Unreadable Political Trades*

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Abstract

Legislators can disclose their stock trading transactions through either typed electronic filings (machine-readable) or handwritten/hand-delivered and subsequently scanned filings (largely "unreadable"), in the latter of which the disclosed information is more difficult to identify, extract, and disseminate. Using a novel dataset of congressional trading from 2013 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 connected through unreadable trades are 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 other known political connections.

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"Voters have a right to know whether Congress is acting in the public's best interest or to advance their own financial interests. But disclosure only works if information is truly accessible. Otherwise, Congress can continue to hold problematic stocks in plain sight."
— *Campaign Legal Center, April 1, 2022*[1]

1 Introduction

The 2013 amendment to the Stop Trading on Congressional Knowledge (STOCK) Act eliminated the statutory requirement that members of Congress report their securities transactions in a searchable, sortable, and downloadable format. Following this change, legislators may fulfill disclosure obligations either through electronically typed, machine-readable submissions, or through hand-delivered paper filings that are subsequently scanned and uploaded. These "unreadable" filings materially diminish transparency, as they are far more difficult for the public to systematically and timely access, parse, and analyze. Using this institutional contrast, we first show that unreadable disclosure files systematically concentrate on economically important trading activity. Relative to readable filings, trades reported in unreadable files generate higher subsequent abnormal returns, involve larger dollar amounts and a broader set of stocks, are more frequently executed through family member accounts, and are disclosed closer to the statutory reporting deadline. Moreover, unreadable filings reveal a latent trading-to-political network: prior to major fiscal legislation events, 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 draws on a newly constructed dataset of congressional stock trades covering the post-amendment period. Specifically, we collect all periodic transaction reports (PTRs) filed by members of the U.S. House of Representatives from 2013 to 2022 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 and 4,492

[1] https://campaignlegal.org/update/how-congress-hides-stock-holdings-plain-sight

distinct stocks. We merge transaction-level data to daily stock returns from CRSP to compute direction-adjusted cumulative abnormal returns and dollar profits over a variety of horizons (i.e., 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 environment control variables.

Our first set of results shows that unreadable filings are associated with trading activity characterized by higher returns, larger dollar amounts, and a greater number of tickers. At the transaction level, purchase trades disclosed in unreadable files earn between 33 and 41 basis points higher abnormal returns over the subsequent one to two months than comparable trades disclosed in readable files. These differences persist after controlling for legislators' age, seniority, party affiliation, stock fixed effects, time fixed effects, Federal Open Market Committee (FOMC) windows, and macroeconomic announcements. To further validate this pattern, we employ an advanced AI model to assess and rank the visual legibility of each unreadable PTR, and the legibility-based measure produces inferences consistent with our baseline analysis.

Unreadable filings also involve substantially larger dollar volumes and broader trading portfolios. At the person-trading day level, trading volume is approximately 68% higher in unreadable files, and at the PTR file level these filings contain, on average, more than 30 additional transactions. Taken together, unreadable filings concentrate both trading profitability and trading scale, indicating that the choice of an unreadable format is systematically associated with more economically significant trading behavior.

Finally, we show that unreadable disclosure formats are closely linked to strategic behaviors 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 originates from a legislator's spouse or child is 16-23 percentage points higher in unreadable filings. Moreover, trades by family members reported through unreadable files are economically dominant, involving 64% higher trading volume and generating $11,000-$13,000 more in monthly dollar profits. Notably, the percentage abnormal returns are comparable, indicating that the larger dollar gains associated with family-member trades in unreadable filings arise from greater scale rather than superior trading ability. Second, unreadable filings appear 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, consistent with keeping economically important trades out of public view for as long as legally permissible.

To study the implications, we examine whether unreadable filings reveal a distinct network of politically relevant trading connections. Focusing on twelve major fiscal spending acts between 2013 and 2022, we analyze whether legislators trade the same stocks in the months preceding each act's passage. Dyads (Pairs) 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. The result is robust 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.

Moreover, these trading links have tangible political consequences. Legislator pairs that share stock trades through unreadable filings are, on average, more likely to co-sponsor six additional bills in the 180 days following a major fiscal spending act, whereas trading overlap in readable files has little predictive power. Network visualizations further demonstrate that unreadable filings generate a dense, cross-partisan web of trading connections, while the same legislators' readable filings display no comparable structure. The cross-party network revealed through unreadable filings is also distinct from those identified through social or institutional connections, such as shared state origin or shared committee membership. Taken together, unreadable disclosure files do not merely hide isolated profitable trades; they capture an economically and politically consequential 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 members of Congress. Prior studies document that legislators 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; Blonien, Crane, and Crotty, 2025; Dong and Xu, 2025; Yan, Yang, Zhang, and Zhou, 2025). Other studies find little evidence of market outperformance by politicians, 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, 2026). The main empirical challenge is to separate skill and information. We contribute to this debate by exploiting disclosure behaviors as a novel approach of empirical evidence. Focusing on the post-STOCK Act period, we show that strategic disclosure not only masks profitable trades by congressional members but also reveals political networks that remain undetectable through traditional measures of political connections. The "unreadable" networks are associated with real political outcomes, such as the likelihood of bill co-sponsorship.

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.

The remainder of the paper proceeds as follows. Section 2 describes the institutional background and legal background governing congressional trade disclosures. Section 3 describes data and sample construction. Section 4 documents systematic differences in legislator trading behaviors (trading profitability, scale, ownership, and disclosure timing) between readable and unreadable filings. Section 5 examines the network implications of unreadable disclosures around major fiscal acts. Section 6 concludes.

2 Institutional Background

The institutional setting for congressional trade disclosures is at the core of our empirical design. The Stop Trading on Congressional Knowledge (STOCK) Act of 2012, enacted on April 4, 2012,[2] amended the Ethics in Government Act of 1978 to enhance transparency in congressional financial activity and clarify that federal insider-trading prohibitions apply to public officials. The Act requires Members of the U.S. House of Representatives and covered family members (i.e., spouses and dependents) to file Periodic Transaction Reports (PTRs) for securities transactions exceeding $1,000 within 30 days of receiving notice, and no later than 45 days after the transaction date, whichever comes first. These timely reporting requirements marked a significant departure from pre-STOCK Act rules, under which Members of Congress were subject only to annual financial disclosure with no prompt reporting mandate for individual transactions.

A key feature of our empirical setting is that disclosure-file unreadability is not a fixed attribute. In fact, the original STOCK Act included electronic filing and online disclosure mandates intended to make reported transaction data more accessible and searchable to the public. In particular, it directed the establishment of an electronic filing system and required that disclosure reports be made available online in a format that would permit searching, sorting, and downloading.[3]

In April 2013, Congress enacted an amendment (S. 716, Public Law 113-7)[4] that substantially curtailed the scope of online posting requirements. The House vote recorded

[2]Link: https://www.congress.gov/bill/112th-congress/senate-bill/2038.

[3]Specifically, the STOCK Act states that "Individuals required under the Ethics in Government Act of 1978 or the Senate Rules to file financial disclosure reports with the Secretary of the Senate or the Clerk of the House of Representatives *shall* file reports electronically using the systems developed by the Secretary of the Senate, the Sergeant at Arms of the Senate, and the Clerk of the House of Representatives."

[4]Link: https://www.congress.gov/113/statute/STATUTE-127/STATUTE-127-Pg438.pdf.

417 members in favor and 2 opposed. The amendment eliminated the statutory mandate that PTRs be filed electronically and that disclosure incorporate technical functionalities such as searchability, sortability, or downloadability. In effect, the post-2013 framework no longer prescribes a uniform filing format: disclosures may be submitted through the electronic system or via paper forms that are subsequently scanned, uploaded, and released as public disclosure documents.[5] In practice, the public may still lawfully obtain these financial disclosure files; however, access is no longer automatic, directly online, or readily searchable. Put differently, Congress's repeal has rendered these reports, while remaining technically "public," far less accessible and user-friendly, thereby limiting the ability of outside groups and the broader public to systematically analyze legislative trading activity.

Given this institutional backdrop, we classify trading-disclosure files into readable and unreadable formats. Readable files are born-digital PDF files generated directly from electronically typed text, whereas unreadable files are PDFs produced by scanning handwritten or printed pages. In essence, the distinction between readable and unreadable files is entirely mechanical: it is determined solely by the file format rather than by the substantive content of the disclosure, hence making the classification a relatively trivial procedure.

While all PTRs include detailed transaction-level information, such as asset names, transaction types, transaction dates, notification dates, and transaction-amount ranges, readable files have all of this information entered in standardized digital fields. Figure 1 presents an example of a readable file.

[Insert Figure 1 here]

Because these files are generated and submitted electronically, the underlying text

[5]For the House, the Committee on Ethics financial disclosure guidance states that filers are strongly encouraged to use the electronic filing system, though it also 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.

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 trading disclosures by legislative members.

By contrast, transaction-level information in unreadable files is embedded in scanned, image-based documents rather than structured text, making it visually legible but not directly machine readable. Figure 2 provides illustrative examples of unreadable files.

[Insert Figure 2 here]

The upper panel of Figure 2 shows a PTR in which the disclosure is handwritten and later scanned; asset names, dates, and transaction details are filled in by hand on standardized paper forms. The lower panel presents an example where the information is typed or printed, but the report is still submitted as a scanned image, so the resulting PDF does not contain searchable text. In both cases, a reader can visually interpret the information on the page, but a machine cannot reliably extract it. As a result, researchers must typically enter the data manually or rely on optical character recognition, which can introduce errors. Consequently, unreadable files impose substantially higher processing costs on both researchers and regulators.

3 Data

Congressional Trading Data. We compile a sample of 5,113 Periodic Transaction Reports (PTRs) filed by 275 members of the U.S. House of Representatives between 2014 and 2022 from the Clerk of the House Disclosure Site. We begin the sample period after 2013 to ensure a stable legal environment following the 2013 amendment. Because some disclosures submitted during this period report trades executed in the prior year, the underlying transactions take place from 2013 through 2022.

We manually screen each PTR PDF and assign it into one of two categories: machine-readable files and machine-unreadable files (scanned, image-based documents). As described above, a file is deemed machine readable when it contains no embedded images, adheres to a standardized digital layout, and preserves a text layer that can be directly parsed by automated scripts. A file is classified as unreadable if it is a scanned, image-based document and/or contains handwritten content.

We focus on stock transactions executed by members of Congress and collect the transaction-level information disclosed in each PTR filing, including asset names, transaction types, transaction dates, notification dates, and transaction-amount ranges.[6] For machine-readable filings, we use Python to extract and structure the trading records. After each file is processed, the extracted output is manually reviewed against the original disclosure to identify parsing errors, missing fields, or inaccurate values, and any necessary corrections are made during this verification stage.

For unreadable files, we collect the transaction-level data manually. Sixteen research assistants read each disclosure and record all required variables, including asset name, ticker, asset type, transaction amount, transaction type, and other relevant details. When the readability of handwritten content in a PTR file is uncertain, a second reviewer is involved to make the final verification. To ensure that the classification is not systematically affected by human judgment biases, all information recorded from each PTR is subsequently reviewed and verified by a randomly assigned second reviewer.

Panel A of Table 1 reveals that 3,532 out of the 5,113 PTRs are classified as readable and 1,581 are classified as unreadable. These PTRs are reported by 276 members of the House of Representatives (122 Democrats, 151 Republicans, 1 Libertarian, and 1 Independent), consisting of 92,713 transaction records and covering 4,492 individual stock tickers. On average, a legislator files 18.6 PTRs during our sample period. This stands in

[6] The STOCK Act's transaction-reporting requirement does not apply to trades involving a widely held investment fund—such as a mutual fund, regulated investment company, pension plan, deferred compensation plan, or other comparable investment vehicle—provided that the fund is publicly traded or its assets are widely diversified, and the reporting individual neither exercises control over nor has the ability to influence the fund's underlying financial interests. See https://uscode.house.gov/view.xhtml?req=granuleid:USC-prelim-title5-section13105&num=0&edition=prelim.

sharp contrast with the two dissenting members who voted against the 2013 amendment bill: John Campbell, who retired from the House in 2015, did not file any PTRs; Rob Woodall, who retired in 2021, appears in our sample only once, through a single filing in a readable format.

The unreadable files cover 2,843 unique tickers, averaging 1.798 tickers per PTR, whereas the readable files involve 3,196 unique tickers, with a lower average of 0.905 tickers per PTR. Among all transactions, 61,171 originate from unreadable trading disclosures filed by 129 congressional members, of which 44,611 come from their family members. By contrast, readable disclosures account for 31,542 transactions filed by 201 congressional members, including 17,038 from family members. Several legislators file trades in both readable and unreadable formats during the sample period. Each unreadable PTR contains 38.691 transactions, whereas each readable PTR contains 8.93 transactions. Overall, unreadable files account for a disproportionate share of total transaction records, reflecting their tendency to bundle multiple trades within a single disclosure.

Stock Market Data. Individual stock and market return data are obtained from Center for Research in Security Prices (CRSP), following standard practice.[7] We merge transaction records to daily stock returns using the ticker identifier and the actual trading date. Following Ravina and Sapienza (2010) and Blonien, Crane, and Crotty (2025), we construct buy-and-hold cumulative abnormal returns (CARs) over horizons of 22, 30, 35, and 40 trading days, in excess of the CRSP value-weighted market index. Specifically, a buy-and-hold CAR for an executed purchase on day t of a stock s over the following $h \in \{22, 30, 35, 40\}$ is denoted as $\text{CAR}^{(h)}_{s,t} = \prod_{n=1}^{h}(1 + r_{i,t+n}) - \prod_{n=1}^{h}(1 + r^{(m)}_{t+n})$, where $r_{i,t+n}$ denotes the daily return of ticker i on trading day $t + n$, and $r^{(m)}_{t+n}$ denotes the market return on the same day. 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, in our main analyses, we compute cumulative abnormal returns based on share purchase records rather than sales transac-

[7]Our stock return measure includes distributions; our market return measure is the CRSP value-weighted market index return.

tions (e.g., Seyhun, 1986, 1992). We follow the literature to winsorize CARs at the 1% and 99% levels.

Other Data. On the legislative side, we obtain the complete bill sponsorship and co-sponsorship records from `Congress.gov`, which provides detailed bill information, including the introduction date and the full list of sponsor and co-sponsors for each bill. Committee assignments for House members in our sample are drawn from from the Congressional Directory (CDIR), available via the *govinfo* website at `https://www.govinfo.gov/app/collection/CDIR`.

On the macro side, we follow Bianchi, Gómez-Cram, and Kung (2024) and incorporate macroeconomic control variables (i.e., surprises) from Bloomberg's Macroeconomic Announcements dataset. The list of macro variables include 50 macroeconomic announcements with the highest relevance scores provided by Bloomberg. We relegates more details to Online Appendix OA3.

Selected Summary Statistics We explore multiple units of observations throughout the paper, in order to reflect the distinct dimensions of disclosure behavior, trading activity, and political interactions. We discuss immediate relevant ones here, with a summary of variables described in Online Appendix OA1. To study evidence of strategic disclosure and trading behavior, our baseline and most granular unit of analysis is the transaction–PTR level, which is equivalent to the person–ticker–trading date level. At this level, each observation corresponds to a legislator's trade in a given stock on a specific date, linked to the disclosure file through which the transaction is reported. Panel B of Table 1 shows that approximately 68.9% of transaction records in the baseline sample are drawn from unreadable filings, highlighting that unreadable formats account for a substantial share of reported congressional trading activity rather than representing a marginal or infrequent disclosure practice. Mean abnormal returns are positive across all horizons, ranging from 0.016% to 0.074%, while standard deviations increase with the return window, consistent with accumulating return volatility over longer horizons.

There is initial evidence that trades disclosed in unreadable files may contain superior information and thus outperform the market (e.g., Ravina and Sapienza, 2010). Table 1 reveals that the abnormal return for trades reported in unreadable formats over the 22-day holding period averages 0.125%, statistically significant at the 1% level; the abnormal return is even higher (i.e., 0.149%) when measured by the median rather than the mean. By contrast, trades disclosed in readable files over the same period yield an average return of -0.128%, which is marginally significant at the 10% level, and is both economically and statistically negligible at 0.07% when measured by the median. This indicates that trades in readable files do not outperform the market. We observe similar patterns in abnormal returns across other investment horizons (untabulated).

Panel B further summarizes transaction-level measures of trading scale, ownership, and reporting time. The disclosure forms (see Figures 1 and 2) do not mandate the reporting of exact trade amounts, but instead require disclosure in predefined dollar ranges. We use midpoints of reported dollar ranges when calculating transaction-level log trading amount. Panel B shows that log(*Trading Volume*) has a mean of 9.40 (or twelve thousand U.S. dollars). Ownership indicators show that approximately 69% of transactions involve family-member accounts, with 18.5% attributed to children, 39.5% to spouses, and the remaining being joint accounts. These statistics underscore the prevalence of non-self ownership in congressional trading disclosures and motivate our analysis of family-member trades in Section 4.2. Finally, *Near Deadline* indicates whether a transaction is disclosed at or near the statutory reporting deadline; roughly 14% of transactions are reported within the 28–31 day deadline window, consistent with strategic clustering around the reporting cutoff.

Panel C of Table 1 reports summary statistics for aggregated trading activity at higher levels of observation — at the person-trading date level and at the disclosure-file level. At the person–trading date level, approximately 47% of observations involve at least one transaction reported through an unreadable disclosure file. Daily trading activity is economically meaningful, with a mean log trading amount of 10.38 and an average of 4.93 transactions per trading date, indicating that legislators often execute multiple trades on the same day. At the disclosure-file level, unreadable filings account for roughly one-third of all files, and individual filings bundle substantial activity, with an average of 17.5 transactions per file and a mean log trading amount of 11.15.

Table OA1 in the online appendix reports the ten most frequently traded stocks across readable and unreadable filings. A notable pattern emerges: unreadable filings are disproportionately concentrated in large technology and growth-oriented firms, such as Amazon, Alphabet, Adobe, Meta, and NetApp, whereas readable filings are more heavily tilted toward traditional value and defensive stocks, including Home Depot, Procter & Gamble, Johnson & Johnson, and Berkshire Hathaway. This contrast is informative. Large technology firms tend to be more exposed to regulatory scrutiny, antitrust oversight, and government contracting, which is consistent with the interpretation that filers submitting unreadable disclosures may strategically trade in stocks with heightened policy sensitivity.

4 Strategic Reporting in Legislative Trades

In this section, we assess whether trades reported in unreadable disclosure files differ systematically from those reported in readable files during the 2013–2022 period. To preclude confounding effects introduced by pandemic-related legislative office closures and the suspension of physical PTR delivery in 2020, we exclude observations from that year from our analysis. We show that unreadable filings are associated with four distinct patterns: higher subsequent trading profitability, larger trading scale and broader portfolio scope (Section 4.1), greater reliance on family member accounts (Section 4.2), and longer delays between transaction dates and public disclosure dates (Section 4.3).

4.1 Profitability, Scale, and Scope of Unreadable Trades

We begin by comparing the characteristics of trades disclosed through readable and unreadable filings. To begin, we estimate the following regression specification (along with variants defined at different levels of observation) for individual i, stock s, and trading day t:

$$\mathrm{y}_{i,s,t} = \beta \cdot \mathrm{Unreadable}_{i,s,t} + \boldsymbol{\Gamma X_t} + \alpha_s + \alpha_t + \varepsilon_{i,s,t},$$

where the outcome variable y captures, respectively, the profitability, the scale, and the scope of congressional trading activities. In particular, *CAR* is the cumulative abnormal return of an individual stock earned over a trading horizon of interest. As described in details in Section 3, we consider this variable for each ticker over horizon windows of 22, 30, 35, and 40 trading days after the actual transaction, respectively. Then later, at various levels of observations, we construct log(*Trading Volume*), defined as the natural logarithm of the total dollar amount, and *# of Trades*, the number of transactions.

The key explanatory variable, $Unreadable_{i,s,t}$, is a dummy variable set to one if the disclosure associated with a transaction of stock s by legislator i in day t is reported through unreadable filing, and zero otherwise. α_s denotes stock ticker fixed effects and α_t denotes year-month fixed effects. $\boldsymbol{X_t}$ includes a set of controls that affect the profitability of legislative trades. An aging legislator may explain both their choice of reporting trades through paper filings and their accumulation of information over time that contributes to profitable trading. Similarly, senior House members may have broader networks than their junior counterparts that allow their trades to earn higher returns, while at the same time being accustomed to paper-based filings and reluctant to switch permanently to electronic formats. We therefore include categorical variables for age quartile bins and seniority quartile bins, where seniority is measured by the number of years an individual has served as a House representative. Since whether a legislator is a Democrat or a Republican also explains the profitability of their trades, we control for party affiliation.[8] Lastly, for some specifications, we also include macroeconomic surprises as in Bianchi, Gómez-Cram, and Kung (2024) (see the full list in Online Appendix OA3), FOMC event indicators, and trading volume.

[8] Unusual Whales Subversive Democratic Trading ETF (NANC) replicates trades disclosed by Democratic members of Congress, while Unusual Whales Subversive Republican Trading ETF (GOP) tracks trades disclosed by Republican members of Congress. According to Morningstar, NANC held an early advantage, outperforming GOP from their inceptions through August 2025. See "*The 2 ETFs That Track Congressional Stock Trades*", https://www.morningstar.com/funds/2-etfs-that-track-congressional-stock-trades.

Profitability We first compare the returns generated by trades reported through readable and unreadable PTRs. For this set of analysis, the unit of observation is at the PTR-ticker-transaction level. Standard errors are double clustered by individual and year-month. Panel A of Table 2 shows that the coefficient in *Unreadable* is positive and is statistically significant in all four holding-period horizons, indicating that legislative trades disclosed through unreadable filings earn significantly higher subsequent abnormal returns than those disclosed through readable filings. These results are obtained after controlling for legislators' age, seniority, party affiliation, stock fixed effects, year-month fixed effects, trading around FOMC meetings, and a rich set of macroeconomic surprise controls, implying that the performance gap is not driven by systematic exposure to market-wide, macroeconomic, monetary policy events, or firm-specific news. The magnitudes are also economically meaningful: transactions of the *same* stock reported in unreadable formats outperform those disclosed through readable files by approximately 35 to 42 basis points over the subsequent one to two months. Economic magnitudes remain stable across horizons, with statistical significance tapering modestly at longer windows.

[Insert Table 2 here]

Panel A of Table 2 provides the first empirical indication that trades reported in unreadable filings may be intended to conceal unusually high profitability. Unlike electronic filings, where the details of legislative trades are typed, standardized, and fully machine-readable, the readability of handwritten submissions varies considerably depending on who completes the form. As illustrated by the contrast between the readable and unreadable examples in Figures 1 and 2, extracting and interpreting information from handwritten filings can be substantially more difficult than from electronic submissions. To this end, the less legible the filing reads, the more effectively the underlying trades can be masked, and the more likely it is that such trades may be associated with higher profitability.

To probe this rationale, we examine an important — and admittedly experimental

— robustness setting in which we construct an alternative "unreadable" variable with additional variation. Specifically, we develop an intensive-margin unreadability measure based on an AI-generated readability score (ranging from 0 to 10, with 10 corresponding to fully electronic and machine-readable filings) assigned to each disclosure PDF according to its visual legibility. Lower scores indicate greater blur, distortion, or handwritten interference that reduces the certainty with which information can be extracted. We then re-define *Unreadable* 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. Online Appendix OA2 provides more technical details on how we use Gemini Pro to produce (un)readability scores for each file.

Table OA4 in the online appendix replicates Panel A of Table 2 using our continuous unreadability measure. There are two main observations. First, the overall 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. Importantly, illegibility could be conceptually different from our main *Unreadable* measure, which captures the procedural frictions inherent in hand-delivery and thus the associated strategic "intent to mask." As a result, in the rest of the paper, we focus on the simple binary variable (as presented in Table 2) as our unreadability measure of interest, for which the classification is extremely straightforward and replicable.

Trading Scale and Scope Panels B and C of Table 2 examine whether disclosure-file unreadability is associated with differences in the scale (volume) and scope (number of tickers) of trading activity. The dependent variable in Panel B is log(*Trading Volume*), defined as the natural logarithm of the total dollar amount summarized at various levels of observations (such as total dollar amount for each person-trading date as in Column (1) of Panel B). For each individual transaction, we only observe dollar range and as used in the literature, we consider the midpoints of the transaction amount ranges.[9] In Panel C, the dependent variable is *# of Trades*, defined as the number of transactions summarized at various levels of observations.[10] Both dependent variables are constructed and examined at four levels of observations: the person-trading date (total) level, the person-trading date (average) level, the person-ticker-trading date level, and the disclosure-file (PTR) level. We include time fixed effects, stock fixed effects, FOMC-window indicators, and macroeconomic surprise controls where applicable.

Panels B and C of Table 2 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 types of data panels, indicating that trades reported in unreadable files involve substantially larger dollar amounts. At the person-trading date level in Columns (1) and (2), trading dollar volume is about 64% higher 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 12-15% higher dollar volume. Column (5) aggregates the dollar volume at the PTR file level; we continue to observe a statistically significant coefficient estimate on *Unreadable*.

Panel C employs similar empirical constructs and reveals a similar pattern for trading breadth. Transactions reported in unreadable files involve a significantly larger number of transactions. At the person-trading date level (Column (1)), unreadable filings are associated with approximately 47% (=exp(0.382)-1) more trades per day, and at

[9]The STOCK Act of 2012 and its amendment in 2013 do not require legislators to disclose exact amount; instead, they can select appropriate dollar ranges.

[10]When computing the total dollar amount of trade and the number of transactions, we include both purchases and sales. This differs from the return construction in Panel A, which is based on purchase trades only, as the existing literature has shown that purchases more clearly capture information-driven trading. Nevertheless, our findings remain robust when we restrict trading volume and the number of trades to purchase transactions only.

the PTR-file level (Column (5)), they record approximately 106% (=exp(0.722)-1) more transactions on average. Taken together, Panels B and C indicate that unreadable files feature not only more profitable trades, but also trades that are larger in scale and broader in portfolio scope.

Note that trades reported in unreadable formats outperform those disclosed through readable files by approximately 35 to 42 basis points per transaction over the subsequent one to two months (Panel A). Combined with their more aggressive trading volume and broader set of stocks traded, this implies that for each legislator, trades disclosed through unreadable formats yield an average 22-day profit of $4,548.91 per year-month, compared with $1,398.29 for trades disclosed through readable formats

4.2 Family Member Trades

Under the Ethics in Government Act (EIGA) of 1978, which the STOCK Act amends and strengthens, members of Congress must report not only their own financial transactions but also those executed by their spouse or dependent children, all of which are subject to the same timely reporting requirements mandated by the STOCK Act. If legislators use unreadable filings to mask or delay the disclosure of trades that yield higher monetary gains, one may further expect such trades to be routed through family-member accounts rather than reported under their own portfolios. In Table 3, we evaluate whether unreadable disclosure files are systematically associated with the use of family-member accounts, and whether trades routed through these accounts carry greater monetary significance in terms of scope, scale, and profitability.

Panel A of Table 3 compares the prevalence of trades submitted through family-member accounts across unreadable and readable filings. The unit of observation is the transaction-file (i.e., person-ticker-trading date) level. The dependent variable in Column (1) is *Family*, a dummy variable equal to one if the trade is executed by a legislator's family member, including a spouse, dependent child(ren), or an account held jointly with a family member of the legislator, and zero otherwise. In Columns (2) and (3), we replace the dependent variable *Family* with *Children* and *Spouse*, respectively, defined as indicator variables equal to one when the transaction is executed through the legislator's dependent children or spouse.

Panel A reveals that unreadable filings are significantly associated with family-based trading. Across all three columns, the coefficient estimates on *Unreadable* are positive and statistically significant at the 1% level. The economic magnitude is also sizable: the likelihood that a family-member trade is reported through an unreadable file is 16.5% higher than for a readable file (Column (1)). Dis-aggregating this effect, trades executed through children's accounts are 20.8% more likely to appear in unreadable filings (Column (2)), and trades executed through spouses' accounts are 22.7% more likely (Column (3)). Together with evidence in Table 2 that trades in unreadable files yield higher returns, these results indicate that unreadable disclosure formats are disproportionately favored when legislators report profitable trades routed through family-member accounts.

In Panel B of Table 3, we directly examine how trading outcomes differ for family-member transactions when they are reported in unreadable filings. For this set of analysis, the unit of observations of interest is at the person-time-account type level. For each person-time trading via each affiliated account, we compute log(*Trading Volume*), defined as the natural logarithm of the dollar value of total trading volume within the year-month, and *# of Trades*, which is the number of transactions executed. The former captures the scale of an individual's trading activity, whereas the latter reflects its scope.

We also construct measures of trading profit over 22, 30, 35, and 40 trading-day horizons. Specifically, for each individual in each month, we compute the cumulative return over each horizon for every stock they trade. We multiply the cumulative return at each horizon by the transaction amount to obtain the dollar profit for each trade and then aggregate profits across all tickers traded by the individual within the month. *Trading Profits (22)* through *Trading Profit (40)* thus capture person–time trading profits at each horizon (in units of $10,000).

To assess how these transaction characteristics vary for trades executed by a legislator's family members across readable and unreadable filings, we estimate regressions that include an interaction between the dummy variable for unreadable filings (*Unreadable*) and an indicator for trades routed through family-member accounts (*Family*). According to Panel B, we observe that the interaction term *Unreadable* × *Family* consistently loads positively across Columns (1)–(6) and is statistically significant at the 1% level. This pattern indicates that trades executed through family-member accounts and disclosed in unreadable files are much larger in scale (Column (1)), scope (Column (2)) and dollar profits (Columns (3)-(6)). Specifically, unreadable family-member trades are associated with 90.6% higher trading volume and 50.5% more trades per month. They also yield markedly higher dollar profits: across 22- to 40-day horizons, the coefficients for the interaction term correspond to an additional $11,250 to $13,220 in monthly profits.

One may argue that family members are inherently more sophisticated professionals than legislators themselves and, as a result, trade more aggressively and generate larger dollar gains. Yet this does not explain why such trading behaviors and profits arise only in unreadable filings. Nevertheless, to further probe this alternative interpretation, we compare the abnormal trading returns between family members and non-family members. If legislators' family members were indeed skilled traders, their transactions should produce higher abnormal returns than those of legislators themselves. We find that the cumulative abnormal return over the 22-day horizon for trades executed through family-member accounts disclosed in unreadable PTRs averages 0.107%, which is statistically indistinguishable from the 0.176% earned by non-family accounts (untabulated). This indicates that family-member trades in unreadable filings do not earn higher percentage returns; instead, they generate higher economic gains because they are executed at a much larger scale.

[Insert Table 3 here]

Taken together, Table 3 shows that family-member trades are disproportionately reported in unreadable filings and are associated with larger trading volume, broader trading scope, and greater profitability. This suggests that legislators strategically pair unreadable disclosure formats with family-member accounts to concentrate economically meaningful trades in settings that are less transparent and more difficult to monitor.

4.3 Reporting Delays

The STOCK Act requires officials to file a PTR within 30 days of receiving confirmation of a stock trade, and in all cases no later than 45 days after the transaction occurs. Because public disclosure exposes trading activity to scrutiny, politicians have strong incentives to report their trades as late as the statutory window allows. Handwritten, hand-delivered filings make such delays both easier to implement and easier to justify. Unlike electronic submissions, which can be transmitted instantaneously and disclosed online at any time, paper filings introduce procedural frictions and timing ambiguities that allow for strategic postponement while preserving the appearance of formal compliance.

Figure 3 depicts the distribution of days elapsed between trade confirmation and filing. The upper panel shows the distribution of days taken for trades reported through unreadable filings, while the lower panel presents the corresponding distribution for readable filings. Unreadable submissions exhibit a sharp concentration around the 30-day mark (allowing for weekend adjustments), which is the statutory reporting deadline. In contrast, readable filings show no comparable clustering near the deadline. This pattern provides illustrative evidence that unreadable filings are disproportionately submitted at the end of the allowable reporting window.

[Insert Figure 3 here]

In Table 4, we formally test the patterns observed in Figure 3 through a regression framework, comparing the timing of disclosures between readable and unreadable filings. The first dependent variable as used in Columns (1) and (2) is *Days Until Deadline*, a continuous variable defined as the absolute distance between the interval from the transaction date to the disclosure date and 30 days. We consider a log transformed measure as the dependent variable in Columns (3) and (4). For this set of analysis, the unit of observation is the person-ticker-trade date level (equivalently, the transaction-file level). The key explanatory variable is *Unreadable*, as defined earlier, a dummy variable set to one if a transaction is reported in an unreadable disclosure file. In Columns (1) and (3), we control for trading around FOMC meetings, transaction amounts, stock fixed effects, and year-month fixed effects. In Columns (2) and (4), we include, additionally, controls for macroeconomic announcement surprises.

Table 4 shows that unreadable filings are significantly more likely to cluster at the statutory reporting deadline. The coefficient estimates on *Unreadable* indicate that transactions reported through unreadable files are approximately 23 days closer to the deadline. Results are not sensitive to extreme values.

[Insert Table 4 here]

The pattern documented in both Figure 3 and Table 4 reveals a systematic tendency for trades to be disclosed near the end of the allowable reporting window when the disclosure is submitted through an unreadable filing. This suggests that legislators use unreadable formats to keep high-stakes trades out of the public domain for as long as legally permissible, thereby increasing the informational opacity surrounding these transactions.[11] Taken together, the results indicate that unreadable filings are not only employed to obscure economically important trades and route them through family-member accounts, but are also associated with consistently later disclosure within the statutory window.

5 Unreadable Political Network

In this section, we examine a key testable implication of unreadable disclosure: their ability to reveal latent legislative trading and political networks. Specifically, we

[11] One may argue that filings submitted in unreadable formats near regulatory deadlines simply reflect the greater volume of paperwork involved and the additional time required to prepare them, rather than any strategic intent. Although this possibility cannot be entirely dismissed, the persistent use of a more costly method when a lower-cost alternative such as electronic online filing is readily available implies that the choice must provide some compensating benefit. In this context, selecting an unreadable format is unlikely to be incidental. Instead, it suggests that the filer perceives an advantage, such as reduced transparency or diminished scrutiny, that outweighs the incremental preparation cost.

assess whether unreadable filings uncover connections among legislators that are not detectable from readable filings or conventional indicators such as party or committee affiliation and state origination. In practice, identifying concrete links among politicians or between politicians and corporate executives is empirically challenging because their interactions and exchanges of favors are largely unobservable and may occur through private phone calls, e-mails, or informal conversations at social or professional events. In support of this logic, a *Wall Street Journal* article notes that when politicians wish to avoid creating a record of communication, they often use the code "LDL," meaning "let's discuss live."(Fulmer, Knill, and Yu, 2023)[12]

We postulate that valuable information shared within a latent political network enables connected politicians to harvest high stake returns through their trades. This implies that politicians who are closely linked through this concealed network should display highly correlated trading behavior when private information becomes available within the network and accessible to them. To evaluate this implication, we focus on legislative trades reported in unreadable files and executed prior to major economic and fiscal spending acts during our sample period. These acts can create substantial informational advantages for legislators, as they carry the highest political and monetary stakes, and the associated fiscal decisions attract substantial public attention.

We identify major economic acts by intersecting enacted federal legislation with two dimensions of economic and political relevance, namely bill level lobbying and spending intensity and contemporaneous public attention. Larger bill-specific lobbying expenditures reflect intensified efforts and substantial resources devoted by interested parties to shape the legislative outcome and therefore, signal the bill's anticipated economic impact and political salience. Public attention is captured by Google search intensity, which provides an independent and timely measure of perceived importance. Unusually high search volume indicates that the proposed policy has entered public discourse and is being closely monitored by citizens, media outlets, and market participants, a pattern that typically emerges only when legislation carries broad economic consequences or implicates salient

[12] "Goldman's Tourre meets with Senate investigators", April 24, 2010, The Wall Street Journal.

political priorities. Another advantage of zooming in on legislative trades executed prior to major acts is that these events generate meaningful cross-industry and cross-time heterogeneity, allowing us to isolate which sectors and firms are differentially exposed to each legislative shock. This variation helps identify the specific information legislators appear to trade on through the unreadable network and clarifies the mechanisms underlying the returns associated with these transactions.

We begin with the universe of bills that become law and record their final passage dates at the Congress. We then merge these bills with lobbying data and retain those associated with lobbying expenditures of at least one million dollars.[13] From this set, we identify major legislative events within each Congress-year by allowing multiple bills to be selected, provided that their passage dates are at least 60 days apart. When multiple high-lobbying bills are passed within a 60-day window, we retain the bill with the higher Google search volume as the more salient event. Figure OA1 further demonstrates that our selected bills attracted substantially greater public attention relative to other major acts passed in the same year, supporting that they represent the highly salient legislative events in the recent U.S. history.

This procedure yields the 12 acts (see the full list in Online Appendix OA4) which constitute major fiscal legislation, including appropriations and budget measures, emergency relief packages, and defense authorizations. These high-stake fiscal bills, which determine how Congress allocates federal resources, are precisely the types of legislation that can trigger economically meaningful pre- or post-enactment actions. We further hypothesize that such actions are more likely to manifest through unreadable filings.

In what follows, we test whether pre-enactment trading network is more likely to be revealed through unreadable files in Section 5.1. Section 5.2 then examines whether legislators who trade together prior to enactment, as identified from their unreadable filings, exhibit tighter political ties with real and measurable consequences, such as a higher likelihood of bill co-sponsorship.

[13]Information on lobbying expenditures is obtained from OpenSecrets, which provides comprehensive, bill-level data on lobbying activities and associated spending (see, e.g., https://www.opensecrets.org/bulk-data/downloads)

5.1 Pre-Enactment Connected Unreadable Trades

We examine whether unreadable disclosure files reveal coordinated trading behavior among legislators prior to the passage of major fiscal legislation. If unreadable filings are used to obscure economically important and time-sensitive trades, then transactions reported through these filings should display stronger cross-legislator similarity precisely when information about upcoming legislation is most valuable.

For each of the 12 major economic and fiscal acts, we construct dyadic (member pair) samples of legislators based on their trading activity within 60-, 90-, and 180-day windows preceding the act's final passage date. For each legislator pair (i, j), we define the indicator variable *Same Stock*$_{ij,a}$, which equals one if both legislators trade at least one common stock in the same direction (purchase or sale) during the pre-passage window for act a. We then estimate the following regression model:

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

where *Unreadable*$_{ij,a}$ is a dummy variable equal to one if the dyadic trading data are drawn from unreadable disclosure files, and zero otherwise. $\boldsymbol{X_{ij,a}}$ includes controls for important conventional variables to identify connected politicians that may also account for coordinated trading behavior within a dyadic pair: committee assignments and home state. Specifically, *Same Committee* is an indicator equal to one if the two legislators in a dyadic pair have served on at least one committee together. We also consider a continuous variant, *# of Same Committees*, defined as the number of House committees on which the pair has served simultaneously. To capture political networks formed through geographic and social ties, we include *Same State*, a dummy variable that equals one if the two legislators in a dyadic pair are from the same state, and zero otherwise. α_a denotes act fixed effects. Standard errors are double-clustered by dyad and act.

Panel A of Table 5 reports results using trades during the 60-day pre-enactment window. Across all specifications, unreadable trading files are associated with substantially higher cross-legislator trading similarity. In the baseline specification (Column (1)), 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.

According to Columns (2) and (3), the effect remains stable as additional controls are introduced. Accounting for shared committee memberships, common state representation, and total trading amounts for each legislator leaves the coefficient on *Unreadable* largely unchanged. Unreadable dyads are 10.3 percentage points more likely to trade the same stock in the pre-enactment window.

Importantly, Columns (2) and (3) of Panel A show that none of the variables for shared committee membership or common home state are statistically significant. This provides the first evidence that the trading network revealed in unreadable files captures a dimension of political connection that standard proxies are unable to identify.

Panel B extends the analysis to the 90-day and 180-day pre-enactment windows. To conserve space, we tabulate only the coefficient estimates for the main variable of interest. The results in Panel A prevail, remaining strong and significant at the 1% level. Over the 90-day window, unreadable dyads are approximately 12 percentage points more likely to trade the same stock in the same direction across all specifications. Over the 180-day window, the effect remains economically and statistically meaningful, with unreadable dyads being 9.5 percentage points more likely to exhibit overlapping portfolios.

[Insert Table 5 here]

As an important robustness test, we conduct a jackknife exercise by dropping one act at a time from the analysis and re-estimating the specification. Table OA5 in the online appendix shows that our results remain significant and intact, both statistically and economically.

Next, we explore cross-industry variation in legislative trading networks. Our selected bills include broad fiscal legislation—such as the Consolidated Appropriations Acts, the Bipartisan Budget Act, the CARES Act, and the American Rescue Plan Act—that potentially affect a wide range of industries, as well as more targeted legislation, such as the Medicare Access and CHIP Reauthorization Act (MACRA) and the National Defense Authorization Acts (NDAA), which are concentrated in specific sectors. To identify the industries most directly exposed to each bill, we map each act to affected NAICS industries based on its primary economic targets, informed by the legislation's substantive provisions and the relevant congressional committees. For most acts, this mapping is at the 2-digit NAICS level. For two healthcare acts—PAMA and MACRA—we supplement NAICS sector 62 (Health Care and Social Assistance) with finer industry codes to capture direct effects on health insurers, medical equipment, and EHR-related services. The full mapping is reported in Table OA2 in the online appendix. We then assign each stock to its corresponding NAICS industry.

Under our hypothesis, information about these directly affected industries should become particularly valuable around enactment, leading to stronger clustering of similar trades among unreadable filers and higher ex post CARs. Table OA3 in the online appendix first validates that, while transactions reported through unreadable formats earn higher 22-day abnormal returns than comparable trades disclosed in readable formats, these returns are even larger for trades involving stocks in industries directly regulated by, or materially exposed to, the provisions of a upcoming act. To formally test this prediction, we replace *Same Stock* with $\textit{Same Stock}^{exposed}$, an indicator variable set to one if a pair of legislators trade the same firm, operating in an industry affected by act a, in the same direction, and zero otherwise. Columns (4) through (6) of Table 5 Panel A show that unreadable dyads are 3.1 percentage points more likely to trade the same stock that is affected by the bill in the pre-enactment window than readable dyads.

Taken together, these results show that unreadable files reveal a trading network that is largely unobserved in readable filings. Politicians exhibit particularly strong trade connections in narrow, well-identified windows prior to the enactment of major economic and fiscal legislation. It is worth noting that the results persist even after controlling for political proximity and trading intensity, consistent with a distinct form of information-driven coordination embedded in opaque disclosure formats.

5.2 Post-Enactment Connected Political Actions

One may argue that two legislators trading the same stock in the same direction prior to a major fiscal bill does not, by itself, demonstrate any connection between them. A plausible alternative is that each legislator independently acquires similar private information and trades on it without any coordination. Under this interpretation, the observed trading synchronicity reflects parallel efforts to obscure informed trading rather than any underlying personal or professional relationship. If a shared financial transaction preceding an economically meaningful bill does not reveal a substantive connection between the two legislators, then we should not expect to observe them collaborating in the period following the bill's passage. In this subsection, we examine whether the trading network identified in Section 5.1 is related to subsequent actual legislative coordination. This is a meaningful test because it indicates that such an "unreadable" trading network among politicians has 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 $CoSponsor_{ij,a}$ as the number of bills jointly sponsored by legislator i and legislator j within 180 days following the act's passage. We then estimate the following regression model:

$$\text{CoSponsor}_{ij,a} = \beta_1 \cdot \text{Unreadable} \times \text{Same Stock}_{ij,a} + \beta_2 \cdot \text{Unreadable}$$
$$+ \beta_3 \cdot \text{Same Stock}_{ij,a} + \mathbf{\Gamma} \boldsymbol{X_{ij,a}} + \alpha_a + \varepsilon_{ij,a},$$

where $Same\ Stock_{ij,a}$ is an indicator for whether the two legislators trade at least one common stock in the same direction (purchase or sales) during the pre-passage window. $\boldsymbol{X_{ij,a}}$ includes the same set of controls for common committee membership, same home state affiliation, and trading intensity as in Section 5.1. α_a denotes act fixed effects. β_1 is the coefficient for the variable of interest.

Column (1) of Table 6 reports the baseline results. Trading links revealed through unreadable disclosure files strongly predict future political coordination, as the coefficient estimate for the interaction term $Unreadable \times Same\ Stock$ is positive and is statistically significant at the 5% level. Dyads that share at least one traded stock through unreadable filings co-sponsor 6.3 more bills on average following the act, relative to dyads with no trading overlap. Columns (2)-(3) confirm this result when we include additional controls.

Similarly, we replace the broad "any stock" similarity measure, *Same Stock*, with $Same\ Stock^{exposed}$, which equals one if both legislators trade at least one common stock in the same direction (purchase or sale) during the pre-enactment window for a given act, where that stock belongs to an industry directly affected by, or materially exposed to, the provisions of the act. The interaction term remains significant and positive. Dyads that share at least one traded stock through unreadable filings subsequently co-sponsor, on average, 8.4 more bills than dyads with no trading overlap. Taken together, Table 6 reveals that political cooperation is driven by economically meaningful trading links. As before, Table OA6 in our online appendix shows a jackknife exercise dropping one act at a time.

[Insert Table 6 here]

Overall, the results from Section 4 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.

5.3 Mapping Unreadable Political Network

In this subsection, we present a graphical illustration of an unreadable political network. To map the extent of connections between two legislators from two opposing parties, we construct a network based on the similarity of their stock portfolios disclosed in unreadable files and the frequency of bills they cosponsor in a subsequent period.

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 common stock–direction pairs (stock, buy or sell) they share, scaled by the total number of distinct stock–direction pairs traded by either legislator in that window. A higher ratio indicates more closely connected politician pairs through their profitable trades in unreadable files. We then consider the 180-day forward period following the end of each window, keeping cross-party legislator pairs that have positive trading similarity and that 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.

Figure 4 presents a visual network of politicians from opposing parties connected through their trades in unreadable files and subsequently coordinated in bill cosponsorship. In this figure, all legislators' identifying information has been anonymized and is not recoverable from the figures; all displayed name labels are randomly generated placeholders with no real-world meaning, except for the first letter indicating their party affiliation. The anonymized names of Democratic congressional members are displayed in blue on the left, whereas those of Republican congressional members are in red on the right.

We also aim to capture the intensity of each legislator's participation (in unreadable trading networks) and the strength of connections between legislator pairs. For intensity, the size of each anonymized name reflects the legislator's frequency of appearance in qualifying cross-party pairs, with larger names denoting more frequent participation.[14] For strength, the thickness of the lines captures the extent of connections between two legislators. Specifically, 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

[14] Legislators are displayed with larger names when they participate more frequently in qualifying cross-party trading and bill-cosponsoring dyads. For example, a Democratic legislator A appears larger when forming qualifying pairs with distinct Republican legislators B, C, D, and E across multiple 60-day windows, rather than only with B and E.

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.

[Insert Figure 4 here]

Figure 4 shows a political network revealed through connected trades in unreadable files that is both dense and distinctly cross-partisan, with several legislators acting as hubs that link otherwise distant segments of the political landscape. These patterns indicate that political collaboration across party lines — motivated by economically meaningful, coordinated trading — is far more substantial than the stark party-line divide commonly portrayed in news media. Rather than appearing sparse or incidental, the cross-party connections embedded in unreadable-file trading suggest a level of interaction that is considerably more closely tied than public narratives would imply.

Instead of using unreadable files, in Figure 5 we repeat the same construction using the same set of legislators and their trades disclosed through readable filings to plot the corresponding "readable" political network. A markedly different pattern emerges: the resulting network is far more fragmented, with sparse cross-party links and limited connection strength. No legislator emerges as a central hub.

[Insert Figure 5 here]

We also construct networks using widely adopted proxies, such as whether politicians originate from the same state or whether they serve on the same House committees. In Figure 6, we present the political network defined by bipartisan pairs who share a state of origin and subsequently collaborate in sponsoring legislation, thereby capturing one dimension of social interaction.

[Insert Figure 6 here]

Figure 6 reveals a network broadly similar to that identified through readable filings (Figure 5). Although the specific connections formed through bipartisan legislators may vary, the overall structure remains highly fragmented and sparse when compared to the denser network revealed in unreadable filings (Figure 4).

In Figure 7, we depict the network constructed on the basis of shared committee membership. As expected, bipartisan legislators exhibit a greater propensity to collaborate in sponsoring legislation when they have previously served on the same House committee. Consequently, the pattern revealed through shared committees indicates that connections among bipartisan House representatives are more evenly distributed. By contrast, the network derived from unreadable filings is not only denser but also organized around critical knots clustered around particular politicians.

[Insert Figure 7 here]

Importantly, some legislators who appear as central and highly connected figures in the network based on unreadable filings are far less prominent in the structure identified through shared committee membership. For example, the Democratic legislator with identifier *D-iwbv3bmt* emerges as a prominent cluster with numerous ties to Republican legislators in the unreadable filings network (Figure 4), yet appears considerably less central and more sparsely connected to members of the opposing party in the committee-based network. Similarly, the Democratic legislator with identifier *D-clz0dw5s* exhibits a strong connection with the Republican legislator identified as *R-9mmv3sb1* in the unreadable filings network, but no such connection is observed in any of the networks constructed from readable filings, shared state origin, or shared committee membership (Figure 5 through Figure 7).

Considering only the unique cross-party connections and abstracting from the intensity of these links, the unreadable network reveals 105 unique bipartisan connections, whereas the readable, same-state, and same-committee networks reveal 13, 11, and 98 connections, respectively. The unreadable network shares only one connection with both the readable and same-state networks, and 33 connections with the same-committee network. Accordingly, the unreadable network contains 104 cross-party connections not identified by the readable network, 104 not identified by the same-state network, and 72 not captured by the same-committee network.

Lastly, the network identified through unreadable files may vary in structure over time. We therefore examine how these connections evolve under unified government, in which the House majority party is aligned with the President's party, as well as under divided government, in which the House majority party differs from that of the President. In the former, the institutional alignment between the executive and legislative branches reduces the strategic value of such a network, as policy initiatives can be advanced more easily. In the latter, the heightened polarization between the administration and the legislature increases the value of maintaining cross-member connections, making the network comparatively more desirable.

Figure 8 plots the unreadable network under unified government, corresponding to the 115th Congress (2017–2018) during the Trump administration and the 117th Congress (2021–2022) during the Biden administration. These two periods together span four years in our sample in which the House majority party is aligned with the President's party. Figure 9 plots the unreadable network under divided government, corresponding to the 113th and 114th Congresses (2013–2016) during the Obama administration and the 116th Congress (2019–2020) during the Trump administration, which together span five years in our sample in which the House majority party differs from the President's party. Consistent with our conjecture, the unreadable network exhibits greater density and tighter clustering under divided government.

[Insert Figure 8 here]

[Insert Figure 9 here]

Overall, the striking distinction between these figures 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. Unreadable files allow us to detect a closely knit political network that readable files or other political-connection measures are unable to identify.

6 Conclusion

Legislators can disclose their stock trading transactions through either typed electronic filings (machine-readable) or hand-written/hand-delivered-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 2013 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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Figure 1: **An Example of A Readable File**

Filing ID #20001601

Periodic Transaction Report

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

Filer Information

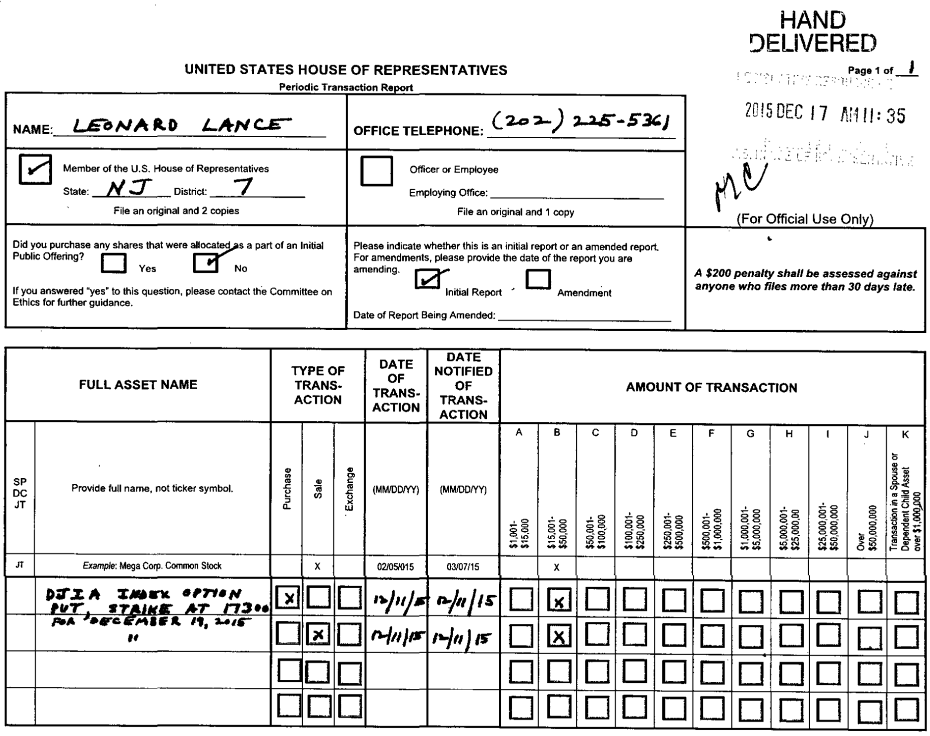
Name: Mr. David B. McKinley
Status: Member
State/District: WV01

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 2: **Examples of Unreadable Files**

Figure (1) is the example of an unreadable file that is handwritten and then scanned. Figure (2) is the example of an unreadable file that is typed or printed but submitted as a scanned image.



HAND DELIVERED

UNITED STATES HOUSE OF REPRESENTATIVES

Periodic Transaction Report

Page 1 of 1

2015 DEC 17 AM 11:35

(For Official Use Only)

NAME: LEONARD LANCE

OFFICE TELEPHONE: (202) 225-5361

[X] 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 [X] No

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

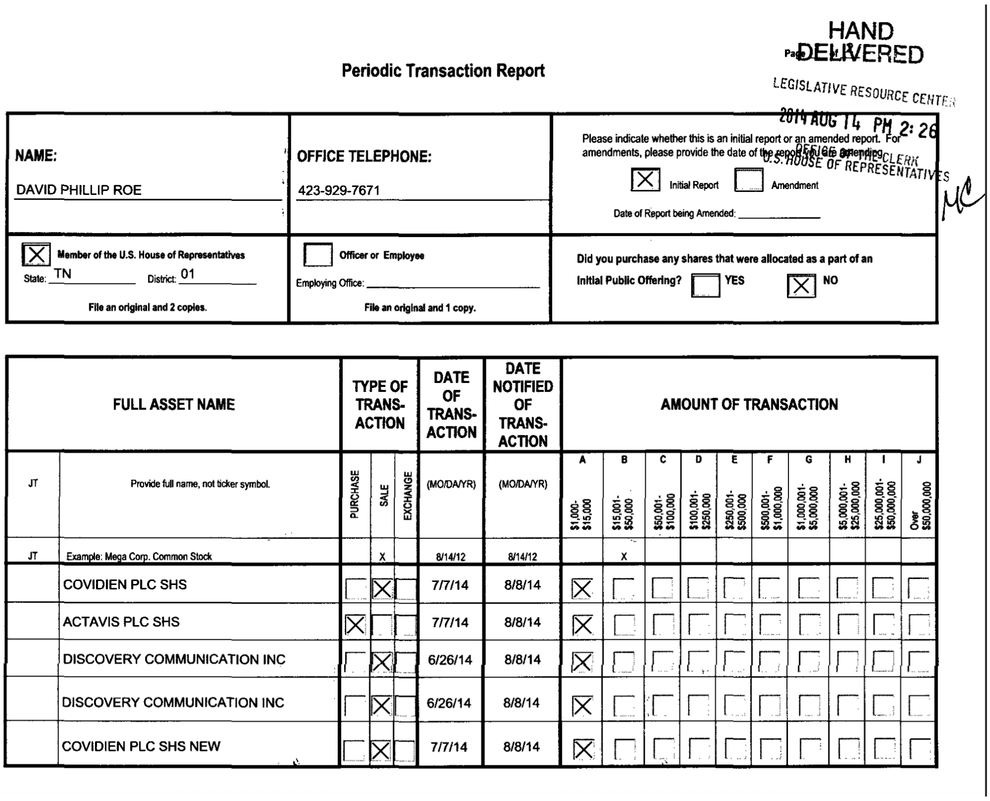
Please indicate whether this is an initial report or an amended report. For amendments, please provide the date of the report you are amending. [X] Initial Report [ ] Amendment

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 FOR DECEMBER 19, 2015	X			12/11/15	12/11/15		X									
	"		X		12/11/15	12/11/15		X									

(1)



HAND DELIVERED

LEGISLATIVE RESOURCE CENTER

2014 AUG 14 PM 2:26

OFFICE OF THE CLERK U.S. HOUSE OF REPRESENTATIVES

Periodic Transaction Report

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. [X] Initial Report [ ] Amendment

Date of Report being Amended:

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

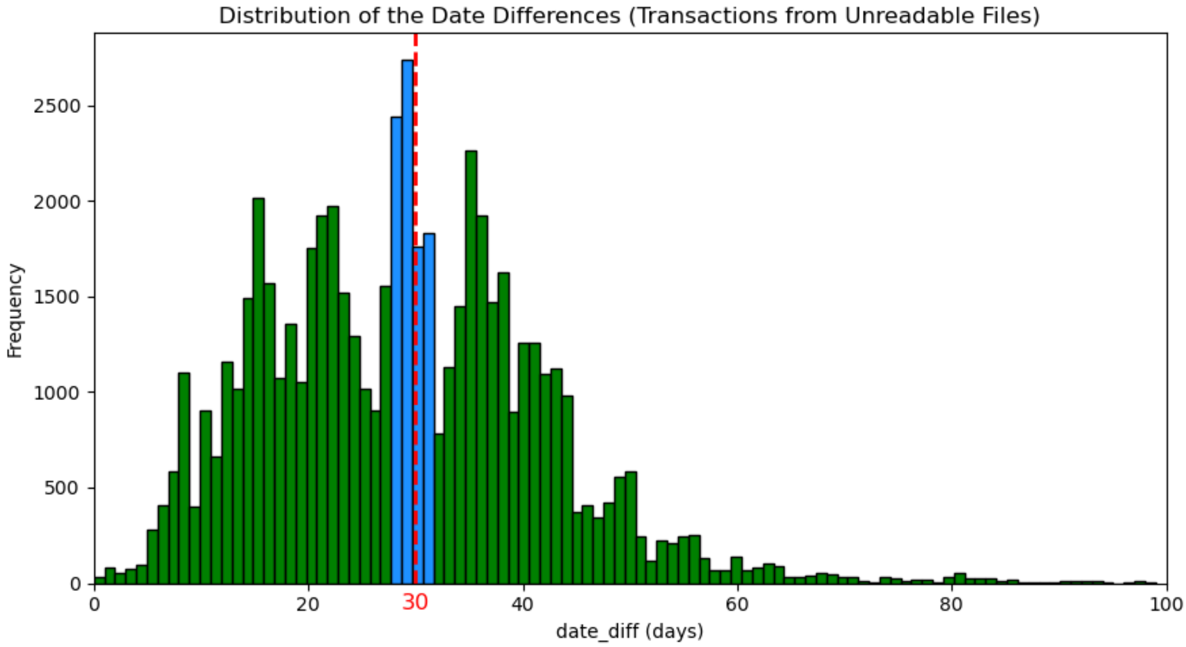
[ ] Officer or Employee Employing Office: File an original and 1 copy.

Did you purchase any shares that were allocated as a part of an Initial Public Offering? [ ] YES [X] NO

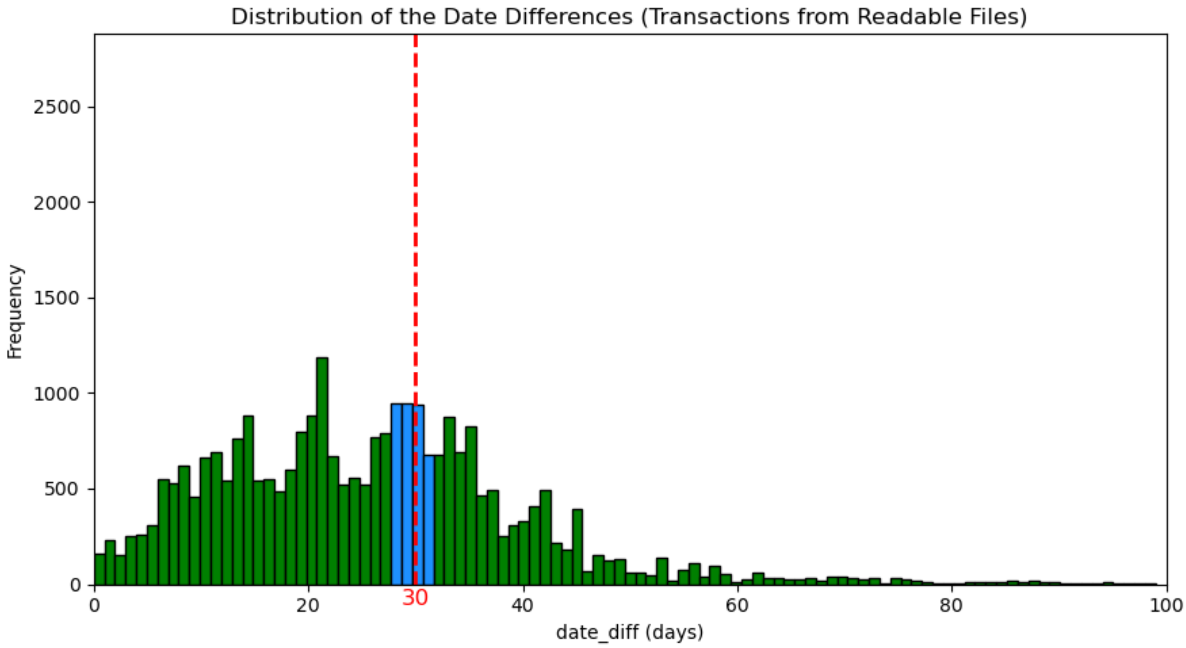
JT	FULL ASSET NAME (Provide full name, not ticker symbol.)	PURCHASE	SALE	EXCHANGE	DATE OF TRANSACTION (MO/DA/YR)	DATE NOTIFIED OF TRANSACTION (MO/DA/YR)	A $1,000-$15,000	B $15,001-$50,000	C $50,001-$100,000	D $100,001-$250,000	E $250,001-$500,000	F $500,001-$1,000,000	G $1,000,001-$5,000,000	H $5,000,001-$25,000,000	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									

(2)

Figure 3: **Distribution of Days Taken to File Legislative Trades**
The upper panel of the figure plots a histogram of the number of days taken to file a legislative trade via unreadable filings, and the lower panel plots the corresponding distribution for trades filed through readable filings. The dashed red line denotes the statutory deadline (30 days) 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).



(1)



(2)

Figure 4: **Political Network via Unreadable Filings**
This figure presents a visual network of politicians from opposing parties connected through their trades in unreadable files and subsequently coordinated in political bill cosponsorship. The size of each anonymized name reflects the legislator's frequency of appearance in qualifying cross-party pairs, with larger names denoting more frequent participation. The thickness of the lines captures the extent of connections between two legislators. The anonymized names of Democratic congressional members are displayed in blue on the left, whereas those of Republican congressional members are in red on the right.

Figure 5: **Political Network via Readable Filings**
This figure presents a visual network of politicians from opposing parties connected through their trades in readable files and subsequently coordinated in political bill cosponsorship. The size of each anonymized name reflects the legislator's frequency of appearance in qualifying cross-party pairs, with larger names denoting more frequent participation. The thickness of the lines captures the extent of connections between two legislators. The anonymized names of Democratic congressional members are displayed in blue on the left, whereas those of Republican congressional members are in red on the right.

Figure 6: **Political Network via Same States**
This figure presents a visual network of politicians from opposing parties connected through the state they represent and subsequently coordinated in political bill cosponsorship. The size of each anonymized name reflects the legislator's frequency of appearance in qualifying cross-party pairs, with larger names denoting more frequent participation. The thickness of the lines captures the extent of connections between two legislators. The anonymized names of Democratic congressional members are displayed in blue on the left, whereas those of Republican congressional members are in red on the right.

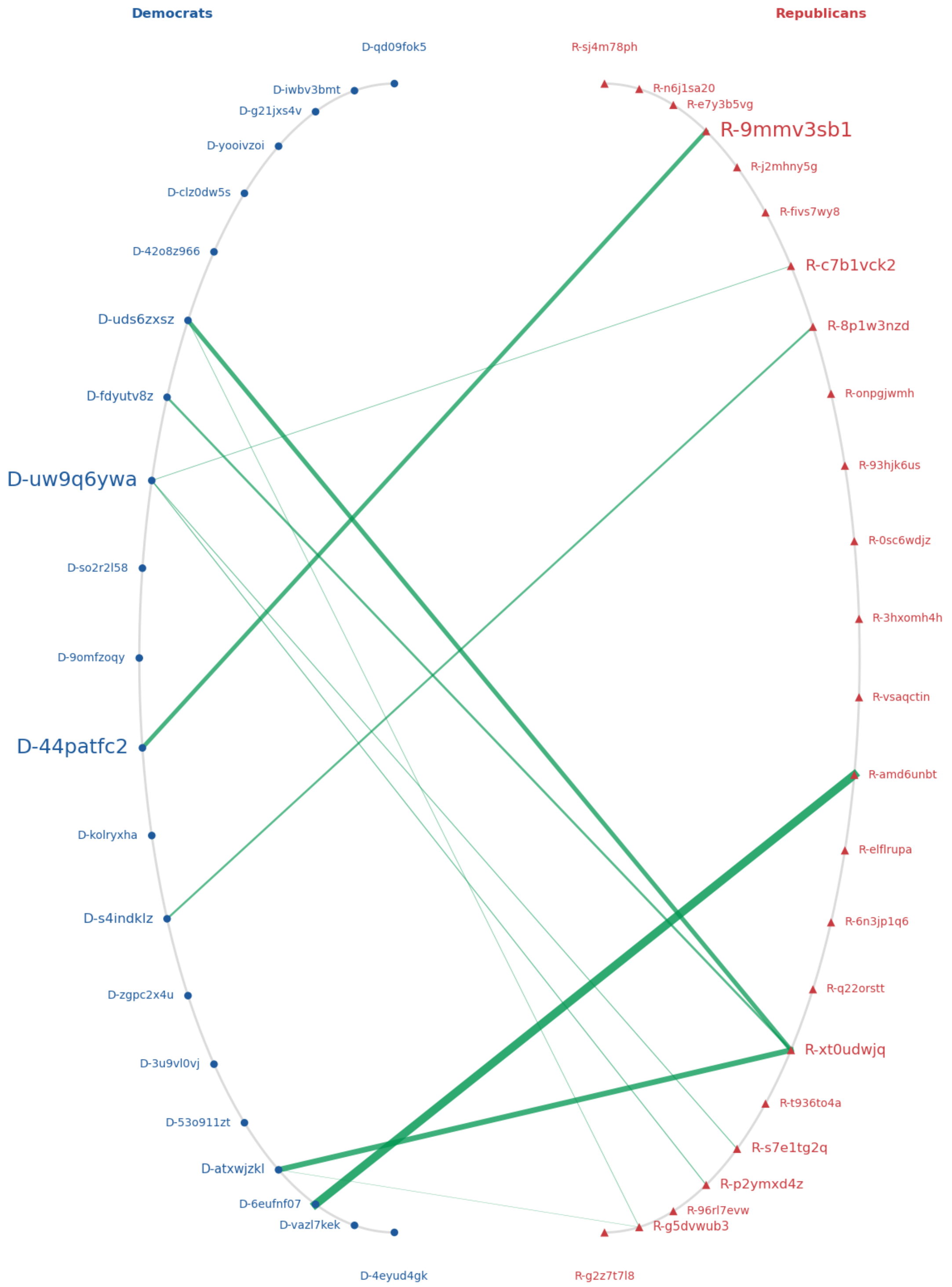


Figure 7: **Political Network via Same Committee**

This figure presents a visual network of politicians from opposing parties connected through their committee in the House of Representatives and subsequently coordinated in political bill cosponsorship. The size of each anonymized name reflects the legislator's frequency of appearance in qualifying cross-party pairs, with larger names denoting more frequent participation. The thickness of the lines captures the extent of connections between two legislators. The anonymized names of Democratic congressional members are displayed in blue on the left, whereas those of Republican congressional members are in red on the right.

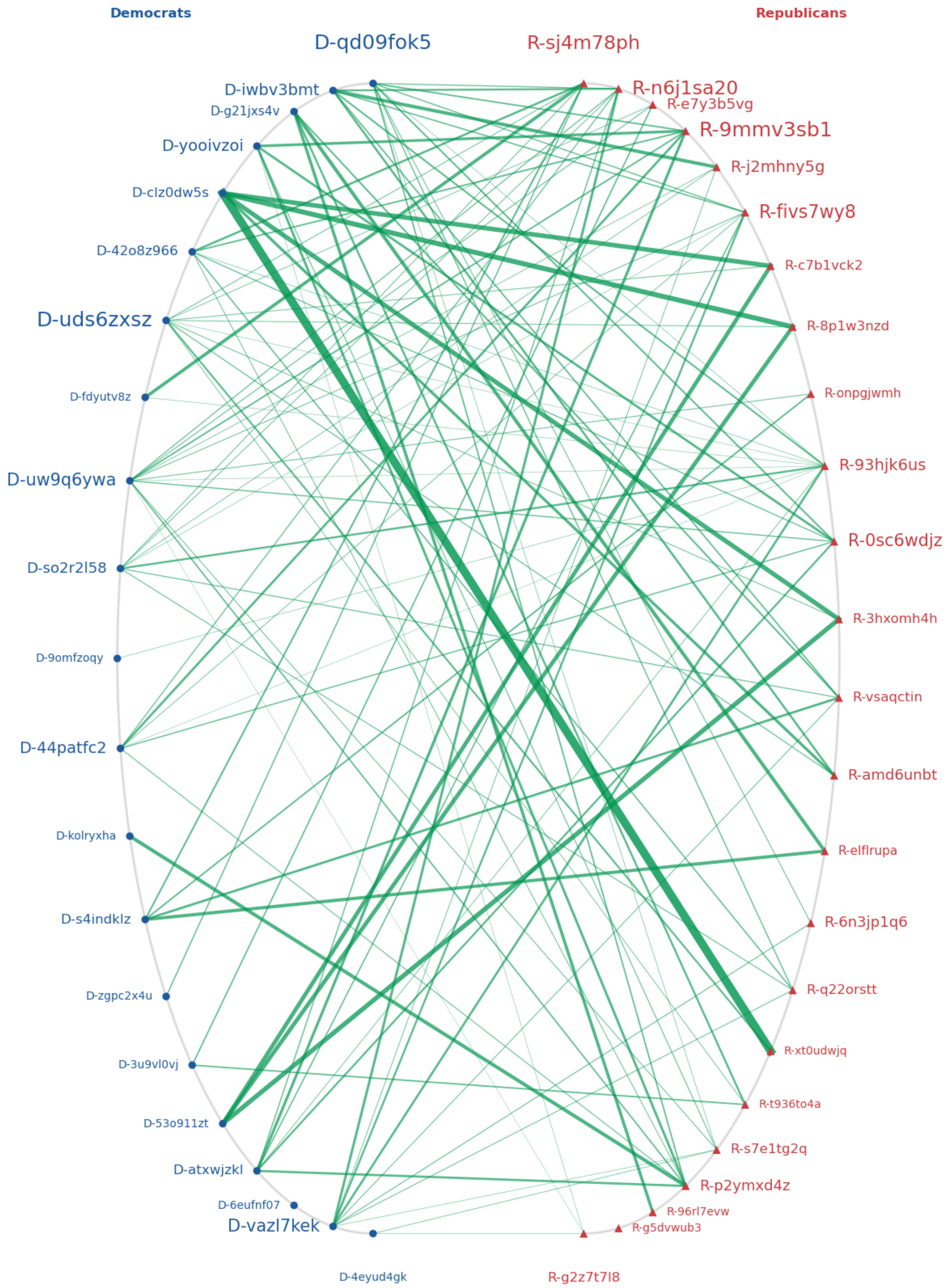


Figure 8: **Political Network via Unreadable Filings under Unified Government** This figure presents a visual network of politicians from opposing parties connected through their trades in unreadable files and subsequently coordinated in political bill cosponsorship. The sample is restricted to periods of unified government, defined as Congresses in which the House majority party is the same as the President's party. The size of each anonymized name reflects the legislator's frequency of appearance in qualifying cross-party pairs, with larger names denoting more frequent participation. The thickness of the lines captures the extent of connections between two legislators. The anonymized names of Democratic congressional members are displayed in blue on the left, whereas those of Republican congressional members are in red on the right.

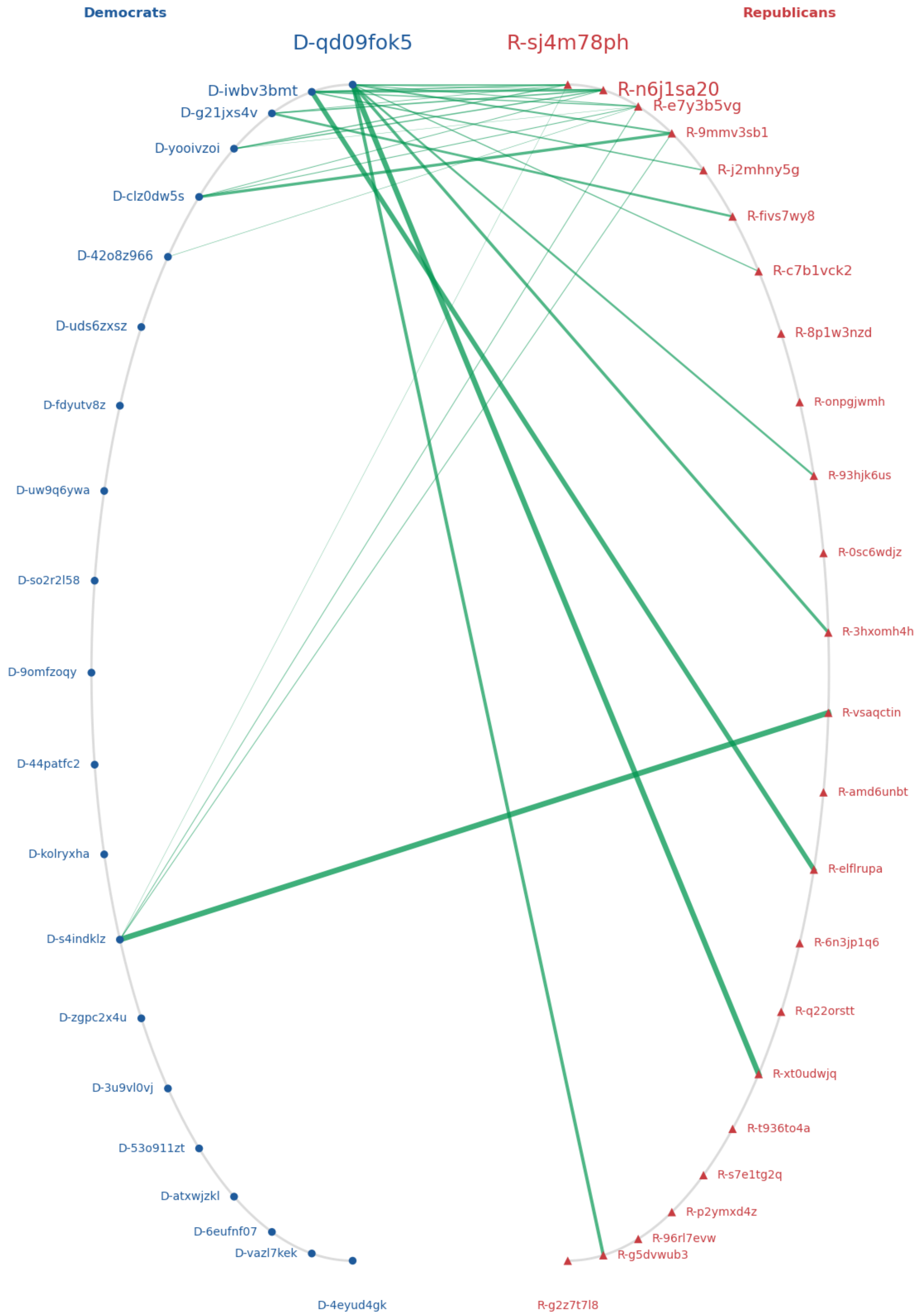


Figure 9: **Political Network via Unreadable Filings under Divided Government** This figure presents a visual network of politicians from opposing parties connected through their trades in unreadable files and subsequently coordinated in political bill cosponsorship. The sample is restricted to periods of divided government, defined as Congresses in which the House majority party differs from the President's party. The size of each anonymized name reflects the legislator's frequency of appearance in qualifying cross-party pairs, with larger names denoting more frequent participation. The thickness of the lines captures the extent of connections between two legislators. The anonymized names of Democratic congressional members are displayed in blue on the left, whereas those of Republican congressional members are in red on the right.

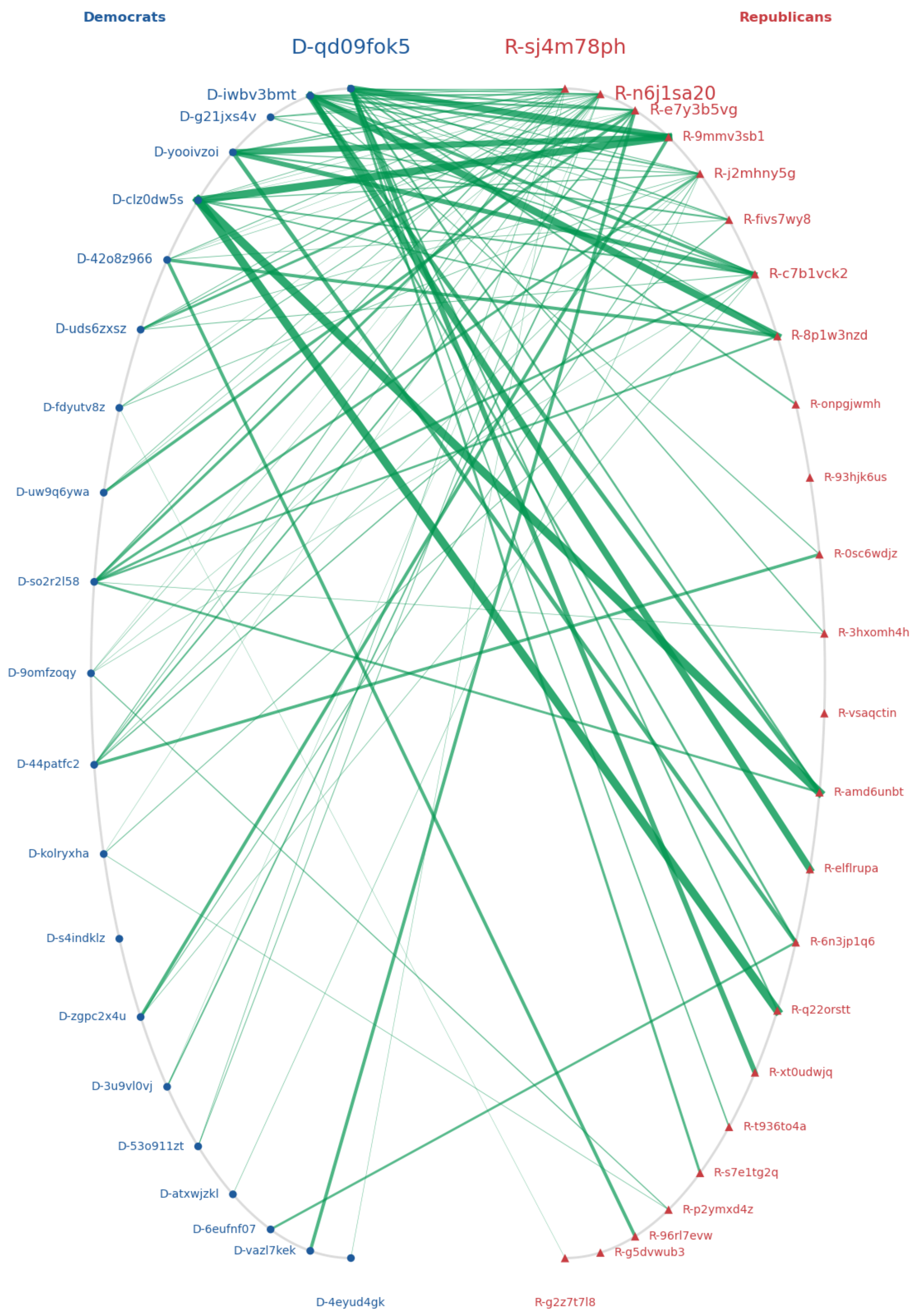


Table 1: **Summary Statistics**

This table presents summary statistics for variables used in our main tables. Panel A is the univariate comparison. For the 22-day abnormal return statistics, mean is tested against zero using a one-sample t-test, while median is tested against zero using a sign test. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Panels B and C correspond to Tables 2-4. Panel D correspond to Tables 5-6. Please find detailed variable descriptions in respective table notes or Appendix OA1.

	Readable	Unreadable	Total
Panel A: Univariate Comparison			
# of PTRs	3,532	1,581	5,113
# of congressional members	201	129	275
Republican	104	67	151
Democrat	95	61	122
Libertarian	1	0	1
Independent	1	1	1
# of unique tickers	3,196	2,843	4,492
# of unique tickers per PTR	0.905	1.798	0.879
# of transactions	31,542	61,171	92,713
# of transactions from family members	17,038	44,611	61,649
# of transactions per PTR	8.930	38.691	18.133
$CAR_{i,s,22}$ **(in %)**			
Mean	-0.128*	0.125***	0.047
Median	0.070	0.149***	0.111***

Variable	Observations	Mean	Median	Std. Dev.
Panel B: Person-Ticker-Trading Date Level				
Unreadable	41,440	0.689	1.000	0.463
$CAR_{i,s,22}$	39,013	0.047%	0.111%	7.701%
$CAR_{i,s,30}$	38,961	0.074%	0.138%	8.962%
$CAR_{i,s,35}$	38,931	0.031%	0.071%	9.744%
$CAR_{i,s,40}$	38,922	0.016%	0.086%	10.334%
log(Trading Volume)	41,324	9.401	8.987	0.867
Age	41,440	1.979	2.000	0.717
Seniority	41,440	1.942	2.000	0.751
Party_Affiliation	41,440	0.591	1.000	0.492
Family	41,440	0.689	1.000	0.463
Children	41,440	0.185	0.000	0.388
Spouse	41,440	0.395	0.000	0.489
Near Deadline	40,215	20.492	10.000	52.491
log(Near Deadline)	40,215	2.312	2.398	1.060

Table 1: **continued**

Variable	Observations	Mean	Median	Std. Dev.
Panel C:				
(C.1) Person-Trading Date Level				
Unreadable	16,013	0.469	0.000	0.499
log(Trading Volume) (Total across tickers)	16,013	10.382	10.086	1.416
log(Trading Volume) (Average by ticker)	16,013	9.705	8.987	1.033
# of Trades (Total across tickers)	16,019	4.933	2.000	15.123
log(1+# of Trades) (Total across tickers)	16,019	1.280	1.099	0.764
# of Trades (Average by ticker)	16,019	1.262	1.000	0.658
log(1+# of Trades) (Average by ticker)	16,019	0.790	0.693	0.209
(C.2) Disclosure File Level				
Unreadable	4,491	0.331	0.000	0.471
log(Trading Volume)	4,491	11.146	10.942	1.821
# of Trades	4,492	17.519	3.000	57.826
log(1+# of Trades)	4,492	1.823	1.386	1.181
Panel D: Legal Act-Dyadic Level				
Unreadable	12,471	0.183	0.000	0.386
Same Committee	12,471	0.156	0.000	0.363
# of Same Committees	12,471	0.162	0.000	0.383
Same State	12,471	0.040	0.000	0.196
log(Trading Volume) (i)	12,471	11.631	11.472	1.923
log(Trading Volume) (j)	12,471	11.618	11.472	1.850
Same Stock$_{ij,a}$(60)	12,471	0.089	0.000	0.284
Same Stock$_{ij,a}$(90)	17,219	0.108	0.000	0.311
Same Stock$_{ij,a}$(180)	24,630	0.143	0.000	0.350
CoSponsor$_{ij,a}$	12,471	13.919	4.000	24.657

Table 2: **Profitability, Scale, and Scope of Unreadable Congressional Trading**
The sample period is 2013-2022. The unit of observation in Panel A is at the transaction-file level, and in Panels B and C is at the person-trading-date level (Columns (1)-(2)), person-trading-date (average by ticker) level (Column (3)), person-ticker-trading-date level (Column (4)), and PTR level (Column (5)), respectively. The dependent variable is $CAR_{i,s,t}$ in Panel A, the cumulative abnormal return earned by individual i over horizon t ($t \in \{22, 30, 35, 40\}$ trading days) from purchasing stock s and reported in percentage points; is log(*Trading Volume*) in Panel B, which is the natural logarithm of the total dollar trading volume for each individual; and is *log(1+# of Trades)* in Panel C, which is the natural logarithm of one plus the number of transactions traded by a legislator. All models, except Column (5) of Panels B and C, include baseline controls (categorical variables for legislators' age and seniority, party affiliation, and indicators for whether a transaction occurs within the $[-3, 1]$ window around each FOMC meeting date), macroeconomic announcement surprises listed in Online Appendix OA3), a constant, and the fixed effects as described in the table, but coefficients are not tabulated. Panel A additionally controls for natural logarithm of the trading volume associated with each transaction. Detailed variable definitions are in Appendix OA1. Robust standard errors are reported in parentheses, with the clustering method specified at the bottom of the table. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Abnormal Returns of Unreadable Congressional Trading				
Dependent Variable:			CAR	
Time Horizon:	22 days	30 days	35 days	40 days
	(1)	(2)	(3)	(4)
Unreadable	0.365**	0.422**	0.408**	0.352*
	(0.180)	(0.189)	(0.201)	(0.197)
Baseline Controls	Yes	Yes	Yes	Yes
Macro Surprises Controls	Yes	Yes	Yes	Yes
log(Trading Volume)	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
SE Clustering			Person+Actual_YM	
Observations	38,261	38,208	38,178	38,168
R-squared	0.20	0.21	0.21	0.22

Table 2: **continued**

Panel B: Trading Amount Patterns of Unreadable Congressional Trading					
Dependent Variable:	log(Trading Volume)				
Data Level:	Person-Trading_date		Person-Trading_date (Average)	Person-Ticker-Trading_date	PTR
	(1)	(2)	(3)	(4)	(5)
Unreadable	0.495**	0.495***	0.145***	0.119***	0.958**
	(0.210)	(0.029)	(0.027)	(0.036)	(0.365)
Baseline Controls	Yes	Yes	Yes	Yes	No
Macro Surprises Controls	Yes	Yes	Yes	Yes	No
Stock FE	No	No	No	Yes	No
Year-Month FE	Yes	Yes	Yes	Yes	Yes
SE Clustering	Person+Actual_YM	Actual_YM	Actual_YM	Ticker+Actual_YM	Person+PTR_YM
Observations	16,011	16,011	16,013	59,850	4,482
R-squared	0.12	0.12	0.068	0.28	0.075

Panel C: Trading Number Patterns of Unreadable Congressional Trading					
Dependent Variable:	log(1+# of Trades)				
Data Level:	Person-Trading_date		Person-Trading_date (Average)	Person-Ticker-Trading_date	PTR
	(1)	(2)	(3)	(4)	(5)
Unreadable	0.382***	0.382***	0.103***	0.082***	0.722***
	(0.107)	(0.017)	(0.010)	(0.013)	(0.272)
Baseline Controls	Yes	Yes	Yes	Yes	No
Macro Surprises Controls	Yes	Yes	Yes	Yes	No
Stock FE	No	No	No	Yes	No
Year-Month FE	Yes	Yes	Yes	Yes	Yes
SE Clustering	Person+Actual_YM	Actual_YM	Actual_YM	Ticker+Actual_YM	Person+PTR_YM
Observations	16,017	16,017	16,017	59,999	4,483
R-squared	0.13	0.13	0.15	0.35	0.091

Table 3: **Unreadable Congressional Family Member Trading**

The sample period is 2013-2022. The unit of observations is at the transaction-file level in Panel A and is at the person-year-month level in Panel B. The dependent variables in Panel A are indicators for whether a purchase in a given stock is executed by a legislator's family member, dependent child(ren), or spouse, respectively; and in Panel B are the natural logarithm of trading volume, the natural logarithm of one plus the number of transactions executed, and the dollar amount (in $10,000) of trading profits over the 22-, 30-, 35-, and 40-day horizons (*Trading Profits (22)*, *Trading Profits (30)*, *Trading Profits (35)*, *Trading Profits (40)*). Robust standard errors are reported in parentheses, with the clustering method specified at the bottom of the table. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Trading by Congressional Family			
Dependent Variable:	Family	Children	Spouse
	(1)	(2)	(3)
Unreadable	0.165***	0.208***	0.227***
	(0.005)	(0.003)	(0.005)
SE Clustering	Robust	Robust	Robust
Observations	41,440	41,440	41,440
R-squared	0.027	0.062	0.046

Table 3: **continued.**

Panel B: Characteristics of Congressional Family Trading						
Dependent Variable:	log(Trading Volume)	log(1+# of Trades)	Trading Profits			
Time Horizon:			22 days	30 days	35 days	40 days
	(1)	(2)	(3)	(4)	(5)	(6)
Unreadable×Family	0.645***	0.409***	1.125***	1.215***	1.280***	1.322***
	(0.083)	(0.034)	(0.356)	(0.391)	(0.448)	(0.488)
Unreadable	0.519***	0.575***	-0.102	-0.020	0.068	0.138
	(0.058)	(0.068)	(0.095)	(0.105)	(0.118)	(0.128)
Family	0.282***	0.170***	-0.332	-0.325	-0.458	-0.347
	(0.047)	(0.027)	(0.283)	(0.273)	(0.310)	(0.355)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustering		Actual_YM				
Observations	3,594	3,594	3,595	3,595	3,595	3,595
R-squared	0.11	0.15	0.053	0.064	0.063	0.062

Table 4: **Days Taken to File Legislative Trades**

The sample period is 2013-2022. The unit of observation at the transaction-file level. The dependent variables are *Days Until Deadline* and *log(1+Days Until Deadline)*. *Days Until Deadline* is a continuous variable defined as the absolute distance between the interval from the transaction date to the disclosure date and 30 days. All models include baseline controls (categorical variables for legislators' age and seniority, party affiliation, and indicators for whether a transaction occurs within the $[-3, 1]$ window around each FOMC meeting date), macroeconomic announcement surprises listed in Online Appendix OA3), natural logarithm of the trading volume associated with each transaction, a constant, and the fixed effects as described in the table, but coefficients are not tabulated. Detailed variable definitions are in Appendix OA1. Robust standard errors are reported in parentheses, with the clustering method specified at the bottom of the table. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Days Until Deadline		log(1+Days Until Deadline)	
	(1)	(2)	(3)	(4)
Unreadable	-22.738**	-22.118***	-0.293**	-0.276**
	(8.717)	(8.304)	(0.131)	(0.125)
Baseline Controls	Yes	Yes	Yes	Yes
Macro Surprises Controls	No	Yes	No	Yes
log(Trading Volume)	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
SE Clustering	Person+Actual_YM			
Observations	39,111	39,111	39,111	39,111
R-squared	0.30	0.31	0.25	0.28

Table 5: **Dyadic Regression Results for Unreadable Trading Connections.** The sample period is 2013-2022. The unit of observation is at the act-dyadic-person level. We construct the dyadic samples based on the 12 major acts enacted during the sample period. For each act, we form legislator-pair dyads using trades executed within 60-, 90-, and 180-day windows prior to the act's congressional passage date. The dependent variables are *Same Stock* and $\textit{Same Stock}^{exposed}$. *Same Stock* is a dummy variable equal to one if both legislators trade at least one common stock in the same direction (purchase or sale) during the pre-passage window for a given act, and zero otherwise. $\textit{Same Stock}^{exposed}$ is a dummy variable equal to one if both legislators trade at least one common stock in the same direction (purchase or sale) during the pre-enactment window for a given act, where the common stock belongs to an industry directly regulated by, or materially exposed to, the provisions of that act; and zero otherwise. *Unreadable* is a dummy variable set to one if the dyadic group is extracted from the transaction records in unreadable files, and zero otherwise. Panel A reports the results for the 60-day pre-enactment window. Panel B reports the results for the 90- and 180-day pre-enactment windows. All models include a constant and the fixed effects as described in the table, but the coefficients are not tabulated. Detailed variable definitions are in Appendix OA1. Robust standard errors double-clustered at the dyadic group and event (bill) level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: 60-day Pre-enactment Window						
Dependent Variable:		Same Stock			$\text{Same Stock}^{exposed}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Unreadable	0.103***	0.103***	0.103***	0.031**	0.031**	0.031**
	(0.027)	(0.027)	(0.026)	(0.013)	(0.013)	(0.013)
Same Committee			-0.002		-0.002	
			(0.009)		(0.004)	
# of Same Committees		-0.001				-0.002
		(0.008)				(0.003)
Same State		0.010	0.010		0.009	0.009
		(0.018)	(0.018)		(0.010)	(0.010)
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustering			Bill+Dyadic			
Observations	12,471	12,471	12,471	12,471	12,471	12,471
R-squared	0.027	0.027	0.027	0.029	0.029	0.029

Table 5: **continued.**

Panel B: 90- and 180-Day Pre-enactment Windows						
Dependent Variable:			Same Stock			
Pre-enactment Window:		90 Days			180 Days	
	(1)	(2)	(3)	(4)	(5)	(6)
Unreadable	0.121***	0.121***	0.121***	0.094***	0.095***	0.095***
	(0.024)	(0.024)	(0.024)	(0.020)	(0.020)	(0.020)
Same Committee			-0.004			0.003
			(0.009)			(0.007)
# of Same Committees		-0.003			0.003	
		(0.009)			(0.007)	
Same State		0.004	0.004		0.014	0.014
		(0.016)	(0.016)		(0.019)	(0.019)
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustering			Bill+Dyadic			
Observations	17,219	17,219	17,219	24,630	24,630	24,630
R-squared	0.030	0.030	0.030	0.025	0.025	0.025

Table 6: **Dyadic Regression Results for Unreadable Political Connections.**
The sample period is 2013-2022. The unit of observation is at the act-dyadic-person level. The dyadic groups are formed under the "60-Day Pre-enactment Window" specification in Table 5. The dependent variable is *CoSponsor*, calculated as the number of bills co-sponsored by the two legislators in each dyadic group during the 180-day window following the passage of each act. *Same Stock* is a dummy variable set to one if both legislators in a dyadic group trade at least one common stock in the same direction (purchase or sale) during the 60-day pre-enactment window for a given act, and zero otherwise. $Same\ Stock^{exposed}$ is a dummy variable equal to one if both legislators trade at least one common stock in the same direction (purchase or sale) during the pre-enactment window for a given act, where the common stock belongs to an industry directly regulated by, or materially exposed to, the provisions of that act; and zero otherwise. *Unreadable* is a dummy variable set to one if the dyadic group is extracted from the transaction records in unreadable files, and zero otherwise. All models include a constant and the fixed effects as described in the table, but the coefficients are not tabulated. Detailed variable definitions are in Appendix OA1. Robust standard errors double-clustered at the dyadic group and event (bill) level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	CoSponsor					
	(1)	(2)	(3)	(4)	(5)	(6)
Unreadable×Same Stock	6.314**	6.291**	6.306**			
	(2.395)	(2.395)	(2.395)			
Unreadable×Same $Stock^{exposed}$				8.365*	8.353*	8.362*
				(4.258)	(4.263)	(4.265)
Unreadable	-15.592**	-15.554**	-15.551**	-15.387**	-15.349**	-15.346**
	(6.757)	(6.759)	(6.761)	(6.731)	(6.733)	(6.735)
Same Stock	-2.835*	-2.834*	-2.839*			
	(1.459)	(1.456)	(1.457)			
Same $Stock^{exposed}$				-2.670	-2.668	-2.677
				(1.758)	(1.759)	(1.759)
Same Committee			1.270			1.272
			(0.780)			(0.776)
# of Same Committees		1.177			1.194	
		(0.795)			(0.798)	
Same State		-3.498***	-3.501***		-3.368***	-3.370***
		(0.830)	(0.829)		(0.775)	(0.771)
Dyadic FE	Yes	Yes	Yes	Yes	Yes	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustering	Bill+Dyadic					
Observations	8,360	8,360	8,360	8,360	8,360	8,360
R-squared	0.69	0.69	0.69	0.69	0.69	0.69

Online Appendix

OA1 Variable Definitions

Variable	Definition
Affected	A dummy variable set to one if the traded stock belongs to an industry directly affected by a contemporaneous bill, based on the bill-to-NAICS mapping reported in Table OA2, and the transaction occurs within the 60-day window prior to the bill's congressional passage date, and zero otherwise
Age	A categorical variable set to 1 if the legislator's age at the time of the transaction is at or below the 25th percentile of the sample (47 years old), 2 if age falls between the 25th and 75th percentiles (48 to 61 years old), and 3 if age is at or above the 75th percentile (62 years old).
$CAR_{i,s,t}$	Cumulative abnormal return earned by individual i over horizon t from trading stock s, multiplied by the trade direction (+1 for buys, -1 for sells). In this paper, $t \in \{22, 30, 35, 40\}$. Winsorized at the 1% and 99% levels. Source: CRSP.
Children	A dummy variable set to one if the transaction is owned by the legislative member's child(ren).
$\text{CoSponsor}_{ij,a}$	The number of bills co-sponsored by legislative members i and j in each dyadic group that are introduced during the 180-calendar-day period following the passage date of act a in the sample.
Days Until Deadline	A continuous variable defined as the absolute distance between the number of days from the transaction date to the disclosure date and 30 days.
Family	A dummy variable set to 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.
FOMC Control	A dummy variable set to one if the actual trading date of a transaction record falls within a $[-3, 1]$ window around each FOMC meeting date in the sample period.
log(1+Days Until Deadline)	Natural logarithm of one plus Days Until Deadline.
log(1+# of Trades)	Natural logarithm of one plus # of Trades, computed at each aggregation level as defined in # of Trades.

Variable	Definition
log(Trading Volume)	In Table 2 Panel B: at the person–trading date level, 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 by that person on that date; at the person–ticker–trading date level, the natural logarithm of the total trading amount for each person–ticker pair on each actual trading date; at the person–trading date (average) level, the natural logarithm of the average (across tickers traded by that person on that actual trading date) of the person–ticker–trading date level trading amounts; at the disclosure file level, the natural logarithm of the total trading amount reported in each disclosure file. In Table 3 Panel B: the natural logarithm of the total trading amount for each person in each year–month pair, computed as the sum of the midpoints of the reported transaction amount ranges across all trades in that month. At the transaction level: the natural logarithm of the trading amount for each transaction record, where the trading amount is the midpoint of the transaction amount range. Transaction amounts in each trading disclosure file are recorded as ranges.
Macro Surprises Controls	Following Bianchi, Gómez-Cram, and Kung (2024), normalized macroeconomic surprise variables are constructed for the 50 announcements with the highest Bloomberg relevance scores. For each macroeconomic event p on date t, the normalized surprise is $\text{macro\_control}_{p,t} = (AC_{p,t} - SUM_{p,t})/\sigma_p$, where $AC_{p,t}$ is the realized value, $SUM_{p,t}$ is the Bloomberg survey median forecast, and σ_p is the standard deviation of the forecast error over the sample period. Source: Bloomberg. See Online Appendix OA3 for further details.
Party Affiliation	A dummy variable set to one if the individual disclosing the transaction is a Republican, and zero otherwise.
Same Committee	A dummy variable set to one if two legislative members in a dyadic group have served on at least one committee in common in the House of Representatives.
Same State	A dummy variable set to one if two legislative members in one dyadic group are from the same state.
Same Stock	A dummy variable set to one if both legislators (i and j) traded at least one common stock in the same trading direction (purchase or sale) during the pre-passage window for act a.

Variable	Definition
Same Stock^{exposed}	A dummy variable equal to one if both legislators trade at least one common stock in the same direction (purchase or sale) during the pre-enactment window for a given act, where the common stock belongs to an industry directly regulated by, or materially exposed to, the provisions of that act; and zero otherwise.
Seniority	A categorical variable set to 1 if the legislator's seniority at the time of the transaction is at or below the 25th percentile of the sample (2 years), 2 if seniority falls between the 25th and 75th percentiles (3 to 10 years), and 3 if seniority is at or above the 75th percentile (11 years).
Spouse	A dummy variable set to one if the transaction is owned by the legislative member's spouse.
Trading Profits (T)	Total trading profit over the T-day horizon following each transaction's trading date, defined at the person–year–month level. For each person in each year–month pair, the cumulative return for each traded ticker over a horizon of T trading days is multiplied by the trade direction (+1 for buys, -1 for sells) and the transaction amount, then aggregated across all transactions within the month. In this paper, $T \in \{22, 30, 35, 40\}$. All trading profit measures are expressed in units of 10,000.
Unreadable	A dummy variable set to one if the transaction record is reported in an unreadable disclosure file.
Unreadable_AI	A variable on the $[0, 10]$ interval, linearly rescaled from the LLM-assigned readability score capturing the unreadability of each disclosure file. See Online Appendix OA2 for details.
# of Same Committees	The number of committees in the House of Representatives on which the two legislative members in one dyadic group have served simultaneously.
# of Trades	In Table 2 Panel C: at the person–trading date level, the total number of trades for each person on each actual trading date; at the person–ticker–trading date level, the total number of trades of a ticker executed by an individual on that trading date; at the person–trading date (average) level, the average (across tickers traded by that person on that actual trading date) of the person–ticker–trading date level trading numbers; at the disclosure file level, the total number of trades reported in each disclosure file. In Table 3 Panel B: the total number of transaction records for each person in each year–month pair.

OA2 Unreadable variables with intensive margins

To obtain the Unreadable_AI measure in Table OA4, we begin with the 2,011 machine-unreadable trading disclosure files in PDF format, focusing on the subset of 1,581 PTRs that include at least one transaction classified as a stock purchase or a stock 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.

We process the 1,581 machine-unreadable PDFs 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.

OA2.1 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.

OA2.2 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.

OA2.3 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.

OA2.4 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.

OA2.5 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.

OA2.6 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.

OA2.7 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.

OA2.8 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.

OA3 List of Macro Announcements Controls.

We follow Bianchi, Gómez-Cram, and Kung (2024) and incorporate macroeconomic control variables (i.e., surprises) from Bloomberg's Macroeconomic Announcements dataset. For each announcement j on its announcement date t, the Bloomberg 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. 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.

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

OA4 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 5.

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 OA1), and it has meaningful budgetary implications through implementation funding and changes in incarceration policy that affect federal costs.[OA2]

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.[OA3]

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

[OA2] 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`.

[OA3] 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`.

final FY2015 Energy and Water Development funding "was included in the Consolidated and Further Continuing Appropriations Act, 2015."[OA4] 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.[OA5] 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.

[OA4] 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.

[OA5] 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.

OA5 Additional Tables and Figures

Table OA1: **Top 10 Most Traded Stocks**
This table reports the top 10 most frequently traded stocks within each subsample. The sample is constructed as in Panel A of Table 2, restricted to purchase transactions and excluding 2020. Panel A restricts the sample to readable filings; Panel B restricts the sample to filings flagged as unreadable. The column *Frequency* reports the number of trades in each stock.

Panel A: Readable			**Panel B: Unreadable**		
Rank	Company	Frequency	Rank	Company	Frequency
1	Microsoft	226	1	Amazon	204
2	Apple	171	2	NetApp	185
3	Amazon	110	3	Alphabet (Google)	166
4	Home Depot	90	4	Adobe	158
5	Procter & Gamble	85	5	Star Group	152
6	Johnson & Johnson	84	6	Culp	152
7	Disney	82	7	Microsoft	149
8	AT&T	72	8	McGrath RentCorp	142
9	UnitedHealth Group	69	9	Regis Corporation	138
10	Berkshire Hathaway	68	10	Facebook (now Meta)	137

Table OA2: **Mapping of Acts to Affected NAICS Industries.**
This appendix table reports the mapping of each of the 12 acts in our sample to its set of affected NAICS industries.

Act	**Affected NAICS Codes**
Protecting Access to Medicare Act (2014)	62, 3345, 3391, 524114
Consolidated and Further Continuing Appropriations Act, 2015	11, 23, 48, 49, 52, 62, 92
Medicare Access and CHIP Reauthorization Act of 2015	62, 524114, 5415
National Defense Authorization Act for Fiscal Year 2017	31, 32, 33, 54, 92
Consolidated Appropriations Act, 2017	11, 21, 22, 23, 31, 32, 33, 48, 49, 51, 52, 54, 61, 62, 92
First Step Act (2018)	56, 92
Bipartisan Budget Act of 2019	92
CARES Act (2020)	48, 49, 52, 61, 62, 71, 72, 92
William M. (Mac) Thornberry National Defense Authorization Act for Fiscal Year 2021	31, 32, 33, 52, 54, 92
American Rescue Plan Act (2021)	61, 62, 71, 72, 92
Consolidated Appropriations Act, 2022	22, 31, 32, 33, 51, 52, 54, 92
Inflation Reduction Act (2022)	21, 22, 23, 31, 32, 33, 52, 62, 92

Table OA3: **Abnormal Stock Return of Unreadable Congressional Trading: Industry Heterogeneity.**
The sample period is 2013-2022. The unit of observation is at the transaction-file level. The dependent variable is $CAR_{i,s,t}$, the cumulative abnormal return earned by individual i over a 22 trading-day horizon from purchasing stock s and reported in percentage points. *Unreadable* is a dummy variable set to one if the transaction record is in an unreadable file, and zero otherwise. *Affected* is a dummy variable set to one if the traded stock belongs to an industry directly affected by a contemporaneous bill, based on the bill-to-NAICS mapping reported in Table OA2, and the transaction occurs within the 60-day window prior to the bill's congressional passage date, and zero otherwise. Baseline controls include categorical variables for legislators' age and seniority, an indicator equal to one for Republican legislators, and an indicator equal to one if a transaction occurs within a $[-3, 1]$ window around each FOMC meeting date. Macro Surprises Controls include the macroeconomic announcement surprises listed in Online Appendix OA3. All models include a constant and the fixed effects as described in the table, but the coefficients are not tabulated. Detailed variable definitions are in Appendix OA1. Robust standard errors are reported in parentheses, and the clustering method is indicated at the top of each column. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	CAR	
Time Horizon:	22 days	
	(1)	(2)
Unreadable×Affected	0.841**	0.878**
	(0.382)	(0.420)
Unreadable	0.344*	0.315*
	(0.176)	(0.178)
Affected	-0.656	-0.601
	(0.525)	(0.534)
Baseline Controls	Yes	Yes
Macro Surprises Controls	No	Yes
log(Trading Volume)	Yes	Yes
Stock FE	Yes	Yes
Year-Month FE	Yes	Yes
SE Clustering	Person+Actual_YM	
Observations	38,261	38,208
R-squared	0.19	0.20

Table OA4: **Abnormal Stock Return of Unreadable Congressional Trading: Unreadable variables with intensive margins.**

The sample period is 2013-2022. The unit of observation is at the transaction-file level. The dependent variable is $CAR_{i,s,t}$ in Panel A, the cumulative abnormal return earned by individual i over horizon t ($t \in \{22, 30, 35, 40\}$ trading days) from purchasing stock s and reported in percentage points. All models include a set of control variables (categorical variables for legislators' age and seniority, indicators equal to one for Republican legislators, indicators set to one if a transaction occurs within a $[-3, 1]$ window around each FOMC meeting date, as well as macroeconomic announcement surprises listed in Online Appendix OA3), a constant, and the fixed effects as described in the table, but the coefficients are not tabulated. Detailed variable definitions are in Appendix OA1. Robust standard errors are reported in parentheses, and the clustering method is indicated at the top of each column. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	CAR			
Time Horizon:	22 days	30 days	35 days	40 days
	(1)	(2)	(3)	(4)
Unreadable_AI	0.082**	0.069*	0.033	0.045
	(0.032)	(0.039)	(0.050)	(0.053)
Baseline Controls	Yes	Yes	Yes	Yes
Macro Surprises Controls	Yes	Yes	Yes	Yes
log(Trading Volume)	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
SE Clustering	Person+Actual_YM			
Observations	38,261	38,208	38,178	38,168
R-squared	0.20	0.21	0.21	0.22

Table OA5: **Dyadic Regression Results for Unreadable Trading Connections (Drop One Act in Each Regression).**
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 unit of observation is at the act-dyadic-person level. Each regression drops one act. The results are obtained using the specification in column (3) of Table 5. *Same Stock* 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. *Same Committee* is a dummy variable set to one if both legislative members in a dyadic group have served on at least one committee in common in the House of Representatives. *# of Same Committees* is the number of committees in the House of Representatives on which the two legislative members in one dyadic group have served simultaneously. Same State equals 1 if two legislative members in one dyadic group are from the same state. 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%.

Dependent Variable:	Same Stock					
	(1)	(2)	(3)	(4)	(5)	(6)
60-Calendar-Day Window Before Each Act						
Unreadable	0.103***	0.093***	0.090***	0.110***	0.100***	0.107***
	(0.027)	(0.024)	(0.022)	(0.030)	(0.026)	(0.032)
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Same Committee:	Yes	Yes	Yes	Yes	Yes	Yes
# of Same Committees:	No	No	No	No	No	No
Same State:	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustering	Bill+Dyadic					
Observations	11,012	11,312	10,809	11,736	11,445	11,565
R-squared	0.030	0.026	0.018	0.028	0.028	0.027

Table OA5: **continued.**

Dependent Variable:	Same Stock					
	(7)	(8)	(9)	(10)	(11)	(12)
60-Calendar-Day Window Before Each Act						
Unreadable	0.097***	0.102***	0.104***	0.119***	0.110***	0.102***
	(0.027)	(0.027)	(0.032)	(0.028)	(0.030)	(0.027)
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Same Committee:	Yes	Yes	Yes	Yes	Yes	Yes
# of Same Committees:	No	No	No	No	No	No
Same State:	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustering	Bill+Dyadic					
Observations	11,505	11,954	11,630	11,292	11,753	11,168
R-squared	0.026	0.027	0.026	0.027	0.028	0.027

Table OA5: **continued.**

Dependent Variable:	Same Stock					
	(1)	(2)	(3)	(4)	(5)	(6)
90-Calendar-Day Window Before Each Act						
Unreadable	0.121***	0.109***	0.114***	0.122***	0.119***	0.128***
	(0.024)	(0.020)	(0.023)	(0.027)	(0.024)	(0.028)
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Same Committee:	Yes	Yes	Yes	Yes	Yes	Yes
# of Same Committees:	No	No	No	No	No	No
Same State:	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustering	Bill+Dyadic					
N	14,980	15,802	15,237	16,021	15,698	15,911
R^2	0.034	0.028	0.021	0.030	0.032	0.030
180-Calendar-Day Window Before Each Act						
Unreadable	0.097***	0.089***	0.093***	0.098***	0.094***	0.082***
	(0.020)	(0.020)	(0.020)	(0.022)	(0.020)	(0.018)
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Same Committee:	Yes	Yes	Yes	Yes	Yes	Yes
# of Same Committees:	No	No	No	No	No	No
Same State:	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustering	Bill+Dyadic					
Observations	21,107	22,461	21,938	22,594	23,045	22,854
R-squared	0.030	0.026	0.021	0.027	0.025	0.024

Table OA5: **continued.**

Dependent Variable:	Same Stock					
	(7)	(8)	(9)	(10)	(11)	(12)
90-Calendar-Day Window Before Each Act						
Unreadable	0.115***	0.122***	0.116***	0.130***	0.134***	0.121***
	(0.024)	(0.024)	(0.027)	(0.026)	(0.024)	(0.024)
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Same Committee:	Yes	Yes	Yes	Yes	Yes	Yes
# of Same Committees:	No	No	No	No	No	No
Same State:	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustering	Bill+Dyadic					
N	15,791	16,471	15,988	15,718	15,965	15,827
R^2	0.030	0.031	0.028	0.030	0.033	0.030
180-Calendar-Day Window Before Each Act						
Unreadable	0.096***	0.096***	0.089***	0.101***	0.105***	0.094***
	(0.022)	(0.020)	(0.022)	(0.021)	(0.019)	(0.020)
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Same Committee:	Yes	Yes	Yes	Yes	Yes	Yes
# of Same Committees:	No	No	No	No	No	No
Same State:	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustering	Bill+Dyadic					
Observations	22,482	23,277	23,000	22,239	22,817	23,116
R-squared	0.026	0.027	0.023	0.026	0.025	0.025

Table OA6: **Dyadic Regression Results for Unreadable Trading and Political Connections (Drop One Act in Each Regression).**
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. The unit of observation is at the act-dyadic-person level. Each regression drops one act. The results are obtained using the specification in column (3) of Table 6. *CoSponsor* 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. *Same Stock* 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. *Same Committee* is a dummy variable set to one if both legislative members in a dyadic group have served on at least one committee in common in the House of Representatives. *# of Same Committees* is the number of committees in the House of Representatives on which the two legislative members in one dyadic group have served simultaneously. Same State equals 1 if two legislative members in one dyadic group are from the same state. 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%.

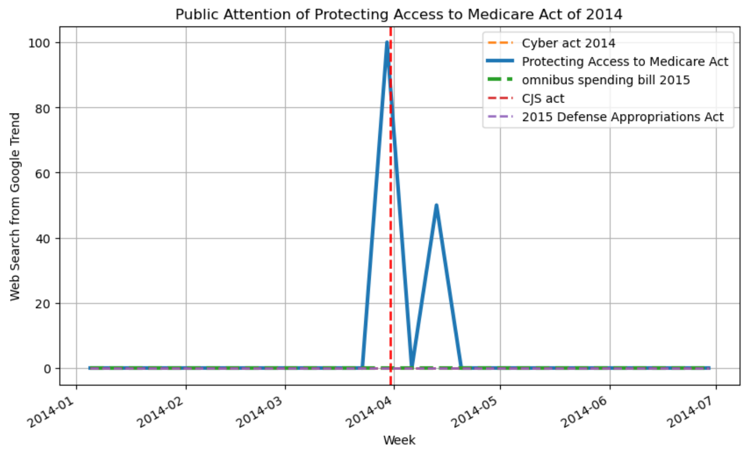
Dependent Variable:	CoSponsor					
	(1)	(2)	(3)	(4)	(5)	(6)
Unreadable×Same Stock	6.477**	5.667*	5.633**	7.006**	7.858**	5.726**
	(2.657)	(2.844)	(2.342)	(2.560)	(2.620)	(2.457)
Unreadable	-16.278**	-18.106**	-16.670**	-17.007**	-15.546**	-20.096**
	(7.074)	(7.158)	(7.050)	(7.536)	(6.884)	(7.497)
Same Stock	-2.853	-2.284	-2.962	-3.185*	-4.114**	-2.637
	(1.606)	(1.735)	(1.785)	(1.587)	(1.586)	(1.527)
Dyadic FE:	Yes	Yes	Yes	Yes	Yes	Yes
Bill FE:	Yes	Yes	Yes	Yes	Yes	Yes
Same Committee:	Yes	Yes	Yes	Yes	Yes	Yes
# of Same Committees:	No	No	No	No	No	No
Same State:	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustering:	Bill+Dyadic					
Observations	6,962	7,292	6,907	7,723	7,326	7,557
R-squared	0.68	0.72	0.71	0.70	0.70	0.69

Table OA6: **continued.**

Dependent Variable:	CoSponsor					
	(7)	(8)	(9)	(10)	(11)	(12)
Unreadable×Same Stock	3.558**	7.290**	6.880**	6.464**	6.232**	6.420**
	(1.322)	(2.532)	(2.872)	(2.683)	(2.729)	(2.610)
Unreadable	-8.787*	-15.583**	-17.086*	-13.923*	-12.086*	-13.262
	(4.024)	(6.841)	(8.385)	(7.164)	(6.553)	(7.606)
Same Stock	-1.476	-3.694**	-2.560	-2.395	-2.836*	-2.892
	(0.945)	(1.553)	(1.418)	(1.525)	(1.488)	(1.708)
Dyadic FE:	Yes	Yes	Yes	Yes	Yes	Yes
Bill FE:	Yes	Yes	Yes	Yes	Yes	Yes
Same Committee:	Yes	Yes	Yes	Yes	Yes	Yes
# of Same Committees:	No	No	No	No	No	No
Same State:	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustering:	Bill+Dyadic					
Observations	7,506	7,752	7,681	7,488	7,844	7,310
R-squared	0.73	0.70	0.70	0.69	0.70	0.68

Figure OA1: **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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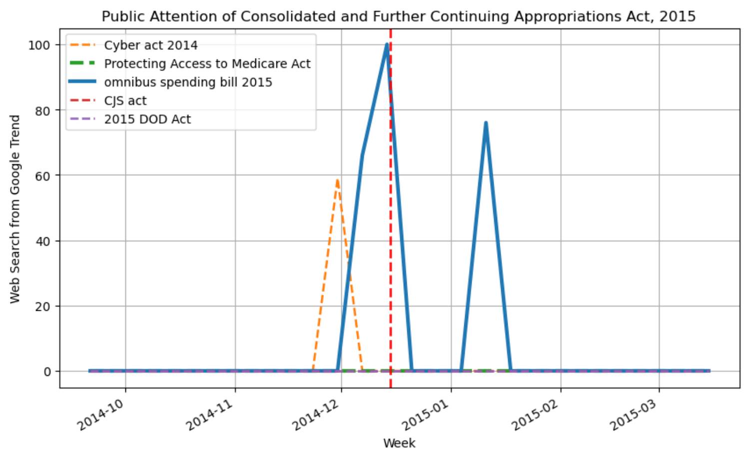

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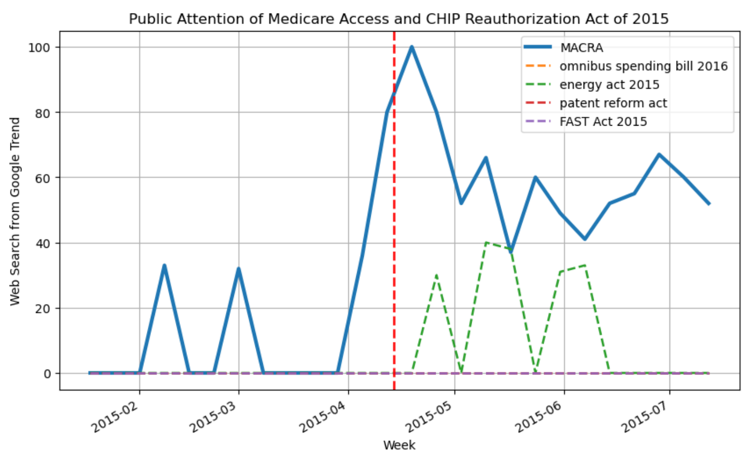
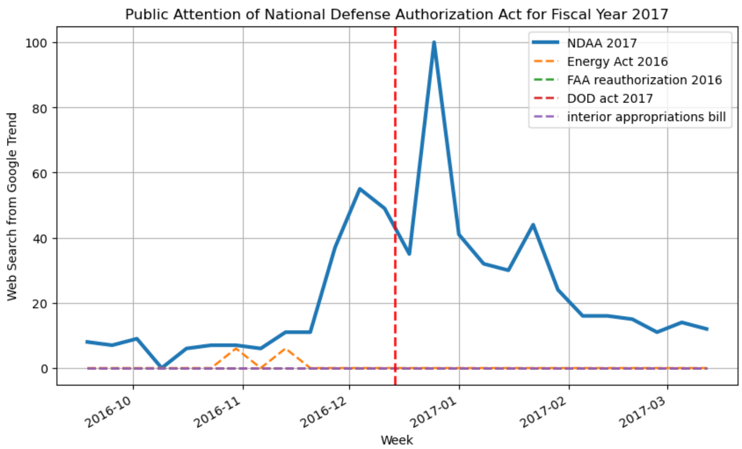


(3)

Figure OA1: **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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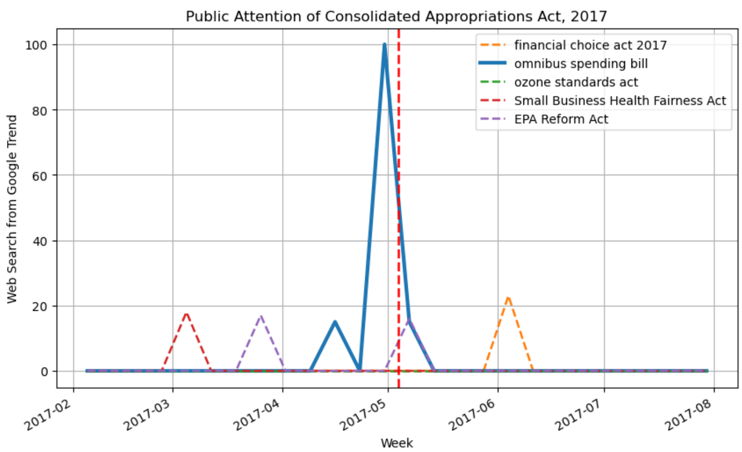

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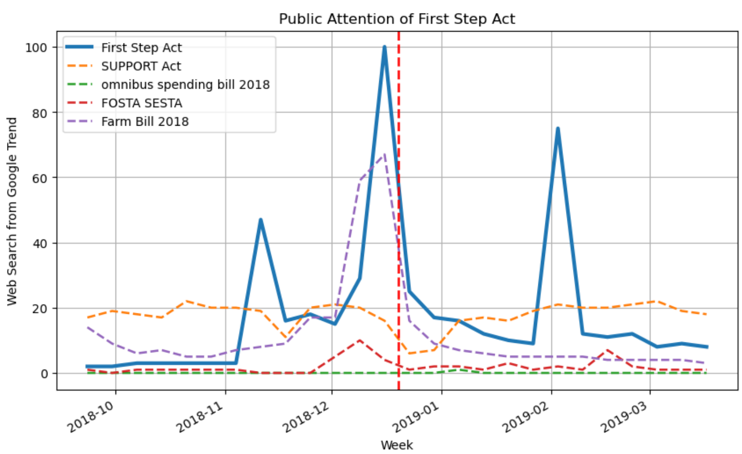
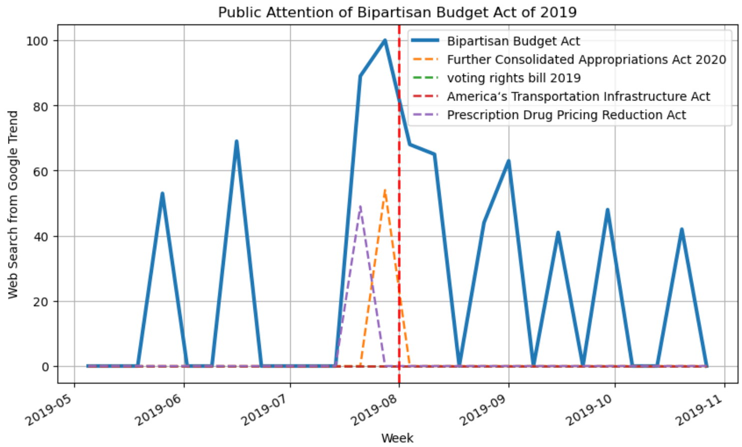


(6)

Figure OA1: **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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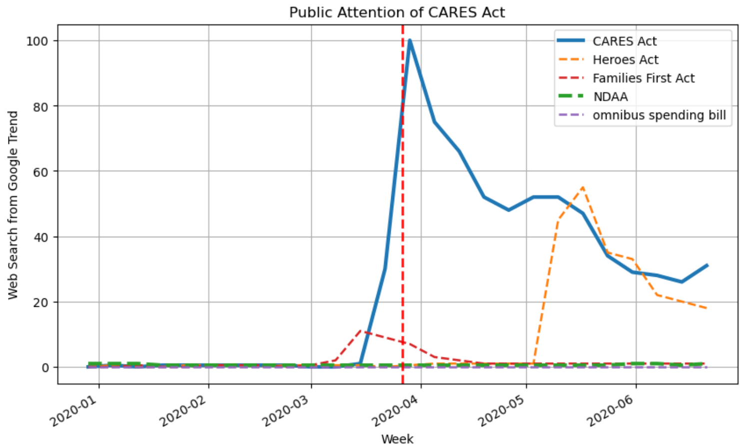

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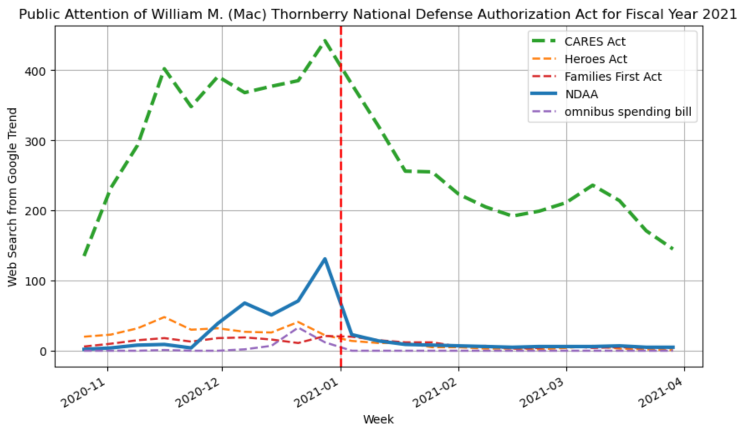
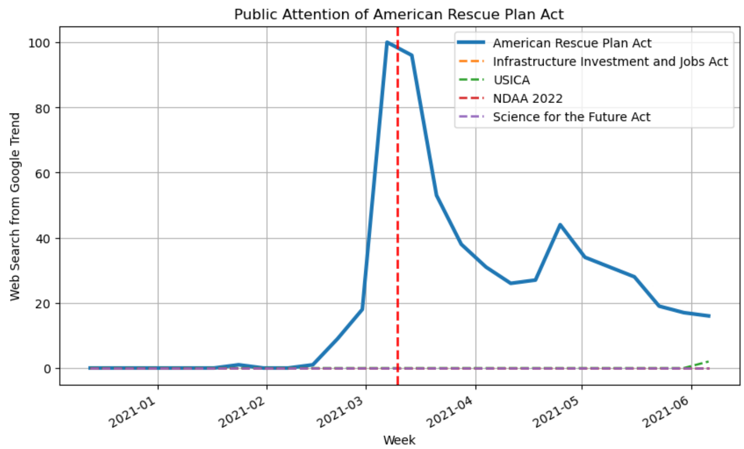


(9)

Figure OA1: **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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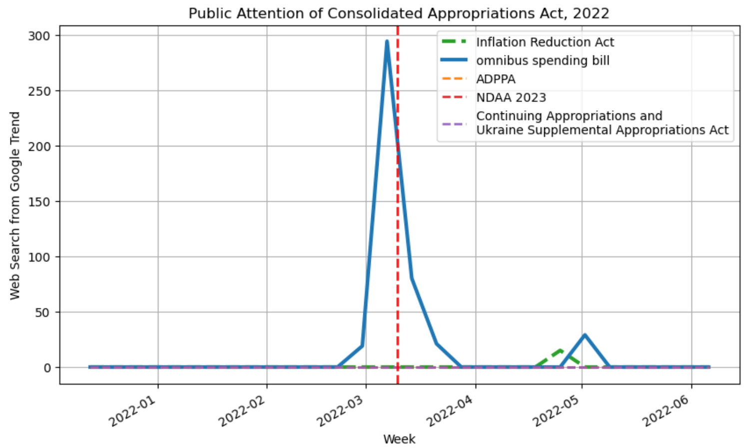

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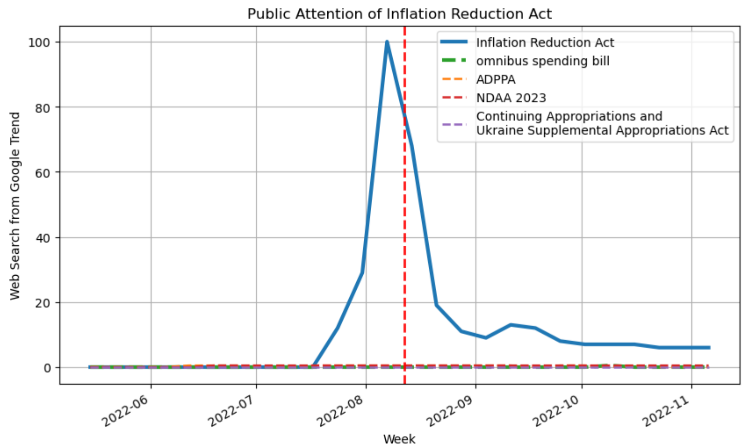

(12)