure in legislative trades and identify political networks embedded in unreadable filings that remain undetectable through readable filings or known political connections.

References

Battaglini, M., Patacchini, E., 2018. Influencing connected legislators. Journal of Political Economy 126, 2277–2322.

Battaglini, M., Sciabolazza, V. L., Patacchini, E., 2020. Effectiveness of connected legislators. American Journal of Political Science 64, 739–756.

Belmont, W., Sacerdote, B., Sehgal, R., Hoek, I., 2022. Do senators and house members beat the stock market? evidence from the stock act. Journal of Public Economics 207, 104602.

Bianchi, F., Gómez-Cram, R., Kung, H., 2024. Using social media to identify the effects of congressional viewpoints on asset prices. The Review of Financial Studies 37, 2244–2272.

Dong, Z., Xu, N., 2025. Legislative trade. Working Paper .

Eggers, A., Hainmueller, J., 2013. Capitol losses: The mediocre performance of congressional stock portfolios. The Journal of Politics 75, 535–551.

Harmon, N., Fisman, R., Kamenica, E., 2019. Peer effects in legislative voting. American Economic Journal: Applied Economics 11, 156–180.

Huang, R., Xuan, Y., 2023. "trading" political favors: Evidence from the impact of the stock act. Working Paper .

Kirkland, J. H., 2011. The relational determinants of legislative outcomes: Strong and weak ties between legislators. Journal of Politics 73, 887–898.

Li, Y., Michelson, G., Mollica, V., Zhou, Q., 2025. Inside the beltway: Senator trading and legislative gains. Journal of Business Ethics .

Masket, S., 2008. Where you sit is where you stand: The impact of seating proximity on legislative cue-taking. Quarterly Journal of Political Science 3, 301–311.

Ravina, E., Sapienza, P., 2010. What do independent directors know? evidence from their trading. Review of Financial Studies 23, 962–1003.

Seyhun, H., 1986. Insiders' profits, costs of trading, and market efficiency. Journal of Financial Economics 16, 189–212.

Seyhun, H., 1992. Why does aggregate insider trading predict future stock returns? Quarterly Journal of Economics 107, 1303–1331.

Stephan, A., Walther, B., Wellman, L., 2021. Profiting from connections: Do politicans receive stock tips from brokerage houses? Journal of Accounting and Economics 72, 101401.

Wei, S., Zhou, Y., 2025. "capital gains" on capitol hill. Working Paper .

Ziobrowski, A. J., Boyd, J., Cheng, P., Ziobrowski, B., 2011. Abnormal returns from the common stock investments of members of the u.s. house of representatives. Business and Politics 13, 1–12.

Ziobrowski, A. J., Cheng, P., Boyd, J., Ziobrowski, B., 2004. Abnormal returns from the common stock investments of the u.s. senate. Journal of Financial and Quantitative Analysis 39, 661–676.

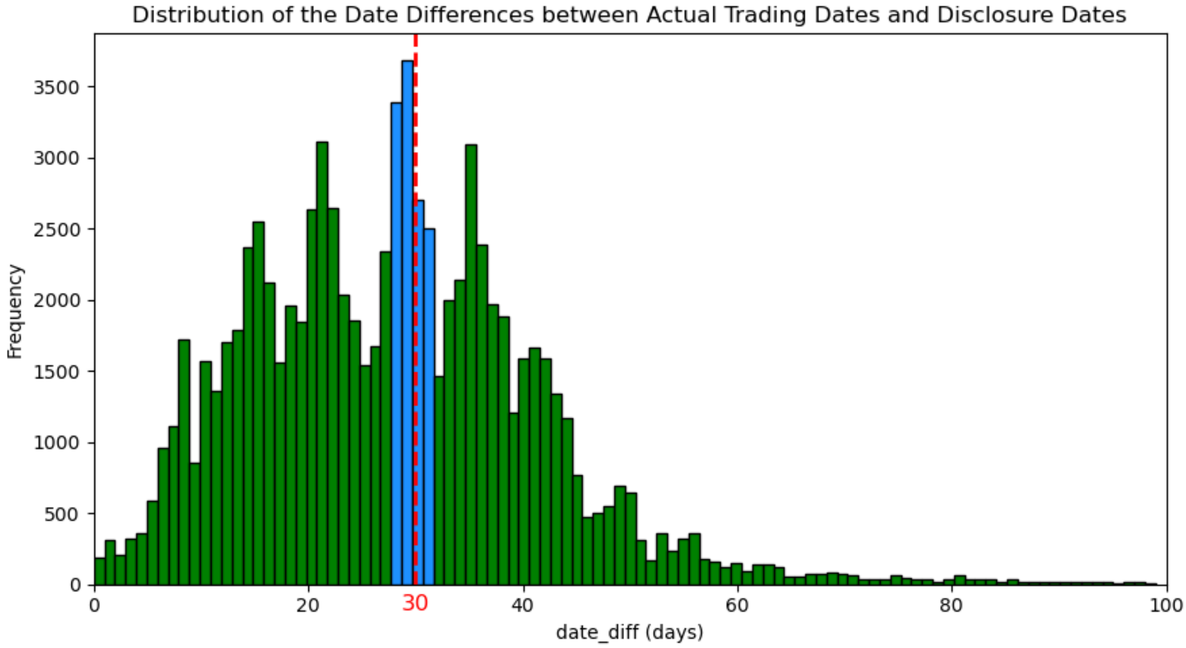
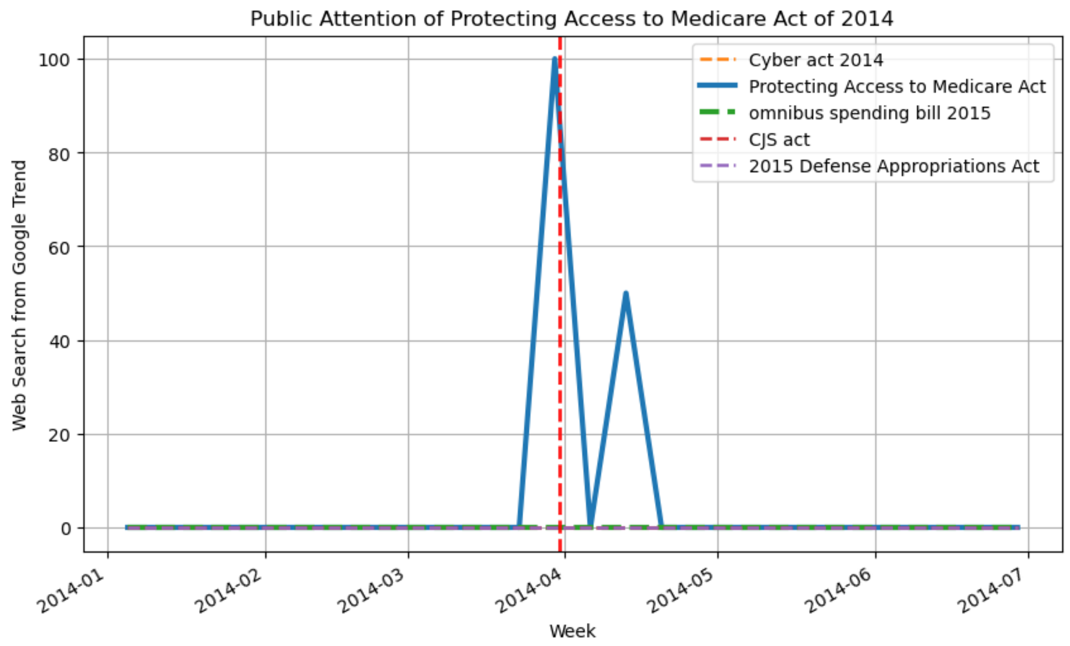


Figure 1: **Distribution of the Date Differences between Actual Trading Dates and Disclosure Dates.**
This figure presents the distribution of the differences between actual trading dates and disclosure dates in transaction records. The dashed red line denotes the due date for legislative members to submit their transaction records. In this figure, we restrict the sample to records with date differences in the range [0,100] (100 is approximately at the 95th percentile of the full-sample distribution of date differences).



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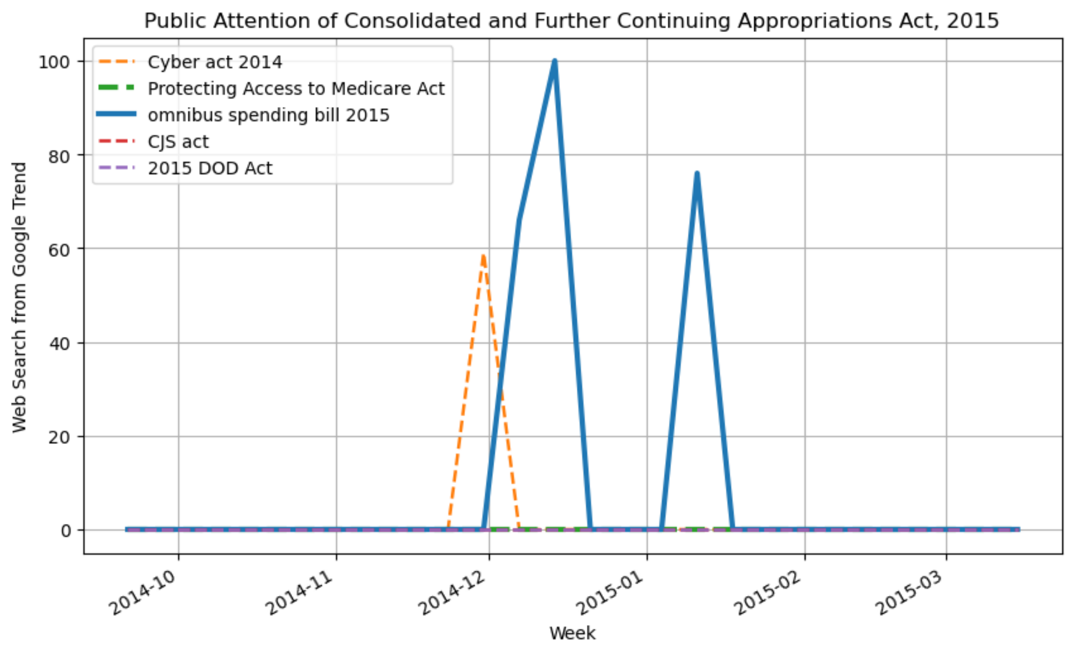

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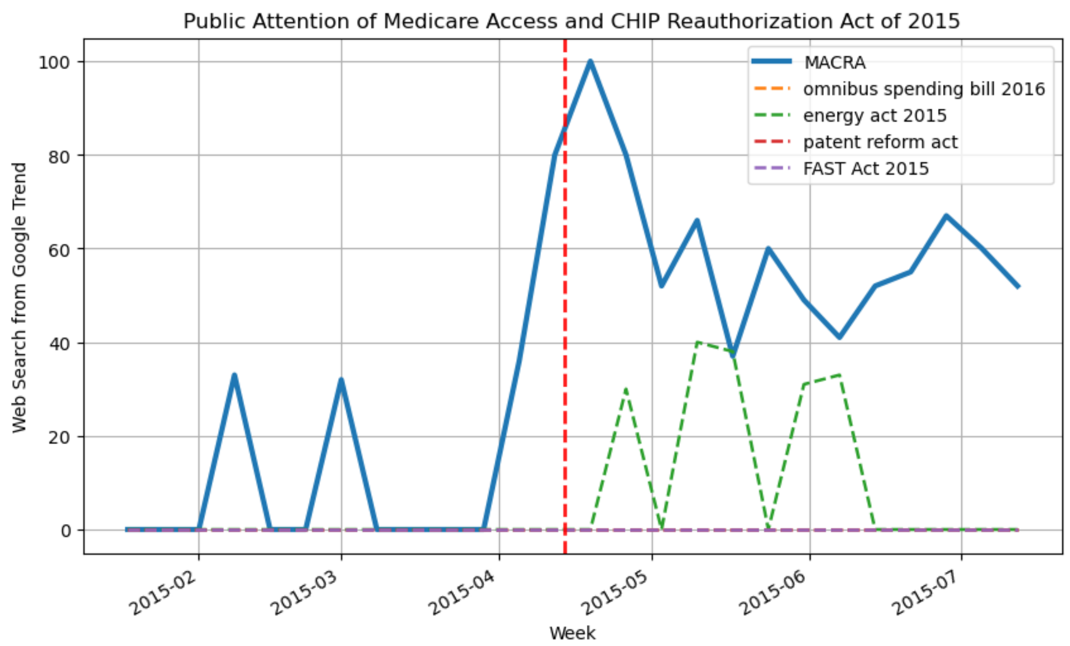
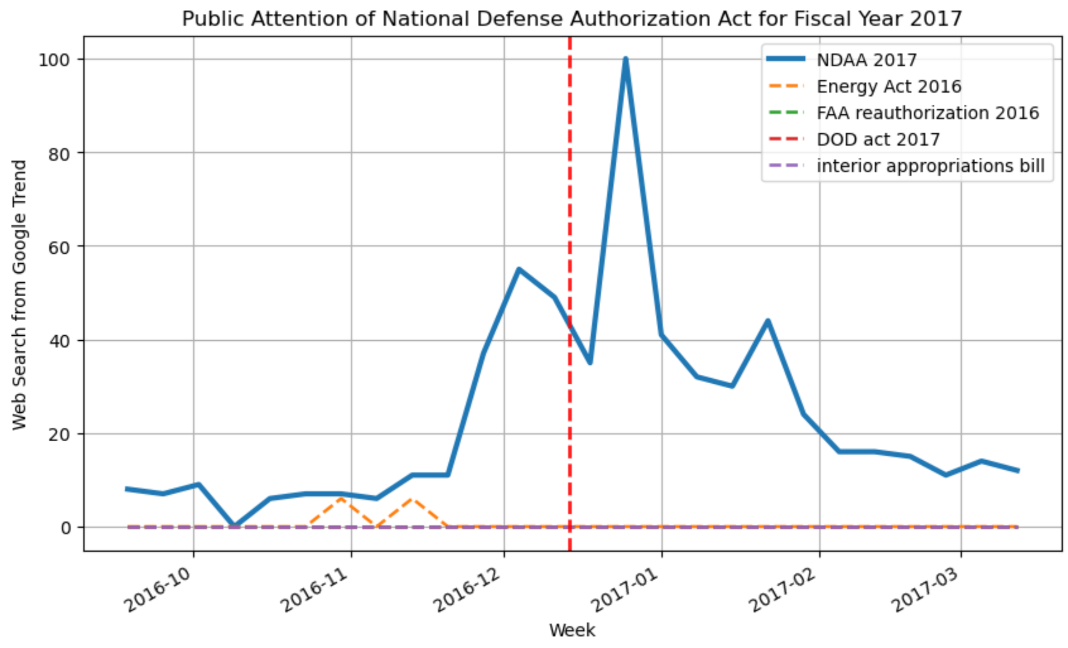


(3)

Figure 2: **Public Attention of Each Acts.**
This set of figures illustrates public attention to each act, proxied by Google Trends "Web Search" search interest for the relevant keywords. The event window spans $[-3, 3]$ calendar months centered on each act's final congressional passage date (day 0). The solid blue line indicates the act selected for inclusion in our sample. The dashed red line presents the act passage date. The keywords used to construct the series are listed in the legends.



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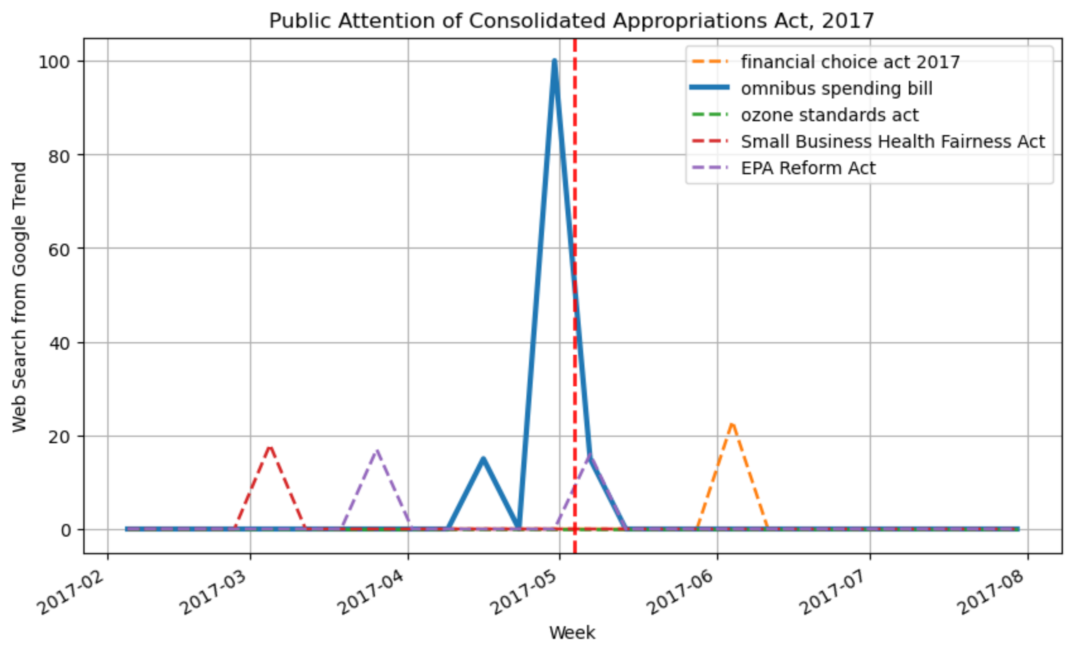

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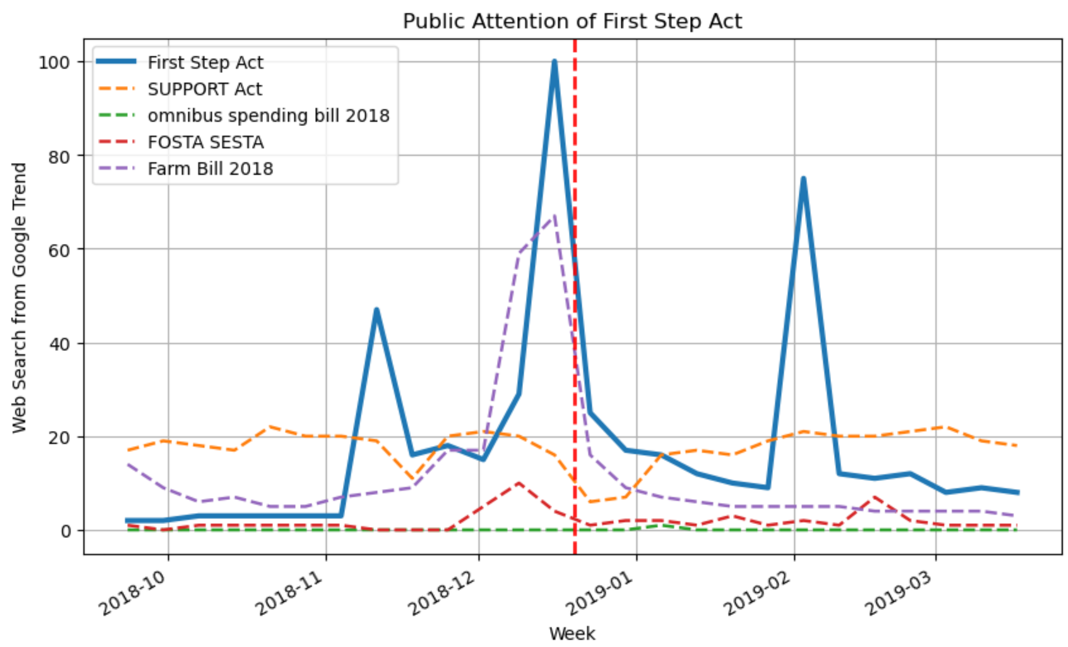
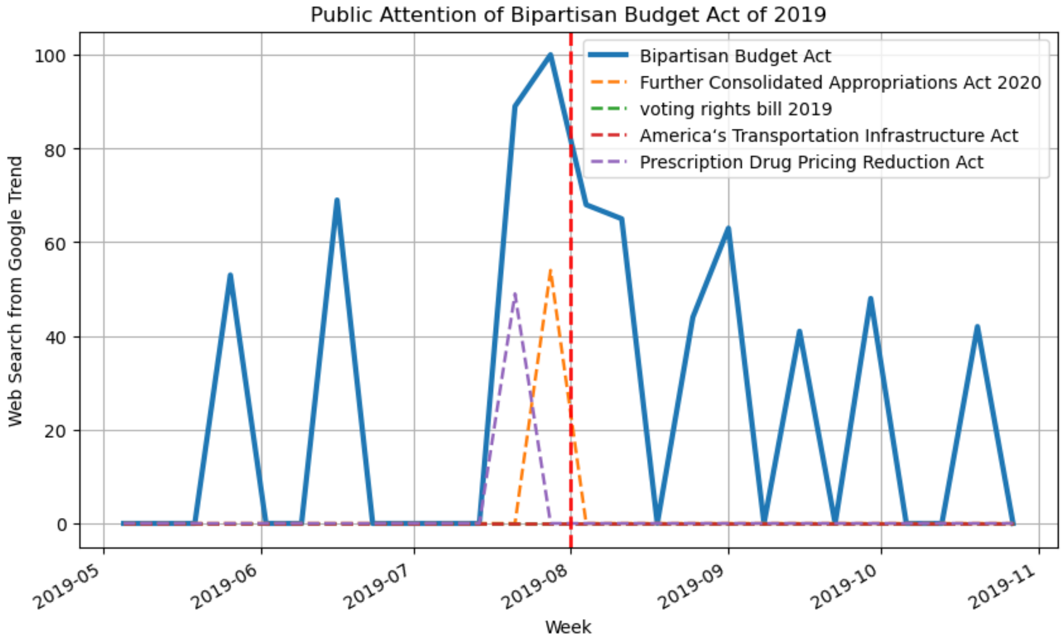


(6)

Figure 2: **Public Attention of Each Acts (Continued).**
This set of figures illustrates public attention to each act, proxied by Google Trends "Web Search" search interest for the relevant keywords. The event window spans $[-3, 3]$ calendar months centered on each act's final congressional passage date (day 0). The solid blue line indicates the act selected for inclusion in our sample. The dashed red line presents the act passage date. The keywords used to construct the series are listed in the legends.



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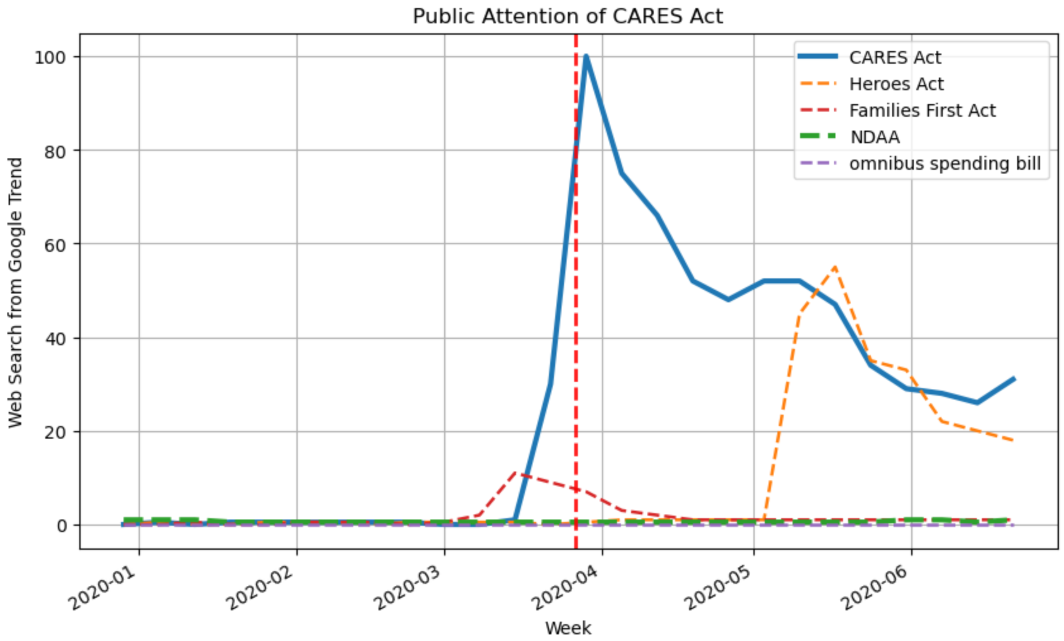

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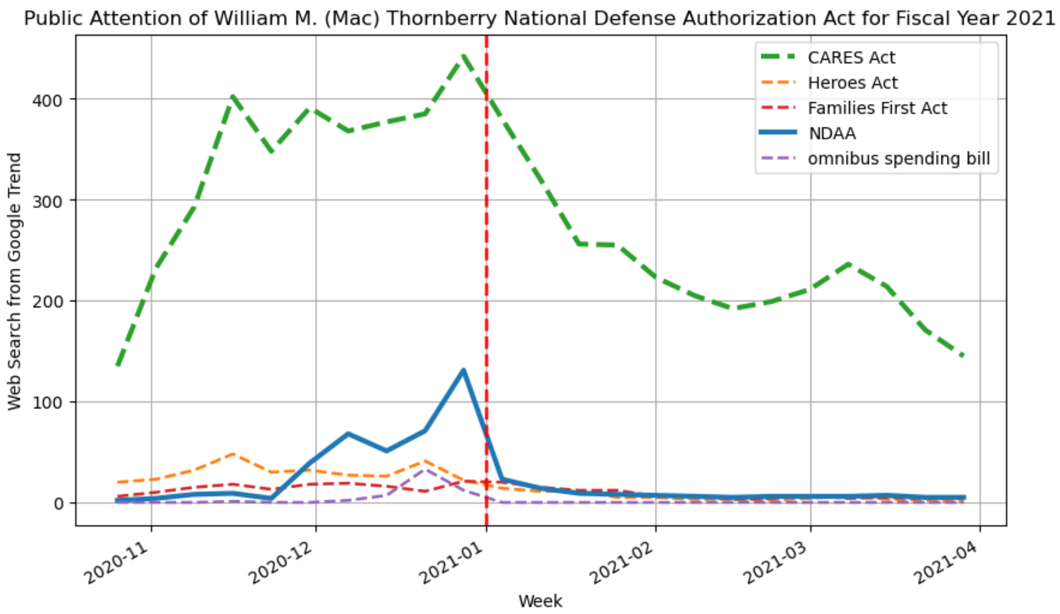

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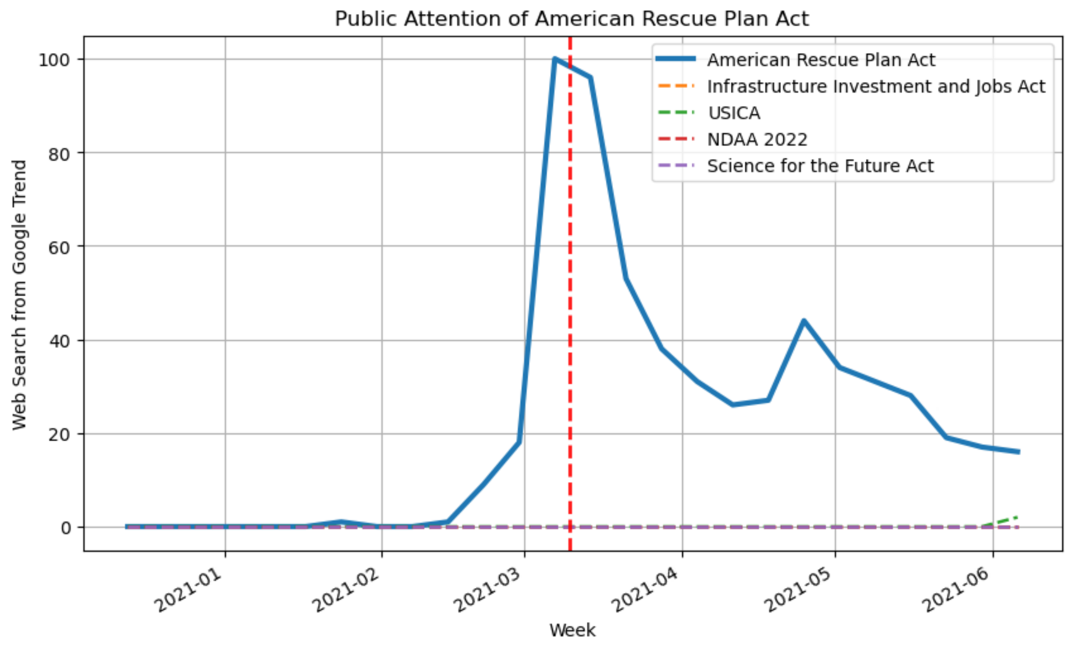
Figure 2: **Public Attention of Each Acts (Continued).**
This set of figures illustrates public attention to each act, proxied by Google Trends "Web Search" search interest for the relevant keywords. The event window spans $[-3, 3]$ calendar months centered on each act's final congressional passage date (day 0). The solid blue line indicates the act selected for inclusion in our sample. The dashed red line presents the act passage date. The keywords used to construct the series are listed in the legends.



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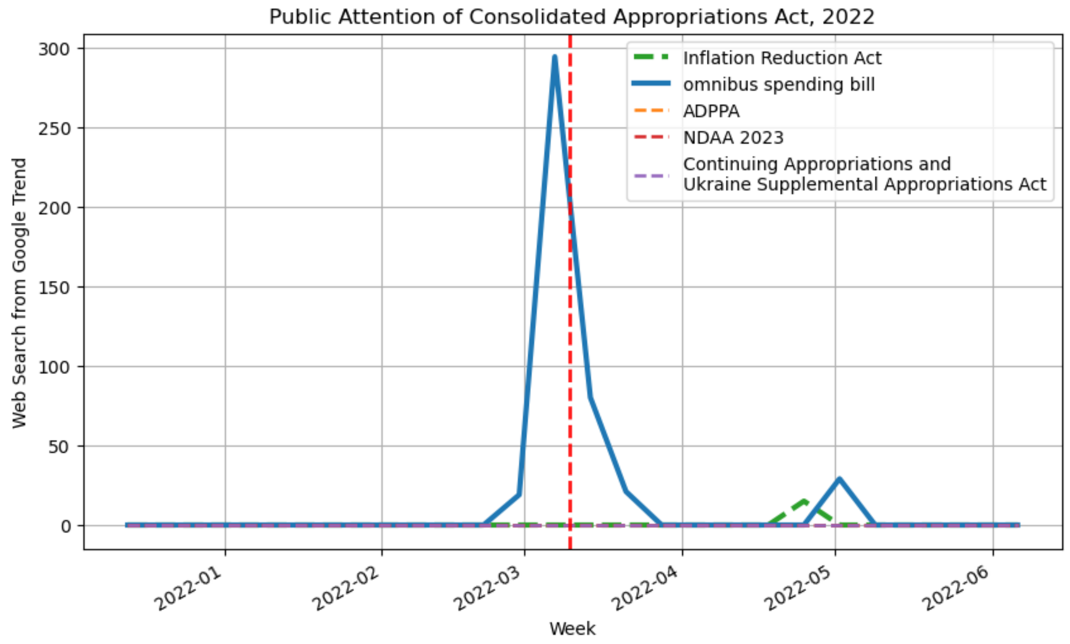

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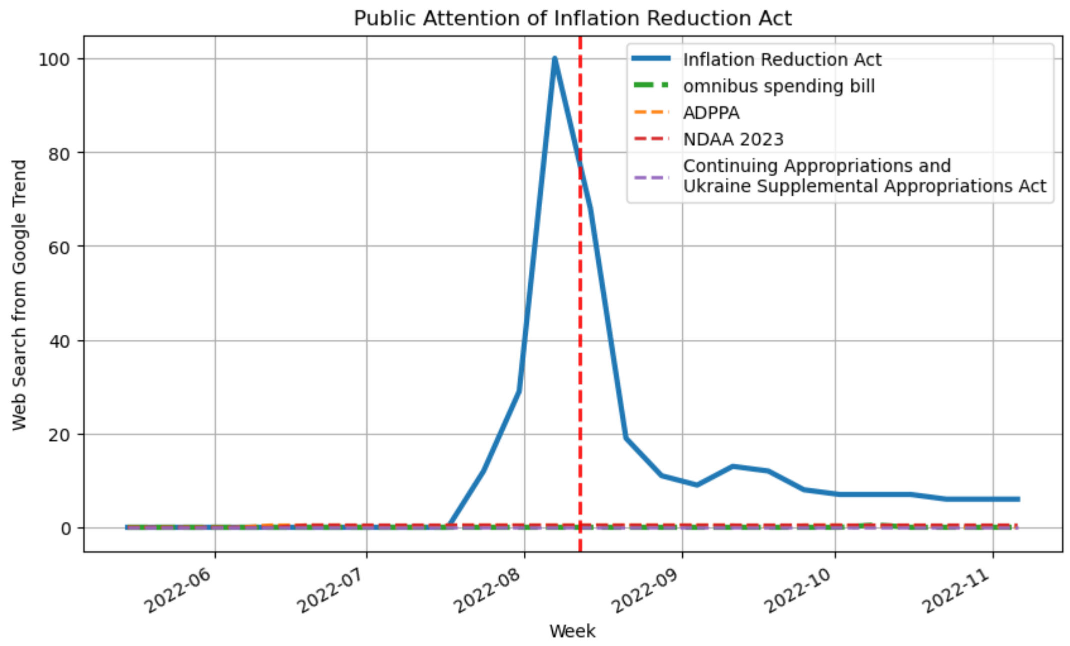

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Figure 2: **Public Attention of Each Acts (Continued).**
This set of figures illustrates public attention to each act, proxied by Google Trends “Web Search” search interest for the relevant keywords. The event window spans $[-3, 3]$ calendar months centered on each act’s final congressional passage date (day 0). The solid blue line indicates the act selected for inclusion in our sample. The dashed red line presents the act passage date. The keywords used to construct the series are listed in the legends.

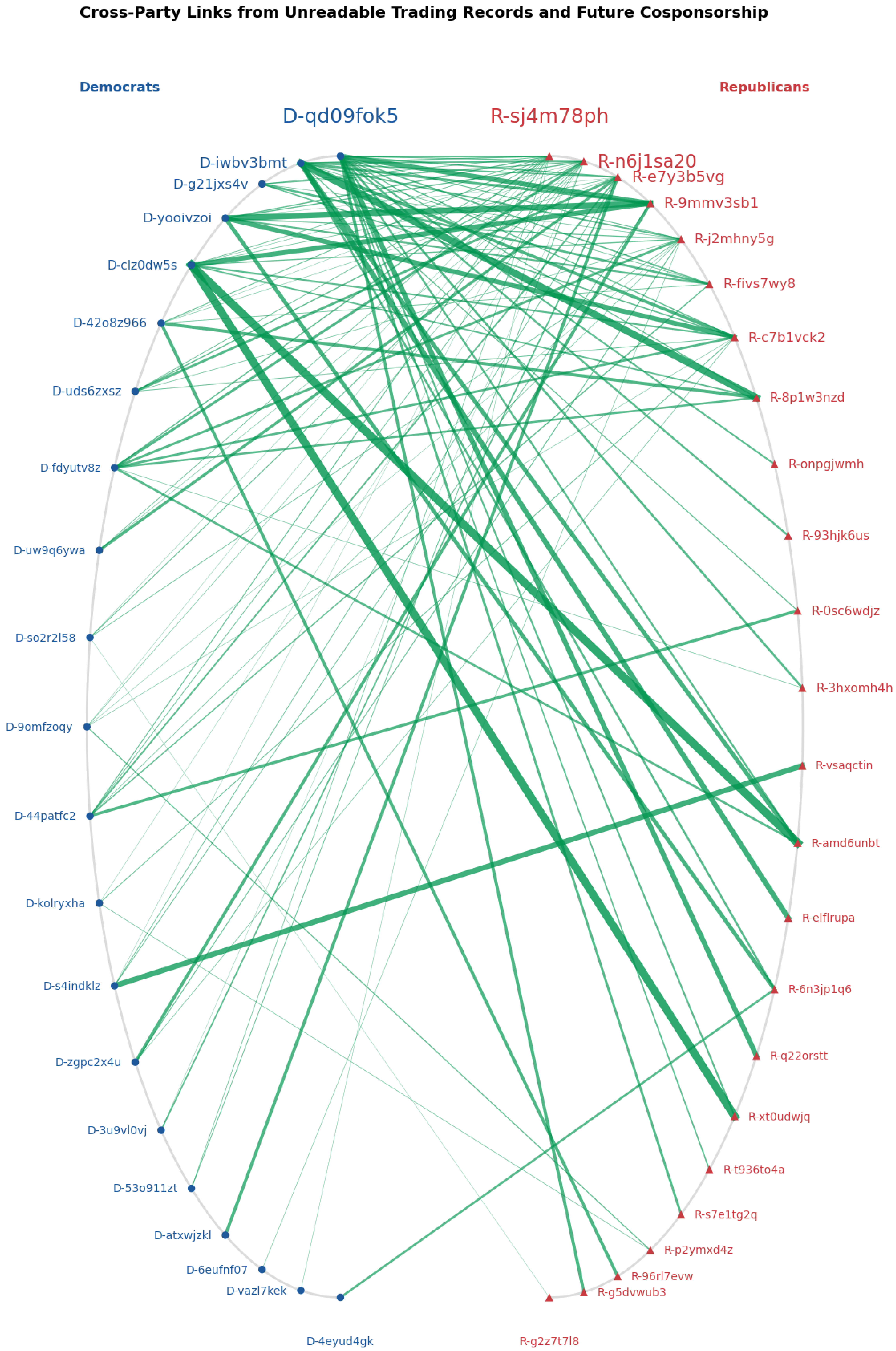


Figure 3: **Unreadable political connections.**
This figure presents potential connections between legislative members from different political parties inferred from unreadable trading disclosure files. Trading similarity between two legislators is defined as the number of stock–direction pairs (stock, buy/sell) they have in common divided by the total number of distinct stock–direction pairs traded by either legislator. Each calendar year is partitioned into six consecutive trading windows (the first five are 60 days long and the sixth covers the remainder of the year); for each window, we compute trading similarity using trades within that window and then count joint bill cosponsorships in the 180 days following the window's end. The network in this figure includes all legislators who appear in at least one cross-party pair of legislators with positive trading similarity and at least one such forward cosponsorship; line thickness reflects the strength of these combined connections, and larger displayed labels indicate legislators who participate in more of these qualifying cross-party pairs. All legislators' identifying information has been anonymized and is not recoverable from the figure; all displayed labels are randomly generated placeholders with no real-world meaning.

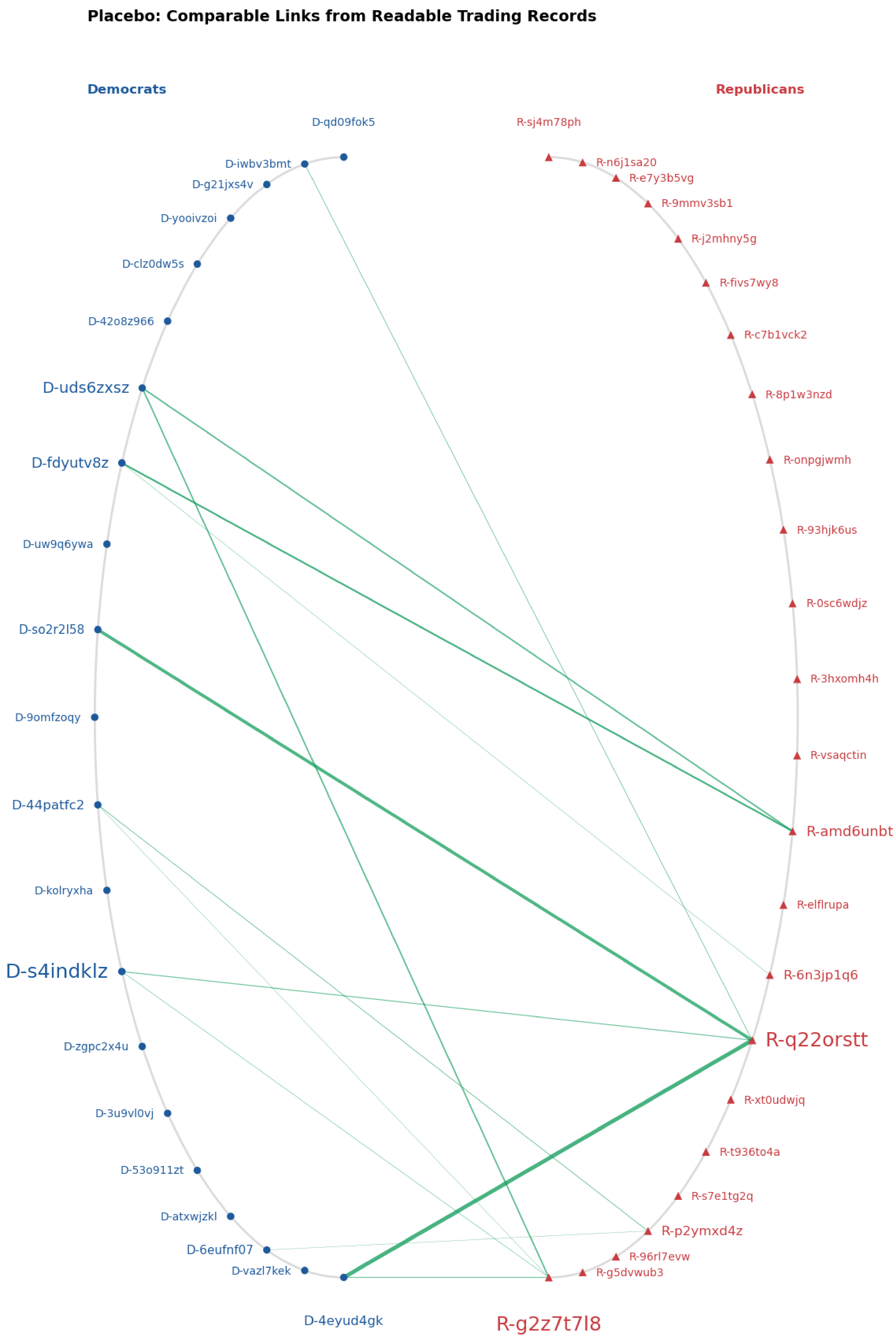


Figure 4: **Unreadable political connections: Placebo.**
This figure presents potential connections among the same set of legislative members from different political parties, as observed in the readable trading files, corresponding to connections identified from the unreadable trading disclosure files in Figure 3. Line thickness indicates the strength of each connection, with thicker lines representing stronger connections. All legislators' identifying information has been anonymized and is not recoverable from the figure; all displayed labels are randomly generated placeholders with no real-world meaning.

Table 1: **Abnormal Stock Return, Trading Amount Patterns and Trading Number Patterns of Unreadable Congressional Trading.**

This table presents three main results in our paper.

Panel A: In Panel A, the unit of observation is at the transaction-file level: each observation represents a legislator's trade in a given stock on a specific date and is linked to a binary variable, Unreadable, which equals one if the observation is reported in an unreadable disclosure file. This panel considers the effects of disclosure-file unreadability on ticker-level abnormal returns over different future trading-day windows, and we restrict this sample to transactions classified as purchases. Abnormal_return_$\{22, 30, 35, 40\}$ denotes the cumulative abnormal return (CAR) for ticker i over the subsequent $\{22, 30, 35, 40\}$ trading days, signed by trade direction (multiplied by $+1$ for purchases and -1 for sales) and reported in percentage points. FOMC control equals one if the actual trading date of a transaction is in a $[-3, 1]$ window around each FOMC meeting date in our sample period. Macro-level control variables include announcement surprises from Bloomberg's Macroeconomic Announcements dataset (please see Appendix Section A.3 for a detailed list of the macro-level control variables).

Panel B: Panel B also has four different levels of samples: Person-Trading_date level, Person-Ticker-Trading_date level, Person-Trading_date (Average by ticker) level and Disclosure_file level. This panel considers effects of disclosure-file unreadability on trading amount in each transaction at four different levels of samples. At the Person-Trading_date level, Log_Trading_Amount is the natural logarithm of the total trading amount for each person on each actual trading date, computed as the sum of the midpoints of the transaction amount ranges across all trades executed by that person on that date (Transaction amounts reported in each trading disclosure file are recorded as ranges). At the Person-Ticker-Trading_date level, Log_Trading_Amount is the natural logarithm of the total trading amount for each person-ticker pair on each actual trading date, computed as the sum of the midpoints of the transaction amount ranges across all trades in that ticker executed by that person on that date. The Person-Trading_date (Average) level is collapsed from the Person-Ticker-Trading_date level: Log_Trading_Amount is the natural logarithm of the average (across tickers traded by that person on that actual trading date) of the ticker-level trading amounts constructed from midpoint transaction amounts. At the Disclosure_file level, Log_Trading_Amount is the natural logarithm of the total trading amount reported in each disclosure file, computed as the sum of the midpoints of the transaction amount ranges across all transaction records included in each trading disclosure file. All other variables are defined as in Panel A. To conserve space, estimated coefficients of constants and control variables are omitted; full estimation results are available upon request.

Panel C: Panel C also has four different levels of samples: Person-Trading_date level, Person-Ticker-Trading_date level, Person-Trading_date (Average by ticker) level and Disclosure_file level. This panel considers effects of disclosure-file unreadability on trading number. At the Person-Trading_date level, Trading_Number is the total trading number for each person on each actual trading date. At the Person-Ticker-Trading_date level, Trading_Number is the total trading number for each person-ticker pair on each actual trading date. The Person-Trading_date (Average) level is collapsed from the Person-Ticker-Trading_date level: Trading_Number is the average (across tickers traded by that person on that actual trading date) of the ticker-level trading numbers. At the Disclosure_file level, Trading_Number is the total trading number reported in each disclosure file. All other variables are defined as in Panel A. To conserve space, estimated coefficients of constants and control variables are omitted; full estimation results are available upon request. ***, p-value <1%; **, <5%; *, <10%.

Panel A: Abnormal Stock Return of Unreadable Congressional Trading.

DV:	Abnoraml_return_22	Abnoraml_return_30	Abnoraml_return_35	Abnoraml_return_40
SE:	Person+Actual_YM			
FOMC control:	Yes	Yes	Yes	Yes
Macro controls:	Yes	Yes	Yes	Yes
Amount control:	Yes	Yes	Yes	Yes
Stock FE:	Yes	Yes	Yes	Yes
Year-Month FE:	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)
Unreadable	0.378**	0.406**	0.367*	0.329*
	(0.166)	(0.182)	(0.191)	(0.194)
N	38,261	38,208	38,178	38,168
R^2	0.20	0.21	0.21	0.22

Table 1: **(Continued) Abnormal Stock Return, Trading Amount Patterns and Trading Number Patterns of Unreadable Congressional Trading.**

Panel B: Trading Amount Patterns of Unreadable Congressional Trading.					
DV:			Log_Trading_Amount		
Data Level:	Person-Trading_date	Person-Trading_date	Person-Trading_date (Average by ticker)	Person-Ticker-Trading_date	Disclosure_file
SE:	Person+Actual_YM	Actual_YM	Actual_YM	Ticker+Actual_YM	Person+Disclosure_YM
FOMC control:	Yes	Yes	Yes	Yes	No
Macro controls:	Yes	Yes	Yes	Yes	No
Stock FE:	No	No	No	Yes	No
Year-Month FE:	Yes	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)	(5)
Unreadable	0.677**	0.677***	0.266***	0.214***	0.958**
	(0.329)	(0.028)	(0.034)	(0.036)	(0.365)
N	16,012	16,012	16,014	59,850	4,482
R^2	0.071	0.071	0.025	0.23	0.075

Panel C: Trading Number Patterns of Unreadable Congressional Trading.					
DV:			Trading_Number		
Data Level:	Person-Trading_date	Person-Trading_date	Person-Trading_date (Average by ticker)	Person-Ticker-Trading_date	Disclosure_file
SE:	Person+Actual_YM	Actual_YM	Actual_YM	Ticker+Actual_YM	Person+Disclosure_YM
FOMC control:	Yes	Yes	Yes	Yes	No
Macro controls:	Yes	Yes	Yes	Yes	No
Stock FE:	No	No	No	Yes	No
Year-Month FE:	Yes	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)	(5)
Unreadable	4.633**	4.633***	0.348***	0.273***	30.526*
	(1.981)	(0.400)	(0.032)	(0.041)	(15.428)
N	16,018	16,018	16,018	59,999	4,483
R^2	0.035	0.035	0.10	0.23	0.073

Table 2: **Unreadable Congressional Family Member Trading.**

This table presents the relationship between disclosure-file unreadability, transaction ownership and various trading outcomes.

Panel A: In Panel A, the unit of observation is at the transaction-file level: each observation represents a legislator's trade in a given stock on a specific date and is linked to a binary variable, Unreadable, which equals one if the observation is reported in an unreadable disclosure file. This panel considers effects of disclosure-file unreadability on transaction ownership, and we restrict this sample to transactions classified as purchases. Family_Member equals one if the transaction is owned by the legislative member's spouse, child(ren), or a joint account held by the legislative member and a family member. Children equals one if the transaction is owned by the legislative member's child(ren). Spouse equals one if the transaction is owned by the legislative member's spouse.

Panel B: The sample of Panel B is in Person–Year–month level. This panel assesses whether disclosure-file unreadability affects trading outcomes differently for transactions owned by family members relative to others. Trading_Number is the total number of transaction records for person j in year–month YM. Log_Trading_Amount is the natural logarithm of the total trading amount for person j in YM, computed as the sum of the midpoints of the reported transaction-amount ranges across all trades executed in that month. Profitability outcomes (Trading_Profit_22, Trading_Profit_30, Trading_Profit_35, Trading_Profit_40) are constructed for horizons $h \in \{22, 30, 35, 40\}$ as the sum, within year–month YM, of trade-level dollar profits defined by the midpoint trading amount multiplied by the cumulative return over the subsequent h trading days for the traded ticker, and are expressed in units of 10,000. The abnormal-return outcome Trading_Abnormal_Return_22 is the mean of transaction-level abnormal returns Abnormal_return_22 for person j in year–month YM, which is reported in percentage points. Family_Member and Unreadable are defined as in Panel A. FOMC control equals one if the actual trading date of a transaction is in a $[-3, 1]$ window around each FOMC meeting date in our sample period. Macro-level control variables include announcement surprises from Bloomberg's Macroeconomic Announcements dataset (please see Appendix Section A.3 for a detailed list of the macro-level control variables). To conserve space, estimated coefficients of constants and control variables are omitted; full estimation results are available upon request. ***, p-value <1%; **, <5%; *, <10%.

Panel A: Unreadable Congressional Family Member Trading.

DV:	Family_Member	Children	Spouse
SE:	Robust	Robust	Robust
	(1)	(2)	(3)
Unreadable	0.165***	0.208***	0.227***
	(0.005)	(0.003)	(0.005)
N	41,440	41,440	41,440
R^2	0.027	0.062	0.046

Panel B: Unreadable Congressional Family Member Trading (Year-Month level).

DV:	Log_Trading_Amount	Trading_Number	Trading_Profit_22	Trading_Profit_30	Trading_Profit_35	Trading_Profit_40	Trading_Abnormal_Return_22
SE:	Actual_YM	Actual_YM	Actual_YM	Actual_YM	Actual_YM	Actual_YM	Actual_YM
Year-Month FE:	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unreadable*Family_Member	0.645***	30.968***	1.125***	1.215***	1.280***	1.322***	-0.003
	(0.083)	(3.635)	(0.356)	(0.391)	(0.448)	(0.488)	(0.382)
Unreadable	0.519***	7.282***	-0.102	-0.020	0.068	0.138	0.018
	(0.058353)	(0.692803)	(0.094507)	(0.104995)	(0.118456)	(0.127580)	(0.296)
Family_Member	0.282***	1.646***	-0.332	-0.325	-0.458	-0.346	-0.031
	(0.047)	(0.358)	(0.283)	(0.273)	(0.310)	(0.355)	(0.256)
N	3,594	3,595	3,595	3,595	3,595	3,595	3,504
R^2	0.11	0.14	0.053	0.064	0.063	0.062	0.033

Table 3: **Date Difference between Actual Trading and Disclosure in Unreadable Congressional Trading.** The unit of observation in this table is at the transaction-file level: each observation represents a legislator's trade in a given stock on a specific date and is linked to a binary variable, Unreadable, which equals one if the observation is reported in an unreadable disclosure file. This table considers effects of disclosure-file unreadability on the date differences between actual trading dates and disclosure dates, and we restrict this sample to transactions classified as purchases. Dummy_Date_Difference equals one if the difference between actual trading date and the disclosure date of a transaction record is in the range of $\{28, 29, 30, 31\}$. FOMC control equals one if the actual trading date of a transaction is in a $[-3, 1]$ window around each FOMC meeting date in our sample period. Macro-level control variables include announcement surprises from Bloomberg's Macroeconomic Announcements dataset (please see Appendix Section A.3 for a detailed list of the macro-level control variables). To conserve space, estimated coefficients of constants are omitted; full estimation results are available upon request. Double-clustered standard errors at the individual and year-month level are reported in parentheses. ***, p-value <1%; **, <5%; *, <10%.

DV:	Dummy_Date_Difference	
SE:	Yes	Yes
FOMC control:	Yes	Yes
Macro controls:	No	Yes
Amount control:	Yes	Yes
Stock FE:	Yes	Yes
Year-Month FE:	Yes	Yes
	(1)	(2)
Unreadable	0.043*	0.038*
	(0.024)	(0.022)
N	39,109	39,109
R^2	0.16	0.20

Table 4: **Dyadic Regression Results for Unreadable Trading Connections.**
This table presents the dyadic regression results for the effect of the transaction disclosure files' unreadability on the legislative trading similarity in our sample. The dyadic samples are constructed based on 12 major acts enacted between 2014 and 2022. For each act, we form dyadic (i.e., member pair) groups using trades executed within pre-passage event windows of 60, 90, and 180 calendar days prior to the act's congressional passage date.
Panel A: The sample of Panel A is in Act-Dyadic_id level. This panel presents results for the 60-day window. Share_Any_Ticker equals 1 if two legislative members in a dyadic group have traded at least one ticker in common during the time window. Unreadable equals 1 if this dyadic group is extracted from the transaction records in unreadable legislative trading disclosure files. Committee control (Binary) equals 1 if two legislative members in a dyadic group have served on at least one committee in common in the House of Representatives. Committee control (Continuous) is the number of committees in the House of Representatives on which the two legislative members in one dyadic group have served simultaneously. State control equals 1 if two legislative members in one dyadic group are from the same state. Trading Amount control includes two variables, which are the total trading amounts of two legislative members in one dyadic group during the time window and are expressed in units of 1,000,000.
Panel B: The sample of Panel B is also in Act-Dyadic_id level. This panel reports results for the 90-day and 180-day windows. All variables are defined as in Panel A. Additionally, we conduct a drop-one-act robustness test using the Column (5) specification in Table A2. To conserve space, estimated coefficients of constants are omitted; full estimation results are available upon request.
Other details: In Panel A and Panel B, double-clustered standard errors at the dyadic group and event (act) level are reported in parentheses. ***, p-value <1%; **, <5%; *, <10%.

Panel A: Results in 60-Calendar-Day Window Before Each Act.					
DV:			Share_Any_Ticker		
Committee control (Binary):	No	No	Yes	No	Yes
Committee control (Continuous):	No	Yes	No	Yes	No
State control:	No	Yes	Yes	Yes	Yes
Trading Amount Control:	No	No	No	Yes	Yes
Event (Act) FE:	Yes	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)	(5)
60-Calendar-Day Window Before Each Act					
Unreadable	0.103***	0.103***	0.103***	0.079***	0.079***
	(0.027)	(0.027)	(0.026)	(0.024)	(0.024)
Committee control (Binary)			-0.002		0.001
			(0.009)		(0.008)
Committee control (Continuous)		-0.001		0.001	
		(0.008)		(0.007)	
State control		0.010	0.010	0.011	0.011
		(0.018)	(0.018)	(0.016)	(0.016)
Trade_Amount_Control_i				0.013***	0.013***
				(0.005)	(0.005)
Trade_Amount_Control_j				0.001292**	0.001292**
				(0.0003)	(0.0003)
N	12,471	12,471	12,471	12,471	12,471
R^2	0.027	0.027	0.027	0.064	0.064

Panel B: Results in 90-Calendar-Day and 180-Calendar-Day Windows Before Each Act.					
DV:			Share_Any_Ticker		
Committee control (Binary):	No	No	Yes	No	Yes
Committee control (Continuous):	No	Yes	No	Yes	No
State control:	No	Yes	Yes	Yes	Yes
Trading Amount Control:	No	No	No	Yes	Yes
Event (Act) FE:	Yes	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)	(5)
90-Calendar-Day Window Before Each Act					
Unreadable	0.120***	0.120***	0.120***	0.088***	0.088***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
N	17,252	17,252	17,252	17,252	17,252
R^2	0.030	0.030	0.030	0.065	0.065
180-Calendar-Day Window Before Each Act					
Unreadable	0.093***	0.094***	0.094***	0.060***	0.060***
	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)
N	24,665	24,665	24,665	24,665	24,665
R^2	0.025	0.025	0.025	0.063	0.063

Table 5: **Dyadic Regression Results for Unreadable Trading and Political Connections.**
The sample of this table is in Act-Dyadic_id level. This table presents the dyadic regression results for the effect of legislative trading similarity and the transaction disclosure files' unreadability on the bill cosponsorship in our sample. The results in this table are based on the dyadic groups constructed under the "60-Calendar-Day Window Before Each Act" specification in Table 4. Cosponsor_Same_Bill_Count measures the number of bills which are co-sponsored by the two legislative members in each dyadic group and are introduced during the 180-calendar-day period following the passage date of each act included in our sample. Share_Any_Ticker equals 1 if two legislative members in a dyadic group have traded at least one ticker in common during the time window. Unreadable equals 1 if this dyadic group is extracted from the transaction records in unreadable legislative trading disclosure files. Committee control (Binary) equals 1 if two legislative members in a dyadic group have served on at least one committee in common in the House of Representatives. Committee control (Continuous) is the number of committees in the House of Representatives on which the two legislative members in one dyadic group have served simultaneously. State control equals 1 if two legislative members in one dyadic group are from the same state. Trading Amount control includes two variables, which are the total trading amounts of two legislative members in one dyadic group during the time window and are expressed in units of 1,000,000.. Additionally, we conduct a drop-one-act robustness test using the Column (5) specification in Table A3. To conserve space, estimated coefficients of constants are omitted; full estimation results are available upon request. Double-clustered standard errors at the dyadic group and event (act) level are reported in parentheses. ***, p-value <1%; **, <5%; *, <10%.

DV:	Cosponsor_Same_Bill_Count				
Committee control (Binary):	No	No	Yes	No	Yes
Committee control (Continuous):	No	Yes	No	Yes	No
State control:	No	Yes	Yes	Yes	Yes
Trading Amount Control:	No	No	No	Yes	Yes
Dyadic FE:	Yes	Yes	Yes	Yes	Yes
Event (Act) FE:	Yes	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)	(5)
Unreadable*Share_Any_Ticker	6.314**	6.291**	6.306**	6.146**	6.160**
	(2.395)	(2.395)	(2.395)	(2.34)	(2.34)
Unreadable	-15.592**	-15.554**	-15.551**	-15.354**	-15.352**
	(6.757)	(6.759)	(6.761)	(6.725)	(6.726)
Share_Any_Ticker	-2.835*	-2.834*	-2.839*	-2.991*	-2.995*
	(1.459)	(1.456)	(1.457)	(1.511)	(1.512)
Committee control (Binary)			1.270		1.216
			(0.780)		(0.753)
Committee control (Continuous)		1.177		1.132	
		(0.795)		(0.773)	
State control		-3.498***	-3.501***	-3.824***	-3.826***
		(0.830)	(0.829)	(0.881)	(0.883)
Trade_Amount_Control_i				0.228	0.228
				(0.212)	(0.212)
Trade_Amount_Control_j				0.132	0.131
				(0.148)	(0.148)
N	8,360	8,360	8,360	8,360	8,360
R^2	0.69	0.69	0.69	0.69	0.69

Paper Appendix

A Data Appendix

A.1 Unreadable variables with intensive margins

To obtain the Unreadable_AI measure in Table A1, we process 2,011 machine-unreadable trading disclosure files in PDF format using an advanced AI model (Gemini 3 Pro), which we configure it to act as a "forensic document analyst." The objective is to rigorously evaluate the readability of diverse machine-unreadable files, such as handwritten or type-and-scanned documents.

When applying our unreadability measures, we focus on the subset of 1,581 machine-unreadable files that include at least one transaction classified as a purchase or a sale. The remaining trading disclosure files either include only transactions other than purchases or sales, or do not contain any stock trades at all, and are therefore excluded from our main sample, although they are still processed by the model.

A.1.1 AI Model Selection

At the model selection stage, we experimented with several large language models, including Grok, Google Gemini 2.5 Flash, Mistral (Le Chat), ChatGPT, Claude, DeepSeek, and Gemini 3 Pro. Among these models, Gemini 3 Pro exhibited the strongest performance in extracting information from machine-unreadable files, whereas the other models failed to reliably process the documents. For example, Claude returned an error message stating: "Could not extract content from '2015_9108075.pdf'. The file format may not be supported or the file may be corrupted," and DeepSeek was unable to read the PDF files. Based on this, we selected Gemini 3 Pro as the primary model for completing the scoring task.

A.1.2 Forensic Extraction Protocol

To ensure consistency and replicability across the dataset, we apply a standardized prompt to the model with explicit logical constraints ("logic locks") that govern classification. These constraints specify the conditions under which an entry can be classified as typed or handwritten and are designed to reduce arbitrary classifications and improve internal consistency.

A.1.3 Classification Logic: Typed vs. Handwritten

To systematically distinguish between machine-generated text and manual entries, the model enforces the following criteria:

- **Coordinate Stability Test (Typed).** Entries are classified as "Typed" if checkmarks (for example, "X") or characters are aligned at nearly identical coordinates (the same relative position within their boxes) across multiple rows. This stable alignment is consistent with machine-generated or printed marks.
- **Variance Test (Handwritten).** Any detectable variation in vertical position, stroke angle, or ink density is taken as evidence of manual input and triggers a "Handwritten" classification.

This logic ensures that even neat handwriting is correctly identified as a manual entry, because handwritten characters and marks almost always exhibit some geometric variance across repetitions, whereas machine-generated characters are highly stable in both shape and position.

A.1.4 Readability Scoring and Rescaling

We assign a readability score on a 1–10 scale to assess the visual legibility of each document:

- **Score 10 (Perfect legibility).** Text is perfectly sharp and clear. This includes both born-digital files and high-quality scanned documents in which there is no ambiguity in character recognition.
- **Scores 7–9 (Clear).** Documents are fully legible but exhibit minor visual artifacts, such as slight skew, mild blur, or standard scanner noise. Complete and reliable data extraction remains possible.
- **Scores < 7 (Degraded).** Documents suffer from substantial blur, low contrast, or handwriting interference that reduces certainty in the extracted information.

A.1.5 Details of the Scoring Procedure

During the scoring process, we focused on the readability of key trading items in each trading disclosure file, including full asset name, type of transaction, date of transaction and amount of transaction. For each file–input cycle, the complete scoring process requires approximately 1–2 minutes, and, with Gemini 3 Pro, we can process at most 10 files per batch. We observed that after analyzing a continuous batch of files (e.g., 10 PDFs within a single chat session), Gemini's adherence to the specified negative constraints gradually deteriorated: the model began to infer readability scores from patterns in previously analyzed files rather than relying solely on the current document. To mitigate this effect, we restarted the Gemini chat session after every 10–20 files so that the "Forensic Analyst" prompt was reinitialized for each batch, thereby reducing carry-over biases from earlier analyses. This procedure substantially improved scoring reliability.

Furthermore, we use Gemini 3 Pro to construct an additional readability variable that measures the readability of the Name Box in each trading disclosure file. This variable is used to identify files that require manual review. In particular, when the identifying information in the Name Box is handwritten, this typically indicates that the document contains a substantial handwritten component. Such cases increase the risk of assigning inaccurate readability scores to the key trading items in the file, so these documents are routed for manual verification.

The following procedure describes how we identify files that require manual review:

To filter out non-substantive markings in the key identification fields (the "Name Box"), we apply a simple semantic filter that governs a binary review flag:

- **"No" flag.** Assigned to boxes that contain only signatures, dates, or standard stamps. These purely formal markings do not, by themselves, trigger manual review.
- **"Yes" flag.** Assigned only if distinct handwritten keywords or status notes (for example, "Correction" or "Amended") are detected in the Name Box or similar fields.

This semantic filtering step ensures that the manual review process focuses on documents with substantive handwritten content rather than routine administrative markings.

A.1.6 Prompt

The following text presents the final prompt used to construct the readability score for each input document.

Role: Senior Forensic Document Examiner

Task:
Analyze the attached files with microscopic precision. Your goal is to eliminate any misclassification between machine-generated (Typed) text and manual (Handwritten) entries.

1. STRICT OUTPUT RULES (POST-PROCESSING)

- **NO CITATIONS**: Do NOT include "" or any reference markers.
- **CLEAN JSON ONLY**: Provide ONLY a valid JSON list inside a Markdown code block.

2. STOCK LIST TYPE: THE "4-STEP VERIFICATION"
Before choosing [Typed] or [Handwritten], you must evaluate these 4 forensic markers:

1. **THE PIXEL-CLONE TEST (For Typed)**:
   - Compare multiple "X" marks. If they are identical pixel-for-pixel (same angle, same width, same "serifs"), it is [**Typed**].
2. **THE COORDINATE TEST (For Typed)**:
   - Check the "X" placement within the boxes. If every "X" is centered at the exact same relative coordinate (mathematically perfect alignment), it is [**Typed**].
3. **THE INK-FLOW & TAPER TEST (For Handwritten)**:
   - Look at the ends of strokes. Handwriting has "tapering" (fading ends) and "pressure points" (thicker ink in some areas). Typed text has uniform stroke thickness.
   - If stroke ends are jagged/faded inconsistently, it is [**Handwritten**].
4. **THE GEOMETRIC VARIANCE (For Handwritten)**:

- If one “X” is slightly taller, wider, or more slanted than another, it is [**Handwritten**].

FINAL RULE: If there is even ONE manual mark in the list, the entire file is [**Handwritten**].

3. NAME BOX: STATUS NOTES VS. SIGNATURES

- **“Yes” ONLY IF**: There are handwritten **WORDS** describing a status (e.g., “Spouse”, “Correction”, “Joint”, “Amended”).
- **“No” IF**:
  - It is a **Signature** (even if handwritten).
  - It is a **Typed Name**.
  - It is an **Official Stamp** (e.g., “HAND DELIVERED”, “RECEIVED”).
  - It is **Scanner Noise** or blank.

4. DATA EXTRACTION (6 VARIABLES)
Extract these 6 variables into a JSON object:

1. **“file_name”**: [EXACT filename]
2. **“name_box_review_flag”**: [Yes / No]
   - *Logic*: “Yes” for Status Notes; “No” for Names/Signatures/Stamps.
3. **“name_box_readability”**: [1–10 or “N/A”]
   - *Logic*: “N/A” if flag is “No”.
4. **“stock_list_type”**: [Typed / Handwritten]
   - *Logic*: Choose [Typed] ONLY if text passes the Pixel-Clone and Coordinate tests.
5. **“stock_list_readability”**: [1–10]
   - 10: Perfect digital | 7–9: Neat block | 1–6: Cursive/Messy.
6. **“reasoning”**: [Max 15 words]
   - *Template*: “Typed: Perfect coordinate alignment and character clones.” OR “Handwritten: Inconsistent stroke geometry and tapering.”

5. OUTPUT FORMAT
Output ONLY the JSON list in a code block. No intro, no outro, no citations.

A.1.7 Output Format

The system outputs all extracted information in a strict, logic-enforced JSON format. This structured representation preserves the internal consistency imposed by the classification rules and facilitates reliable conversion to Excel for subsequent quantitative analysis.

A.1.8 Construction of the Final Unreadable_AI Variable

Using the readability scores generated by the above procedure,, we obtain the raw stock_readability measure. Following this, we linearly rescale the readability scores for these input documents. The final LLM-generated readability scores for input documents range from 3 to 10. Given this range, we define

$$\text{stock\_readability\_2} = 9 \times \frac{\text{stock\_readability} - 3}{10 - 3},$$

which maps the support $[3, 10]$ to $[0, 9]$. For electronically generated files, we keep the readability score fixed at 10. This adjustment helps separate the effect of scanner-related issues (such as jagged edges or scanner noise) from the intrinsic quality of fully digital files.

Finally, we construct our main unreadability measure, denoted Unreadable_AI, by inverting the rescaled readability index for all observations, including both machine-readable and machine-unreadable files:

$$\text{Unreadable\_AI} = 10 - \text{stock\_readability\_2}.$$

Under this transformation, higher values of Unreadable_AI indicate lower readability (that is, higher unreadability). Fully electronic documents with stock_readability_2 = 10 therefore receive Unreadable_AI = 0, while highly degraded scanned documents with low rescaled readability scores receive values of Unreadable_AI closer to 10.

A.2 Demonstrations of unreadable and readable files

The Stop Trading on Congressional Knowledge Act of 2012, commonly known as the STOCK Act, amended the Ethics in Government Act framework to require covered officials to file periodic transaction reports for many securities transactions within 30 days of receiving notice of the transaction and no later than 45 days after the transaction. Consistent with this framework, official guidance from congressional ethics offices permits periodic transaction reports to be submitted either through electronic filing systems or as paper forms with original signatures, which are then made available as public disclosure documents.[A2] This institutional flexibility generates disclosure files that are heterogeneous in machine readability, because the information disclosed in electronically filed reports is structured digital text while paper submissions are typically made public as scanned image based documents. Motivated by this feature of the disclosure process, we classify trading disclosure files into readable files and unreadable files. Readable files are typed electronic filings that have an underlying text layer and standardized fields, which make transaction information directly extractable by machines. Unreadable files are disclosure files that appear in scanned form, including files that are handwritten and then scanned and files that are typed or printed but submitted as scanned images, where the information is visually legible but not directly machine readable.

Readable files include detailed transaction level information, including asset names, transaction types, transaction dates, notification dates, and transaction amount ranges, all entered in standardized digital fields. Because these files are generated and submitted electronically, the underlying text layer is preserved even when the documents are distributed in PDF format. As a result, the information in readable files can be directly searched, copied, and programmatically extracted with minimal manual intervention, enabling large scale data collection and systematic empirical analysis. These features make readable files effectively machine readable and substantially reduce the cost and error associated with processing the trading disclosures from legislative members. Figure A1 presents example of machine-readable files, respectively.

Unreadable files also present transaction level information such as asset names, transaction dates, and transaction amounts. However, this information is embedded in scanned image based documents rather than structured text. We observe two distinct forms of unreadable files. The first consists of handwritten disclosures that are later scanned, where asset names, dates, and transaction details are filled in by hand on standardized paper forms. The second consists of files where the information is typed or printed but the report is still submitted as a scanned image, so the PDF does not contain searchable text. In both cases, a reader can see the information on the page, but a machine cannot reliably extract it. As a result, researchers typically must enter the data manually or rely on optical character recognition, which can introduce errors. Consequently, unreadable files generate substantially higher processing costs for researchers and regulators alike. Figures A2 and A3 show examples of handwritten then scanned files and typed but scanned files, respectively.

[A2] For the House, the Committee on Ethics financial disclosure guidance states that filers are strongly encouraged to use the electronic filing system and provides instructions for submitting paper forms with an original signature, available at `https://ethics.house.gov/financial-disclosure/`. The House instruction guide further specifies that reports must contain an original signature or be transmitted personally through the electronic filing system and that paper forms must be hand delivered or mailed, available at `https://ethics.house.gov/wp-content/uploads/2024/11/FDInstructionGuide_current_2023.pdf`.

Filing ID #20001601

PERIODIC TRANSACTION REPORT

Clerk of the House of Representatives • Legislative Resource Center • B-106 Cannon Building • Washington, DC 20515

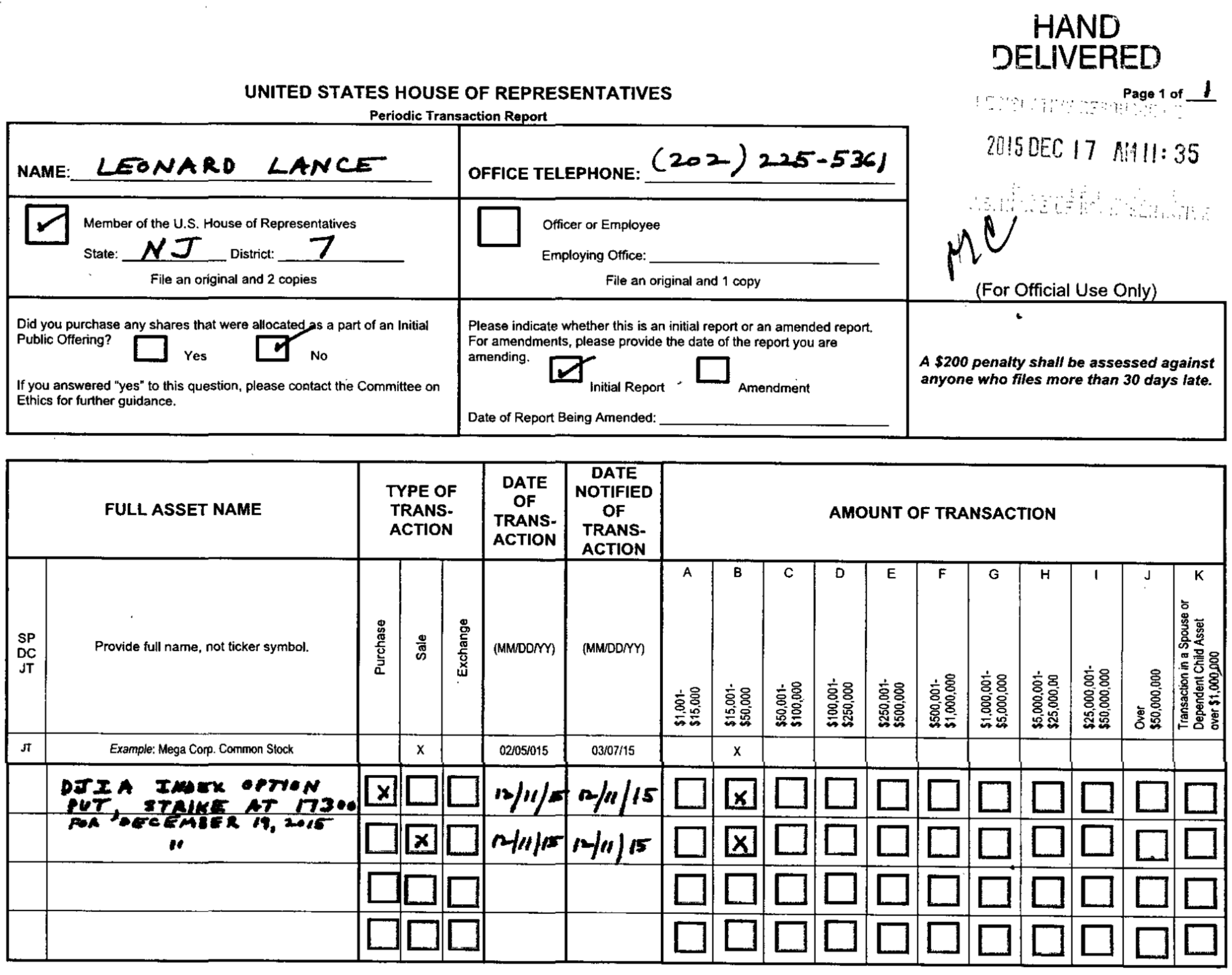
FILER INFORMATION

Name: Mr. David B. McKinley
Status: Member
State/District: WV01

TRANSACTIONS

ID	Owner	Asset	Transaction Type	Date	Notification Date	Amount
		Amgen Inc. (AMGN) FILING STATUS: New SUBHOLDING OF: IRA's> Rollover IRA	P	08/19/2014	08/29/2014	$1,001 - $15,000
		AutoZone, Inc. (AZO) FILING STATUS: New SUBHOLDING OF: IRA's> Rollover IRA	S	08/19/2014	08/29/2014	$1,001 - $15,000
		Bed Bath & Beyond Inc. (BBBY) FILING STATUS: New SUBHOLDING OF: IRA's> Rollover IRA	S	08/19/2014	08/29/2014	$1,001 - $15,000
		Church & Dwight Company, Inc. (CHD) FILING STATUS: New SUBHOLDING OF: IRA's> Rollover IRA	P	08/19/2014	08/29/2014	$1,001 - $15,000
		Costco Wholesale Corporation (COST) FILING STATUS: New SUBHOLDING OF: IRA's> Rollover IRA	S	08/19/2014	08/29/2014	$1,001 - $15,000
		Dollar Tree, Inc. (DLTR) FILING STATUS: New SUBHOLDING OF: IRA's> Rollover IRA	P	08/19/2014	08/29/2014	$1,001 - $15,000
		Ecolab Inc. (ECL) FILING STATUS: New SUBHOLDING OF: IRA's> Rollover IRA	P	08/19/2014	08/29/2014	$1,001 - $15,000

Figure A1: Example of a readable filing submitted through a typed electronic format.



HAND DELIVERED

UNITED STATES HOUSE OF REPRESENTATIVES

Periodic Transaction Report

Page 1 of 1

2015 DEC 17 AM 11:35

MC

(For Official Use Only)

NAME: LEONARD LANCE

OFFICE TELEPHONE: (202) 225-5361

☑ Member of the U.S. House of Representatives
State: NJ District: 7
File an original and 2 copies

☐ Officer or Employee
Employing Office: ______
File an original and 1 copy

Did you purchase any shares that were allocated as a part of an Initial Public Offering? ☐ Yes ☑ No

If you answered "yes" to this question, please contact the Committee on Ethics for further guidance.

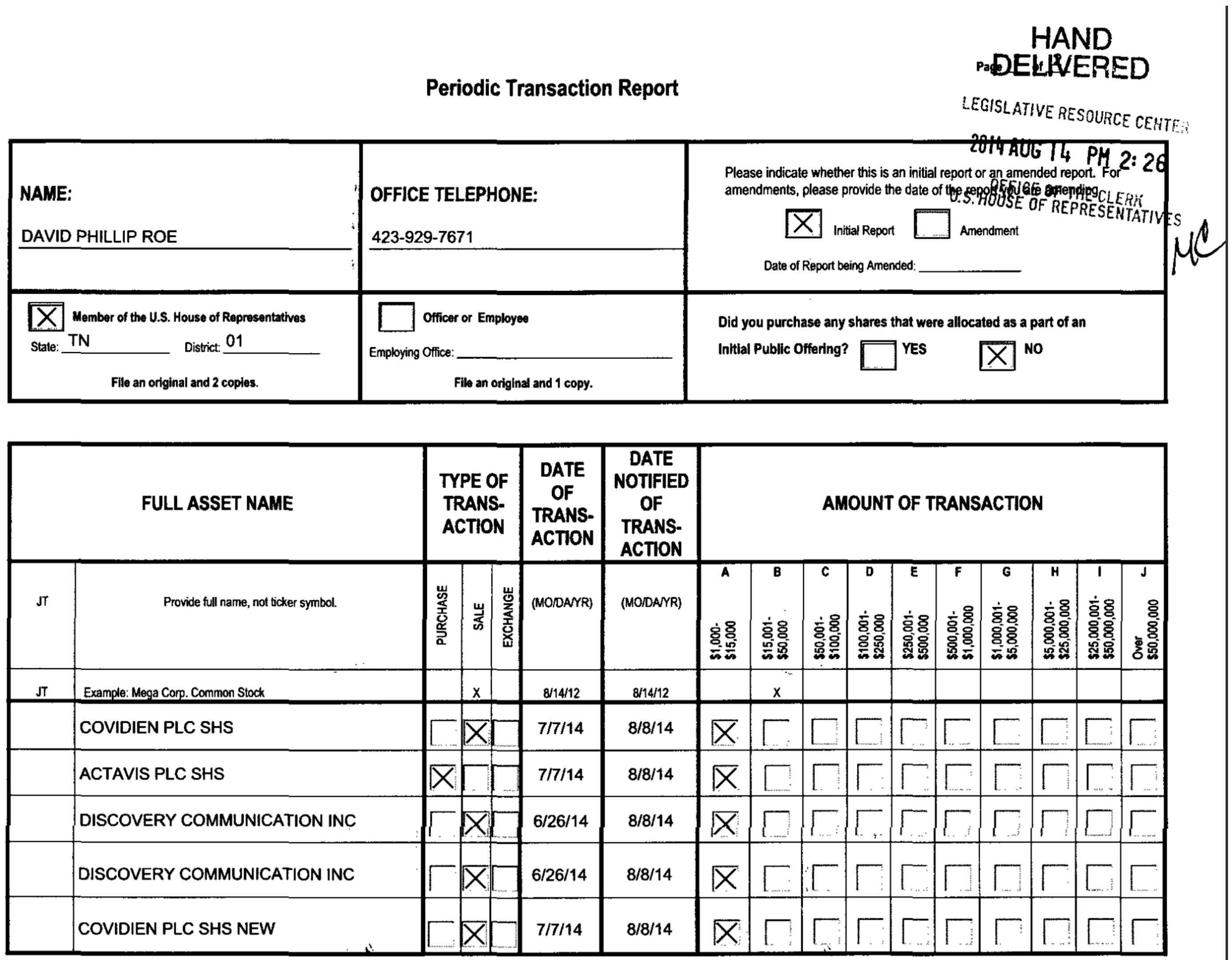
Please indicate whether this is an initial report or an amended report. For amendments, please provide the date of the report you are amending. ☑ Initial Report ☐ Amendment

Date of Report Being Amended: ______

A $200 penalty shall be assessed against anyone who files more than 30 days late.

SP DC JT	FULL ASSET NAME (Provide full name, not ticker symbol.)	Purchase	Sale	Exchange	DATE OF TRANSACTION (MM/DD/YY)	DATE NOTIFIED OF TRANSACTION (MM/DD/YY)	A $1,001-$15,000	B $15,001-$50,000	C $50,001-$100,000	D $100,001-$250,000	E $250,001-$500,000	F $500,001-$1,000,000	G $1,000,001-$5,000,000	H $5,000,001-$25,000,000	I $25,000,001-$50,000,000	J Over $50,000,000	K Transaction in a Spouse or Dependent Child Asset over $1,000,000
JT	*Example*: Mega Corp. Common Stock		X		02/05/015	03/07/15		X									
	DJIA INDEX OPTION PUT, STRIKE AT 17300	X			12/11/15	12/11/15		X									
	FOR DECEMBER 19, 2015 "		X		12/11/15	12/11/15		X									

Figure A2: Example of an unreadable filing that is handwritten and then scanned.



HAND DELIVERED

Periodic Transaction Report

LEGISLATIVE RESOURCE CENTER

2014 AUG 14 PM 2:26

OFFICE OF THE CLERK
U.S. HOUSE OF REPRESENTATIVES

MC

NAME: DAVID PHILLIP ROE

OFFICE TELEPHONE: 423-929-7671

Please indicate whether this is an initial report or an amended report. For amendments, please provide the date of the report you are amending. ☒ Initial Report ☐ Amendment

Date of Report being Amended: ______

☒ Member of the U.S. House of Representatives
State: TN District: 01
File an original and 2 copies.

☐ Officer or Employee
Employing Office: ______
File an original and 1 copy.

Did you purchase any shares that were allocated as a part of an Initial Public Offering? ☐ YES ☒ NO

JT	FULL ASSET NAME (Provide full name, not ticker symbol.)	PURCHASE	SALE	EXCHANGE	DATE OF TRANSACTION (MO/DA/YR)	DATE NOTIFIED OF TRANSACTION (MO/DA/YR)	A $1,000-$15,000	B $15,001-$50,000	C $50,001-$100,000	D $100,001-$250,000	E $250,001-$500,000	F $500,001-$1,000,000	G $1,000,001-$5,000,000	H $5,000,001-$25,000,000	I $25,000,001-$50,000,000	J Over $50,000,000
JT	Example: Mega Corp. Common Stock		X		8/14/12	8/14/12		X								
	COVIDIEN PLC SHS		X		7/7/14	8/8/14	X									
	ACTAVIS PLC SHS	X			7/7/14	8/8/14	X									
	DISCOVERY COMMUNICATION INC		X		6/26/14	8/8/14	X									
	DISCOVERY COMMUNICATION INC		X		6/26/14	8/8/14	X									
	COVIDIEN PLC SHS NEW		X		7/7/14	8/8/14	X									

Figure A3: Example of an unreadable filing that is typed or printed but submitted as a scanned image.

A.3 List of Macro Announcements Controls.

This table reports the macro announcement indices used to construct our macro announcements control variables. We select the indices with the top 50 relevance scores as reported by Bloomberg.

Macro Announcements Control Index	Relevant Score	Rank
NFP TCH Index	99.3289	1
INJCJC Index	98.6577	2
FDTR Index	97.9866	3
CPI CHNG Index	97.3154	4
GDP CQOQ Index	96.6443	5
CPI YOY Index	95.9732	6
NAPMPMI Index	95.302	7
CONSSENT Index	94.6309	8
RSTAMOM Index	93.9597	9
FDIDFDMO Index	93.2886	10
ADP CHNG Index	92.6174	11
CONCCONF Index	91.9463	12
DGNOCHNG Index	91.2752	13
IP CHNG Index	89.9329	14
USURTOT Index	89.396	15
NHSPSTOT Index	89.2617	16
NHSLTOT Index	88.5906	17
ETSLTOTL Index	87.2483	18
PITLCHNG Index	86.5772	19
PCE CRCH Index	86.5772	19
TMNOCHNG Index	85.906	20
EMPRGBCI Index	85.2349	21
USTBTOT Index	84.5638	22
LEI CHNG Index	83.8926	23
NAPMNMI Index	83.2215	24
CHPMINDX Index	82.5503	25
MWINCHNG Index	81.8792	26
CNSTTMOM Index	80.5369	27
OUTFGAF Index	79.1946	28
IMP1CHNG Index	78.5235	29
USPHTMOM Index	77.8523	30
CPUPXCHG Index	77.8523	30
GDP PIQQ Index	77.3154	31
ECI SA% Index	77.1812	32
CPI XYOY Index	76.5101	33
NAPMPRIC Index	75.8389	34
FDDSSD Index	75.1678	35
RCHSINDX Index	74.4966	36
FDIUFDYO Index	73.8255	37
USCABAL Index	73.1544	38
DGNOXTCH Index	73.0201	39
FRNTTOTL Index	72.4832	40
HPIMMOM% Index	71.1409	41
MPMIUSSA Index	70.4698	42
MPMIUSCA Index	70	43
FDIDSGMO Index	69.7987	44
USMMMNCH Index	69.5302	45
FDIUSGYO Index	69.1275	46
INJCSP Index	69.0604	47
FDTRFTRL Index	68.4564	48

A.4 Legislation Bills.

This table presents 12 Acts we have chosen to construct our network samples in different time windows. Please read more details in Section 4.

Congress	Legislation Number	Act	Passage Year
113	H.R.83	Consolidated and Further Continuing Appropriations Act, 2015	2014
113	H.R.4302	Protecting Access to Medicare Act of 2014	2014
114	H.R.2	Medicare Access and CHIP Reauthorization Act of 2015	2015
114	S.2943	National Defense Authorization Act for Fiscal Year 2017	2016
115	H.R.244	Consolidated Appropriations Act, 2017	2017
115	S.756	First Step Act of 2018	2018
116	H.R.3877	Bipartisan Budget Act of 2019	2019
116	H.R.748	CARES Act	2020
116	H.R.6395	William M. (Mac) Thornberry National Defense Authorization Act for Fiscal Year 2021	2021
117	H.R.1319	American Rescue Plan Act of 2021	2021
117	H.R.5376	An act to provide for reconciliation pursuant to title II of S. Con. Res. 14. (Inflation Reduction Act)	2022
117	H.R.2471	Consolidated Appropriations Act, 2022	2022

Among our choices, several cases warrant brief discussion. We retain the First Step Act because it attracts unusually high public attention relative to other heavily lobbied or expansionary bills in 2018 (Figure 2), and it has meaningful budgetary implications through implementation funding and changes in incarceration policy that affect federal costs.[A3]

The Consolidated Appropriations Act, 2022 is also distinctive because it incorporates congressionally directed spending (earmarks), namely project specific allocations that can channel federal funds to specific recipients or projects; earmarks were suspended for several years and later reestablished as CPF/CDS with disclosure and certification requirements, making FY2022 appropriations a particularly informative setting for detecting potential political network underlying in legislative members' trading disclosure files.[A4]

Additionally, the Consolidated and Further Continuing Appropriations Act, 2015 is a useful event in our setting because Senate committee markup "was postponed because of Administration objections," "[n]o further action on the Senate draft bill was taken," and final FY2015 Energy and Water Development funding "was included in the Consolidated and Further Continuing Appropriations Act, 2015."[A5] This shifts key decisions into a narrower, end-stage negotiation period tied to a single passage date, sharpening the timing of information resolution and making coordinated activity more likely to cluster near the passage date of this act.

The final case is the Consolidated Appropriations Act, 2017. This act was enacted at an imminent shutdown deadline: a continuing resolution signed on April 28, 2017 funded the government only through May 5, 2017 (or earlier upon enactment of appropriations legislation), and the omnibus was agreed to by the House on May 3, 2017 and by the Senate on May 4, 2017 (the final congressional passage date), before being signed into law on May 5, 2017.[A6] This near-shutdown deadline exacerbates time pressure and uncertainty, increasing the value of timely information about the bill's final terms. As a result, coordination is more likely to concentrate around the passage date, creating a particularly informative environment for identifying potential political networks through legislative members' trading disclosure files.

[A3] U.S. Department of Justice, Office of the Attorney General, *The First Step Act of 2018: Risk and Needs Assessment System* (July 19, 2019), Letters from Leadership, stating that "the Department will fully fund the $75 million authorized by the First Step Act in FY2019." Available via the Office of Justice Programs (OJP): `https://www.ojp.gov/First-Step-Act-of-2018-Risk-and-Needs-Assessment-System`.

[A4] The enacted text of H.R.2471 (Consolidated Appropriations Act, 2022) repeatedly states that specified funds "shall be ... in the amounts ... specified ... in the table titled 'Community Project Funding/Congressionally Directed Spending'" in the explanatory statement referenced in section 4, thereby incorporating congressionally directed spending items into the appropriations instructions. Congress.gov (Library of Congress), accessed Dec. 30, 2025, `https://www.congress.gov/bill/117th-congress/house-bill/2471/text`.

[A5] Congressional Research Service, David M. Bearden et al., *Energy and Water Development: FY2015 Appropriations* (R43567, Version 13, updated Jan. 30, 2015), p. 1: "Full committee markup scheduled for June 19, 2014, was postponed because of Administration objections ...". Available via Congress.gov, accessed Jan. 2, 2026, `https://www.congress.gov/crs_external_products/R/PDF/R43567/R43567.13.pdf`.

[A6] A continuing resolution signed on April 28, 2017 (Pub. L. 115–30) extended FY2017 funding through May 5, 2017, `https://www.govinfo.gov/content/pkg/PLAW-115publ30/pdf/PLAW-115publ30.pdf`. The *Consolidated Appropriations Act, 2017* (Pub. L. 115–31) was agreed to by the House on May 3, 2017 (309–118) and by the Senate on May 4, 2017 (79–18), and signed into law on May 5, 2017; see Congress.gov "All Actions," `https://www.congress.gov/bill/115th-congress/house-bill/244/all-actions`, and the enacted text, `https://www.congress.gov/115/plaws/publ31/PLAW-115publ31.pdf`. On a funding lapse, CRS notes that agencies "must shut down non-excepted activities" (RL34680, at p. 7), `https://www.congress.gov/crs_external_products/RL/PDF/RL34680/RL34680.27.pdf`.

B Additional Tables and Figures

Table A1: **Abnormal Stock Return of Unreadable Congressional Trading: Unreadable variables with intensive margins.**
The unit of observation in this table is at the transaction-file level: each observation represents a legislator's trade in a given stock on a specific date. This table considers effects of disclosure-file unreadability identified by LLM on future ticker-level abnormal returns over different trading-day windows, and we restrict this sample to transactions classified as purchases. Abnormal_return_$\{22, 30, 35, 40\}$ denotes the cumulative abnormal return (CAR) for ticker i over the subsequent $\{22, 30, 35, 40\}$ trading days, signed by trade direction (multiplied by $+1$ for purchases and -1 for sales) and reported in percentage points. Unreadable_AI is a measure between $[0, 10]$, linearly rescaled from the LLM-assigned readability score which captures the unreadability of each disclosure file (see more details in Appendix Section A.1). FOMC control equals one if the actual trading date of a transaction is in a $[-3, 1]$ window around each FOMC meeting date in our sample period. Macro-level control variables include announcement surprises from Bloomberg's Macroeconomic Announcements dataset (please see Appendix Section A.3 for a detailed list of the macro-level control variables). To conserve space, estimated coefficients of constants and control variables are omitted; full estimation results are available upon request. Double-clustered standard errors at the dyadic group and event (act) level are reported in parentheses. ***, p-value <1%; **, <5%; *, <10%.

DV:	Abnoraml_return_22	Abnoraml_return_30	Abnoraml_return_35	Abnoraml_return_40
SE:		Person+Actual_YM		
FOMC control:	Yes	Yes	Yes	Yes
Macro controls:	Yes	Yes	Yes	Yes
Amount control:	Yes	Yes	Yes	Yes
Stock FE:	Yes	Yes	Yes	Yes
Year-Month FE:	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)
Unreadable_AI	0.081**	0.063*	0.029	0.040
	(0.032)	(0.038)	(0.049)	(0.048)
N	38,261	38,208	38,178	38,168
R^2	0.20	0.21	0.21	0.22

Table A2: **Dyadic Regression Results for Unreadable Trading Connections (Drop One Act in Each Regression).**
The sample of this table is in Act-Dyadic_id level. This table presents the dyadic regression results for the effect of the transaction disclosure files' unreadability on the legislative trading similarity in our sample. Each regression drops one act. The results are obtained using the specification in column (5) of Table 4. Share_Any_Ticker equals 1 if two legislative members in a dyadic group have traded at least one ticker in common during the time window. Unreadable equals 1 if this dyadic group is extracted from the transaction records in unreadable legislative trading disclosure files. Committee control (Binary) equals 1 if two legislative members in a dyadic group have served on at least one committee in common in the House of Representatives. Committee control (Continuous) is the number of committees in the House of Representatives on which the two legislative members in one dyadic group have served simultaneously. State control equals 1 if two legislative members in one dyadic group are from the same state. Trading Amount control includes two variables, which are the total trading amounts of two legislative members in one dyadic group during the time window and are expressed in units of 1,000,000. To conserve space, estimated coefficients of constants are omitted; full estimation results are available upon request. Column (1) drops American Rescue Plan Act (2021); Column (2) drops Bipartisan Budget Act of 2019; Column (3) drops CARES Act, 2020; Column (4) drops Consolidated Appropriations Act, 2017; Column (5) drops Consolidated Appropriations Act, 2022; Column (6) drops Consolidated and Further Continuing Appropriations Act, 2015; Column (7) drops First Step Act, 2018; Column (8) drops Inflation Reduction Act (2022); Column (9) drops Medicare Access and CHIP Reauthorization Act of 2015; Column (10) drops National Defense Authorization Act for Fiscal Year 2017; Column (11) drops Protecting Access to Medicare Act of 2014; Column (12) drops William M. (Mac) Thornberry National Defense Authorization Act for Fiscal Year 2021. Double-clustered standard errors at the dyadic group and event (act) level are reported in parentheses. ***, p-value <1%; **, <5%; *, <10%.

DV:	Share_Any_Ticker											
Committee control (Binary):	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Committee control (Continuous):	No	No	No	No	No	No	No	No	No	No	No	No
State control:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trading Amount Control:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Event (Act) FE:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
60-Calendar-Day Window Before Each Act												
Unreadable	0.080***	0.071***	0.071***	0.086***	0.075***	0.087**	0.074**	0.078***	0.070**	0.094***	0.087***	0.078***
	(0.024)	(0.022)	(0.022)	(0.027)	(0.024)	(0.028)	(0.024)	(0.024)	(0.026)	(0.025)	(0.026)	(0.024)
N	11,012	11,312	10,809	11,736	11,445	11,565	11,,505	11954	11,630	11,292	11,753	11,168
R^2	0.066	0.063	0.055	0.065	0.067	0.062	0.063	0.064	0.071	0.064	0.065	0.067
90-Calendar-Day Window Before Each Act												
Unreadable	0.089***	0.077***	0.086***	0.088***	0.084***	0.095***	0.084***	0.090***	0.074***	0.096***	0.100***	0.087***
	(0.023)	(0.020)	(0.023)	(0.026)	(0.023)	(0.026)	(0.024)	(0.023)	(0.023)	(0.025)	(0.024)	(0.024)
N	15,013	15,835	15,270	16,054	15,731	15,944	15,824	16,504	15,988	15,751	15,998	15,860
R^2	0.070	0.063	0.055	0.065	0.069	0.063	0.064	0.065	0.068	0.064	0.067	0.066
180-Calendar-Day Window Before Each Act												
Unreadable	0.064***	0.057**	0.062***	0.063**	0.057**	0.051**	0.061**	0.064***	0.052**	0.067***	0.070***	0.057**
	(0.019)	(0.019)	(0.019)	(0.020)	(0.019)	(0.018)	(0.020)	(0.018)	(0.019)	(0.020)	(0.018)	(0.019)
N	21,142	22,496	21,973	22,629	23,080	22,889	22,517	23,312	23,000	22,274	22,852	23,151
R^2	0.069	0.063	0.059	0.064	0.063	0.060	0.065	0.062	0.061	0.062	0.060	0.066

Table A3: **Dyadic Regression Results for Unreadable Trading and Political Connections (Drop One Act in Each Regression).** The sample of this table is in Act-Dyadic_id level. This table presents the dyadic regression results for the effect of legislative trading similarity and the transaction disclosure files' unreadability on bill cosponsorship in our sample. Each regression drops one act. The results are obtained using the specification in column (5) of Table 5. Cosponsor_Same_Bill_Count measures the number of bills which are co-sponsored by the two legislative members in each dyadic group and are introduced during the 180-calendar-day period following the passage date of each act included in our sample. Share_Any_Ticker equals 1 if two legislative members in a dyadic group have traded at least one ticker in common during the time window. Unreadable equals 1 if this dyadic group is extracted from the transaction records in unreadable legislative trading disclosure files. Committee control (Binary) equals 1 if two legislative members in a dyadic group have served on at least one committee in common in the House of Representatives. Committee control (Continuous) is the number of committees in the House of Representatives on which the two legislative members in one dyadic group have served simultaneously. State control equals 1 if two legislative members in one dyadic group are from the same state. Trading Amount control includes two variables, which are the total trading amounts of two legislative members in one dyadic group during the time window and are expressed in units of 1,000,000. To conserve space, estimated coefficients of constants are omitted; full estimation results are available upon request. Column (1) drops American Rescue Plan Act (2021); Column (2) drops Bipartisan Budget Act of 2019; Column (3) drops CARES Act, 2020; Column (4) drops Consolidated Appropriations Act, 2017; Column (5) drops Consolidated Appropriations Act, 2022; Column (6) drops Consolidated and Further Continuing Appropriations Act, 2015; Column (7) drops First Step Act, 2018; Column (8) drops Inflation Reduction Act (2022); Column (9) drops Medicare Access and CHIP Reauthorization Act of 2015; Column (10) drops National Defense Authorization Act for Fiscal Year 2017; Column (11) drops Protecting Access to Medicare Act of 2014; Column (12) drops William M. (Mac) Thornberry National Defense Authorization Act for Fiscal Year 2021. Double-clustered standard errors at the dyadic group and event (act) level are reported in parentheses. ***, p-value <1%; **, <5%; *, <10%.

DV:	Cosponsor_Same_Bill_Count											
Committee control (Binary):	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Committee control (Continuous):	No	No	No	No	No	No	No	No	No	No	No	No
State control:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trading Amount Control:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dyadic FE:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Event (Act) FE:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Unreadable*Share_Any_Ticker	6.271**	5.440*	5.609**	6.784**	7.554**	5.593**	3.426**	7.122**	6.946**	6.442**	6.016**	6.265**
	(2.636)	(2.739)	(2.328)	(2.512)	(2.550)	(2.371)	(1.326)	(2.466)	(2.808)	(2.625)	(2.680)	(2.565)
Unreadable	-16.019**	-17.964**	-16.460**	-16.802**	-15.181*	-19.839**	-8.647*	-15.302**	-17.141*	-13.909*	-11.873*	-12.955
	(7.017)	(7.102)	(7.043)	(7.497)	(6.813)	(7.476)	(4.029)	(6.793)	(8.403)	(7.139)	(6.491)	(7.592)
Share_Any_Ticker	-2.982	-2.461	-3.185	-3.320*	-4.288**	-2.761	-1.587	-3.934**	-2.565	-2.451	-3.000*	-3.140
	(1.660)	(1.773)	(1.815)	(1.653)	(1.631)	(1.578)	(0.976)	(1.589)	(1.471)	(1.608)	(1.543)	(1.749)
N	6,962	7,292	6,907	7,723	7,326	7,557	7,506	7,752	7,681	7,488	7,844	7,310
R^2	0.68	0.72	0.71	0.70	0.71	0.69	0.73	0.70	0.70	0.69	0.70	0.68