Legislative Trades*

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Abstract

This paper examines how the market responds to the public disclosure of congressional stock trades by exploiting the difference in timing between when trades occur and when they are disclosed. Using S&P 500 ticker-daily data from 2014 to 2022 and 4,254 reports, we find that individual stock returns are significantly higher – by 17 basis points on average – on days when a purchase record is reported. The disclosure effect is stronger for trades by relevant committee members, trades in industries with greater procurement exposure, and those reported during periods of fiscal or political uncertainty. We interpret our main finding through a "fiscal expectation" mechanism: market participants revise their beliefs about future policy in response to congressional trades. Consistent with this interpretation, we show that such trades indeed predict the likelihood of future bill passage. While public concerns about insider trading persist, our findings suggest that trade disclosures may also convey timely and systematic signals about fiscal policy to financial markets.

JEL Classification:xx
Keywords: fiscal policy, congress trading record, stock returns, uncertainty

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1 Introduction

Members of Congress trade financial assets frequently, and these transactions have drawn increasing media scrutiny in recent years (e.g., New York Times, Wall Street Journal, Business Insider). Before 2012, there were no explicit legal restrictions on trading based on non-public information; disclosure requirements were governed by the Ethics in Government Act of 1978, which mandated only annual reporting. The landscape shifted with the passage of the STOCK Act in 2012, which required members to report trades within 30 to 45 days of execution—though penalties for noncompliance remain minimal.

This raises an important hypothesis: If insider trading concerns are real, then the 2012 STOCK Act may have facilitated the passage of such information to capital markets more effectively through timely disclosures. While prior literature has largely focused on evaluating whether congressional portfolios outperform the market –interpreting outperformance as potential evidence of insider trading – our paper asks a new question: Does the stock market respond to the disclosure of these trades, regardless of their content? How and why? Under the null hypothesis, there should be no asset pricing effect if investors view these disclosures as uninformative.

In this paper, we analyze all 4,254 electronically readable trading reports filed by U.S. House Representatives between 2014 and 2022. Our analysis covers the full universe of daily S&P 500 stocks over the same period. We find that congressional trade disclosures trigger meaningful stock market reactions. Specifically, when a stock purchase is disclosed on a given day, the corresponding stock's daily return increases by approximately 17 basis points on average, or 0.12 standard deviations. This stock market effect is stronger during periods of split Congress, for trades made by members on relevant committees, in industries more fiscally dependent on federal government (through procurement contracts), and around major budgetary uncertainty periods such as debt ceiling episodes. Therefore, our first result suggests that investors could view some disclosures as more informative than others – particularly when the political context or legislative influence enhances the perceived relevance of the trade.

To be more specific, one interpretation is that congressional stock trades may serve as forward-looking signals of fiscal policy outcomes, hence a "fiscal expectation shock" mechanism. If trades in industry j systematically increase before a bill benefiting that industry passes, it suggests that legislators possess and act on private information about the bill's legislative prospects. This implies that some congressional trades function as anticipatory responses to likely fiscal changes, which hence gets capitalized in asset prices as such trades are getting disclosed.

We find two consistent evidence in support of this mechanism. First, mechanism should have two implications. First, congressional trades may reveal private expectations about the future success of industry-relevant legislation. The analysis begins by collecting a comprehensive dataset of all bills introduced in the U.S. House of Representatives between 2014 and 2022, totaling 29,142 observations, with only 8% ultimately becoming law. Each bill is mapped to its relevant industry or industries (using committee assignment as a proxy), creating a bill-industry (Bill-NAICS) level dataset. Then, we construct actual trades of a relevant NAICS prior to the bill decision date. Consistent with this view, we show that actual stock purchases in a given industry help predict whether bills benefiting that industry are more likely to pass. A one standard deviation increase in industry-specific purchase volume is associated with roughly a 1 percentage point increase in the probability of bill passage, which is sizable given the bill survival rate is only 8% in the House.

Second, we test the fiscal expectations interpretation more directly by comparing asset price reactions to disclosures based on their timing relative to legislative events. Specifically, we distinguish between disclosures that occur before the relevant bill is passed and those that occur after. If congressional trades contain future policy information, then disclosures made prior to the bill's passage should be more informative to investors and thus elicit stronger market responses. Our findings confirm this prediction. We find that market reactions are significantly larger when the disclosure precedes the legislative outcome. This temporal asymmetry strengthens the interpretation that trade disclosures are not merely retrospective records but serve as credible signals of future fiscal developments.

Our paper contributes to several strands of research. The literature linking fiscal policy and financial markets often highlights the role of political connections in shaping firm and institutional outcomes. Existing research shows that firms with ties to policymakers benefit through increased financial support (Acemoglu, Johnson, Kermani, Kwak, and Mitton (2016)), improved firm values (Goldman, Rocholl, and So (2009)), and greater access to government bailouts (Faccio, Masulis, and McConnell (2006)). Politicians may also channel economic favors through contracts (Brogaard, Denes, and Duchin (2021); Tahoun (2014)) or influence hedge funds and private equity (Gao and Huang (2016); Faccio and HSU (2017)). Beyond these mechanisms, recent work explores how fiscal expectations affect market participants. Bianchi, Gómez-Cram, and Kung (2024) and Xu and You (2025) study how investors, including analysts (Xu, Yang, and You (2025)), price policy-relevant information. Our research is the first to establish congressional trade disclosures as fiscal shocks to the capital market, offering a novel perspective within the fiscal expectations literature.

Second, in the context of the congressional insider trading debate, research has traditionally centered on abnormal returns (e.g., C. Eggers and Hainmueller (2013); Blau, Whitby, and Wilson (2018); Belmont, Sacerdote, Sehgal, and Van Hoek (2022)). Our approach shifts the focus to the timing and content of actual trades. Using the universe of bills and their alignment with disclosed trades, we provide a new empirical strategy to assess whether congressional trading behavior embeds informational advantages tied to legislative outcomes. In addition, by tracing trade disclosures to subsequent bill progress and asset price reactions, we show that these disclosures can signal future policy in ways that markets absorb.

2 Legal Background and Data

2.1 A history of U.S. laws on congressional trading

Understanding the legislative context that enables and shapes congressional stock trading is crucial for interpreting the financial market's response to these transactions. This section outlines the legal framework governing congressional financial disclosures, key policy changes over time, and the renewed public scrutiny triggered by recent political events.

Before 2012, there was no statutory framework explicitly prohibiting members of the United States Congress from trading securities based on *non-public* information acquired through their official duties. Instead, ethical obligations were loosely defined under the Ethics in Government Act of 1978, which required *annual* disclosure of financial holdings and transactions by public officials: https://www.congress.gov/bill/95th-congress/senate-bill/555. However, these filings were often delayed and incomplete.

In response to mounting public and media scrutiny regarding potential conflicts of interest and the misuse of insider knowledge, Congress enacted the STOCK Act in April 2012: https://www.congress.gov/bill/112th-congress/senate-bill/2038. For the first time, the law explicitly prohibited members of Congress, their staff, and other federal employees from leveraging non-public information gained through their roles for personal financial gain. More concretely, the STOCK Act mandated that trades exceeding $1,000 be disclosed within 30 days of notification or 45 days of the transaction date, whichever comes earlier. There are asset class exemptions (e.g., mutual funds, ETFs, U.S. Treasury bonds etc.).[1] Late disclosures incur only

[1] The list of exemptions is also long, which gives members an opportunity (if they wish) not "to report any transactions involving mutual funds, exchange traded funds, or any other asset that is an excepted investment fund (EIF) (see the financial disclosure report instructions for the definition of an EIF); holdings in a blind trust; real property; cash accounts (e.g., checking, savings, and money markets); U.S. Treasury bonds, bills, and notes; pensions; and any asset that is solely incidental to the trade or business of an entity."

a $200 fine. In April 2013, Congress passed an amendment that rolled back certain transparency provisions of the original legislation: https://www.congress.gov/bill/113th-congress/senate-bill/716. Notably, the amendment eliminated the requirement for electronic filing of financial disclosure forms and removed the provision mandating that these documents be made available in an online, searchable database.

The COVID-19 pandemic brought renewed scrutiny to congressional stock trading. Notably, Senators Richard Burr and Kelly Loeffler faced allegations of insider trading after selling substantial stock holdings following private briefings on the virus's potential impact. While investigations were conducted, no charges were filed, highlighting the difficulties in enforcing the STOCK Act's provisions. The congress proposed two bills – the Ban Congressional Stock Trading Act and the TRUST in Congress Act – and non of them was advanced further.

What is relevant to our research is threefold. First, following the STOCK Act and its 2013 amendment, members of Congress are required to disclose all stock transactions. This requirement motivates our focus on stock trading as the asset class of interest and defines the starting point of our sample period in 2014. Second, we focus on digitally typed disclosure PDFs, which reflect the format most accessible to the media and the public in real time. Additional details on data sources are provided in Section 2.2. Third, this statutory requirement significantly reduced the lag between a transaction and its public disclosure, thereby creating observable "disclosure events" that our research exploits to test asset pricing responses. The enforcement mechanisms remain limited, with no automatic criminal liability. As a result, while the law established a formal disclosure obligation, it is unclear whether – if insider trading occurs – it has become less prevalent. If anything, more timely disclosures could accelerate the market's incorporation of the information. These disclosures serve as the basis of our empirical dataset and underpin the identification strategy used throughout this study.

2.2 Data and summary statistics

Our raw data source is the complete database of https://disclosures-clerk.house.gov/FinancialDisclosure, which offers all House representatives' disclosures – if they had trades to report – or what the website formally refers to as the "Periodic Transaction Reports."[2] These reports are obtained in a PDF file format.

Figure 1 provides a PDF report sample. Each periodic transaction report filed by a member of the House of Representatives includes several key fields. The Owner field indicates whether the transaction was conducted by the member themselves, their spouse, or a dependent. The Asset field provides the name, type, the ticker symbol of the security (if available), along with a basic description – for example, whether the asset is held in a blind trust hence a passive investment. The Transaction Type specifies whether the asset was purchased (P) or sold (S). The Transaction Date records the calendar date on which the trade took place, while the Notification Date refers to when the filer was notified of the transaction, which could be immediate, via a monthly account statement or from a broker. The Amount field reports the dollar value of the trade, although this information is approximate, as only a range (e.g., $1,001-$15,000) is disclosed. Finally, the Digitally Signed Date – the date the report was electronically certified – serves as the immediate Publication Date, marking when the information becomes publicly available.

[Insert Figure 1 here]

Between 2014 and 2022 (covering 113th House to the 117th House), we are able to obtain 6,366 periodic transaction reports filed by members of the U.S. House of

[2]There is a separate website for Senate disclosures (https://efdsearch.senate.gov/search/home/). In this study, we focus on the House for two reasons. First, senators typically attract greater public attention due to the higher stakes associated with each seat; therefore, testing our hypothesis using House members provides a more conservative benchmark. Second, while we considered incorporating Senate disclosures into our framework, differences in legislative schedules across chambers would complicate the analysis and make interpretation more difficult. To maintain a cleaner and more coherent setting, we limit our focus to the House.

Representatives. Among them, we focus on 4,254 files that are not hand-written, scanned files. These disclosures come from 110 unique House members and account for a total of 37,168 reported trades across all asset types, including 12,521 trades specifically involving stocks. In terms of market breadth, the dataset spans 640 distinct stock tickers in the S&P 500 universe,[3] indicating a wide range of corporate securities actively traded by congressional members during this period.

[Insert Figure 2 here]

[Insert Figure 3 here]

Figure 2 plots the rolling 30-day total number of congressional stock "actual" purchases (in thin blue) alongside the number of "disclosed" purchases (in thick green). As expected, the disclosed transactions consistently lag behind actual trades by approximately one month, aligning with the STOCK Act's 30- to 45-day disclosure requirement. This consistent delay supports the assumption that disclosure timing is possibly, simply driven by regulatory deadlines rather than strategic release behavior — an important exogeneity consideration for our identification strategy. We provide more formal evidence of this later in the paper (Section 3.1). The use of a 30-day rolling window also provides a natural lens to assess the timeliness of reporting practices, showing that most trades are indeed disclosed within the required timeframe. In fact, we are able to validate validate that most trades are being disclosed within 45 days (see Figure 3).

In addition to illustrating the obvious lagging pattern, Figure 2 also reveals meaningful variation in congressional trading activity over time. Several notable disclosure peaks correspond to major macro volatility events, such as the mid-2015 global stock market volatility, the early 2020 Covid events, and a pronounced increase around mid-2022 during heightened geopolitical tension linked to the Russia-Ukraine conflict. There are also disclosure peaks that coincide with political events. For instance, there

[3]The S&P 500 universe constituents change over time.

is a disclosure surge in early 2017 following the start of a new (Trump) administration, and another disclosure spike in late 2021 when the SEC announced efforts to strengthen enforcement of the STOCK Act.

These aggregate fluctuations are not the primary focus of our paper – as we explain later, which exploits ticker-level return responses – but Figure 2 provides valuable insights into our empirical design. For one, our main specification should include year-month fixed effects to address overall macroeconomic trends and regulatory signals. Appendix Figure A1 offers a very different pattern.

[Insert Figure 4 here]

The distribution of congressional stock purchases across industries, as categorized by NAICS 2-digit codes, reveals a strong concentration in a few key sectors. Notably, the Information sector (NAICS 51), which includes technology firms, and the Finance and Insurance sector (NAICS 52) account for a substantial share of total trades. This is consistent with the broader market dominance and investor interest in these sectors during the sample period. Additionally, Manufacturing (NAICS 31-33) emerges as the single most traded category, with over 1,500 transactions, which is expected as the Tech firms typically use NAICS 33, 51 and/or 54.

- How many trades on the same day?
- Is reporting a random event? (How to prove?)
- Do they have a relatively diversified stock portfolios? Or people have clear tendency of trading stocks that are consistent with their committee?
- How often do they trade?

3 Stock Market Effects

3.1 Exogeneity test

Previous evidence discussed in Section 2.2 suggests that disclosure timing seems to be simply driven by regulatory deadlines rather than strategic release behavior, hence generating the lag pattern in Figure 2. In this section, we formally test whether disclosure dates appear strategic: macro event announcements, individual stock past performance, and day-of-the-week effect.

We first conduct the following specification,

$$\begin{aligned} ReportBuy\_1_{i,t} &= \alpha + \beta_1 \times I_{FOMC,[-3,1]} + \beta_2 \times I_{BillPassing,[-3,1]} \\ &+ \beta_3 \times PastPerformance_{i,t-N} + \beta_4 \times EPU_{ym(t)} + \epsilon_{i,t}, \end{aligned} \tag{1}$$

where $ReportBuy\_1_{i,t}$ indicates whether purchases of stock i are reported on day t. This is a binary variable (1 if disclosed, 0 otherwise). $I_{FOMC,[-3,1]}$ and $I_{BillPassing,[-3,1]}$ are indicator variables equal to 1 if a disclosure occurs within the window of three days before to one day after an FOMC meeting or major fiscal legislation, respectively. These variables reflect potential strategic timing as major macro or fiscal events will distract investors, and disclosures during these windows may draw less attention. $PastPerformance_{i,t-N}$ captures past performance metrics for stock i, including short-term lagged returns, realized volatility, and Amihud (2002)'s illiquidity over 5- and 10-day horizons. These variables reflect another potential strategic timing, as if one expects the disclosure to boost the price, she may disclosure trading records when the ticker's recent performance has been weak. Finally, $EPU_{ym(t)}$ is the Economic Policy Uncertainty index measured at the year-month level, controlling for broader macroeconomic and political uncertainty. β_1, β_2 and β_3 are of interest to test strategic timing.

[Insert Table 1 here]

Table 1 presents the regression results. We find no evidence that congressional trade disclosures are systematically timed to avoid or coincide with major macroeconomic announcements. Moreover, the timing of disclosures is not predictable based on recent stock-specific performance or non-linear measures such as volatility or illiquidity. However, disclosure dates are (contemporaneously) correlated with the Economic Policy Uncertainty (EPU) index at the aggregate level, which motivates the inclusion of time fixed effects in later specifications.

Another concern is potential variation by day of the week, as Fridays could be perceived . Appendix Figure A2 demonstrates that most of the trading records are released during week days, and from Mondays to Fridays, we continue to observe evenly-distributed frequencies. For convenient matching with trading days, we only consider reports published on a weekday.

3.2 Main specification

Next we estimate the following specification to examine the individual stock return reaction $Ret_{i,t}$ to congressional purchase trade disclosures $ReportBuy_{i,t}$:

$$Ret_{i,t} = \alpha + \beta \times ReportBuy_{i,t} + \boldsymbol{\delta} \times \boldsymbol{Macro_t} + \boldsymbol{\gamma} \times \boldsymbol{Firm_{i,t}} + \varepsilon_{i,t}, \tag{2}$$

where $Ret_{i,t}$ denotes the return of stock i on day t, and $ReportBuy_{i,t}$ captures whether purchases of stock i are disclosed on day t – either as a binary variable (1/0) or as the number of purchases reported on the same day t. The specification includes control variables following Bianchi, Gómez-Cram, and Kung (2024) and Pástor and Stambaugh (2003). These include $\boldsymbol{Macro_t}$, a vector of top-50 macroeconomic announcement variables (capturing both timing and direction effects), and $\boldsymbol{Firm_{i,t}}$, which includes intraday illiquidity, lagged returns, and analysts' forecast revisions and surprises. We include fixed effects at the stock and year-month levels (following

Bianchi, Gómez-Cram, and Kung (2024); Chen, De, Hu, and Hwang (2014)), and cluster standard errors by firm and date. The analysis uses daily data from the full S&P 500 universe over 2014-2022, excluding windows surrounding FOMC meetings ([-3,1]) and the initial COVID-19 NBER-recession period (February to April 2020) to avoid confounding macro shocks.

[Insert Table 2 here]

Table 2 report the results, with Panel A using the binary report buy variable and Panel B using the number of reported purchases. In Column (1), where only double clustering is applied and no controls are included, the coefficient on $ReportBuy\_1_{i,t}$ is 0.002000 and statistically significant at the 1% level, suggesting a 20 basis point increase in returns on the day a purchase is disclosed. Columns (2)-(4) add firm-level controls, macroeconomic announcement controls and stock FE, and demonstrate highly significant results with similar coefficient magnitudes. Finally, Column (5) addresses the observations in Table 1 and includes year-month fixed effects. The coefficient estimates is 0.001671, which is both statistically and economically significant. When a new stock purchase record is published today, the corresponding ticker-daily returns increase by 17 bps (or 0.12 SD).

To put the estimated return effect into perspective, consider the market capitalization ($MCAP) of the affected firms. For a large stock with a market cap between $1–3 trillion, a 17 basis point increase in daily return translates to a market value gain of approximately $2–5 billion. For an average stock in the sample with a market cap around $80 billion, the same return impact implies a gain of about $140 million in market value.

Panel B exhibits similar conclusions. Because the number of trades reported on the same days ranges from 1 to 8 typically (i.e., 1∼8 House Representative(s) disclosing purchase trades of the same ticker on the same day), results including intensive margin are not very different from a binary right-hand-side variable. Appendix Table A1 shows that stock market returns do not change if we use actual transaction day of this ticker purchase.

Table 3 reports a series of robustness checks to validate the main result that stock returns respond positively to congressional trade disclosures. Across all specifications – ranging from excluding post-2020 data (Column (1)), removing the Technology sector stocks (Column (2)), excluding weekend disclosures (Column (3)), dropping majority leaders (Column (4)), and adding controls for prior-day returns (Column (5)) or contemporaneous sell disclosures (Column (6)) – the estimated effect of $ReportBuy\_1$ remains consistently positive, statistically significant, and economically meaningful. The stability of these estimates under different subsample and control conditions strengthens confidence that the observed market reaction is not driven by sample-specific crisis events, industries, outliers, or omitted variable bias.

3.3 Heterogeneities

Table 4 presents a series of heterogeneity results that are consistent with a fiscal information shock interpretation to our main results above. Specifically, we study whether the return response to congressional trade disclosures varies systematically with institutional (i.e., split congress or not?), individual role (i.e., whether the report comes from members of the relevant, industry-wide committee?), political (i.e., whether the firm is fiscally more dependent on the government?), or economic conditions (i.e., when government budgetary uncertainty is heightened?). Panel A shows that the return effect is significantly positive in Congresses with divided partisan control (113th and 116th). This aligns with the possibility that market participants may view disclosures as more informative or consequential during periods of legislative friction or uncertainty. Panel B shows that the effect is stronger for members serving on relevant committees. Panel C uses firm-level fiscal dependence (FD) measures (constructed by Xu, Yang, and You (2025) using procurement data) and find that the stock market effect more than doubled for firms with higher-than-median fiscal dependence.

[Insert Table 4 here]

Panel D explores whether budgetary uncertainty period amplifies the return effect of disclosures. The analysis includes interaction terms between ReportBuy variables and an event variable of debt ceiling percentage changes (see Appendix Figure A3). The interaction terms are positive and significant across all columns, suggesting that market responses to trade disclosures are more pronounced during periods of elevated fiscal uncertainty. One interpretation is that disclosures could be viewed to convey more information when fiscal policy or law making process becomes more uncertain.

4 Mechanism: A Fiscal Expectation Shock Interpretation

One interpretation of our empirical evidence above is that congressional stock trades may serve as forward-looking signals of fiscal policy outcomes. If trades in industry j systematically increase before a bill benefiting that industry passes, it suggests that legislators possess and act on private information about the bill's legislative prospects. This implies that some congressional trades function as anticipatory responses to likely fiscal changes, which hence gets capitalized in asset prices as such trades are getting disclosed.

This mechanism should have two implications:

1. Actual trades should be informative about real policy direction.
2. Disclosure effects prior to the relevant bill's passage should be stronger than those occurring after the bill has already passed.

We test these two implications in Sections 4.1 and 4.2.

4.1 Bill Pass Prediction

Can actual trades of an industry j prior to the decision day of a bill predict the likelihood of its passing? This empirical design investigates whether congressional stock trades contain predictive information about the legislative success of pending bills. The analysis begins by collecting a comprehensive dataset of all bills introduced in the U.S. House of Representatives between 2014 and 2022, totaling 29,142 observations, with only 8% ultimately becoming law.

Each bill is mapped to its relevant industry or industries (using committee assignment as a proxy), creating a bill-industry (Bill-NAICS) level dataset. This structure allows the researchers to examine industry-specific trading activity in the days leading up to major legislative decisions.

The core empirical test here asks whether actual buying activity in a given industry j, measured in the 21 days prior to a bill's b decision date, is associated with a higher probability of that bill passing $BillPass_{b,j}$:

$$BillPass_{b,j} = \alpha + \beta \times ActualBuy_{t(b)-1,t(b)-21,j} + \boldsymbol{\gamma} \times \boldsymbol{Controls_b} + \varepsilon_{b,j}. \quad (3)$$

Control variables in $\boldsymbol{Controls_b}$ include two variables (as used in Yano, Smith, and Wilkerson (2012)) to predict bill survival: the day durations since the proposal date, and whether the sponsor representative was in the same party of the majority party in the House Chamber. Both variables are used as our benchmark variables. The regression specification also includes industry and time fixed effects to account for persistent sector-level traits and macroeconomic shocks.

[Insert Table 5 here]

Table 5 presents regression results examining whether actual stock purchases in a bill-relevant industry predict the likelihood of that bill's passage. The two benchmark variables to explain the bill survival, $DecisionLength_b$ and $I_{SameParty,b}$ capturing the legislative calendar and political alignment, respectively, exhibit expected signs and significance levels given prior literature (e.g., Yano, Smith, and Wilkerson (2012)), providing additional validation of the model's structure.

Column (5) includes our key variable $ActualBuy_{t(b)-1,t(b)-21,j}$. The coefficient estimate is positive and statistically significant at the 1% test. This indicates that greater buying activity in an industry-measured in the 21 days before a bill decision is associated with a higher probability that the bill favoring that industry will pass. The magnitude of the effect is economically meaningful: a one standard deviation increase in industry-specific purchase volume is associated with roughly a 1 percentage point increase in the probability of bill passage. The average passage rate is 8%. As a robustness test, Column (6) further controls for total number of actual sell trades during the same time interval prior to the bill decision date. In another robustness test, Appendix Table A2 considers alternative horizon choices and finds robust results.

One important heterogeneity to further convince us with the mechanism is to classify bills into expansionary bills versus contractionary ones. We should anticipate results being stronger using obvious expansionary bills. We classified U.S. House bills into Expansion (P), Neutral (N), and Contraction (S) using a two-step approach. First, we applied a keyword-based method, labeling bills based on the relative frequency of spending- versus selling-related terms in their titles and descriptions. Bills were labeled as Expansion if spending-related keywords (e.g., "financial aid," "funding," "public expenditure," "budget approval") appeared more frequently, and as Contraction if selling- or cutback-related terms (e.g., "downsizing," "divestment," "budget cut," "liquidation") dominated.[4] Bills with no matches or equal counts were labeled

[4]The set of expansionary words include: spend, spending, expenditure, expenditures, budget, appropriation, appropriations, funding, allocation, allocations, grant, grants, subsidy, subsidies, disbursement, disbursements, fiscal, outlay, outlays, financing, monetary, government spending, public funds, public spending, treasury, exchequer, revenue expenditure, financial support, financial aid, aid, public expenditure, investment, investments, expense, expenses, operational cost, cost, costs, budgetary, appropriated, disbursed, allocated, financial allocation, fiscal allocation, government aid, program spending, spending measure, fiscal policy, expenditure measure, budget approval. The set of contractionary words include: sell, selling, divest, divestment, divestitures, privatize, privatization, disinvestment, cutback, cutbacks, reduction, reduce, downsizing, liquidate, liquidation, asset sale,

Neutral, while others were assigned based on which keyword type dominated. Second, we manually reviewed Neutral cases and reclassified them when their content clearly aligned with expansionary or contractionary fiscal intent.

[Insert Figure 5 here]

Out of 29,142 House bills introduced between 2014 and 2022, we classify 3,956 as expansionary and 555 as contractionary. Over time, Figure 5 shows the rolling 3-month count of expansionary and contractionary bills introduced in the U.S. House of Representatives from 2014 to 2022. Expansionary bills – those involving proposed increases in government spending or investment – consistently outnumber contractionary bills during this historical sample of U.S. Peaks in expansionary activity often align with major political or economic moments, with largest ones including transitions in Congress. In contrast, contractionary bills remain relatively stable and lower in volume throughout the sample, suggesting that legislative focus tends to skew more toward fiscal expansion than restraint during most periods in our sample.

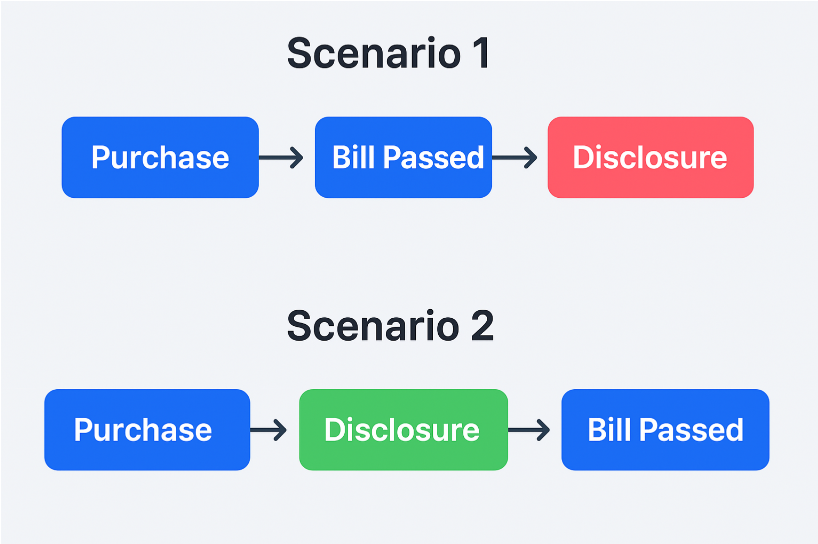
[Insert Table 6 here]

Table 6 complements Table 5 by showing that the predictive power of congressional purchase trades for bill passage is indeed stronger if we focus on expansionary bills. For expansionary bills, actual purchases in the relevant industry significantly predict a 2.0086% higher chance of an expansionary bill passing, suggesting that legislators may act on anticipations of increased government spending. In contrast, for contractionary bills, the coefficient on actual buys is negative, which is the expected direction, but it is statistically insignificant.

sale, sell-off, disposal, dispose, auction, auctioning, cost-cutting, streamline, streamlined, efficiency, efficiencies, cost saving, savings, contraction, austerity, defunding, budget cut, privatise, offload, outsourcing, restructure, restructuring, reorganization, reorganize, fiscal restraint, expense reduction, reduce spending, sell government assets, privatize public assets, asset disposal, government sale, divestiture, expenditure reduction, operational cutback.

4.2 Main results conditioning on the timing of bill passes

In this section, we provide our second evidence of this mechanism, exploiting the timings of relevant bill passing and trade disclosures. To illustrate the conceptual framework, we produce the following diagram,



Intuitively, if the fiscal expectations interpretation is real, the asset pricing impact of a disclosure should be weaker when the relevant bill has already passed before the disclosure date. This is described in Scenario 1 above. In Scenario 2, the disclosure of a congressional stock purchase occurs before the relevant bill is passed. In this setting, the disclosed trade may be interpreted by investors as a signal of insider knowledge about upcoming legislative action. Because the policy has not yet been enacted, the disclosure serves as a potential source of new fiscal information, leading to stronger asset pricing effects. This anticipatory interpretation aligns with the fiscal expectations hypothesis, in which disclosures are viewed as informative about future congressional action.

[Insert Table 7 here]

To empirical test it, we constrain a clean sample where there are no other FOMC, bill voting, or other ticker disclosure event within +/- 21 days of the a buy disclosure event for a ticker. In Scenario 1 (Scenario 2), a relevant bill passed before (after) the disclosure event, from Day -21 to Day -1 (from Day 1 to Day 21). Table 7 formalizes the test results. Results show that individual stock returns respond more strongly to trade disclosures when they precede the passage of a relevant bill passing (Scenario 2) compared to when the bill has already passed (Scenario 1). In Scenario 1, the coefficients on *ReportBuy_1* range from 0.0132 to 0.0160, while in Scenario 2, they are notably larger, ranging from 0.0197 to 0.0235 – all statistically significant.

This gap in magnitude supports the fiscal expectations interpretation: When disclosures occur before a bill passes, they are more likely to be seen by investors as revealing forward-looking policy information, leading to stronger asset price reactions. This evidence further supports the interpretation of trade disclosures as fiscal information shocks to financial markets.

20241204:

Ran – there is already a big WSJ article about the x variable.

4.3 Our paper in one case

David B. McKinley represented West Virginia's 1st congressional district as a member of the U.S. House of Representatives. He served on the Committee on Energy and Commerce and was affiliated with the Republican Party. His term in office spanned from January 3, 2011, to January 3, 2023.

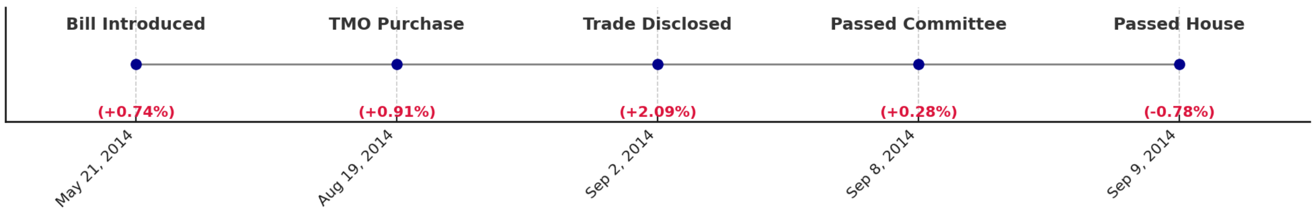
- 5/21/2014: 113th congress H.R. 4701 was introduced, which amends the Public Health Service Act to require the Secretary of Health and Human Services (HHS) to conduct or support epidemiological, basic, translational, and clinical research such as Lyme disease and other tick-borne diseases. The budget was \$338 million.[5]
  TMO daily ret = 0.74%
- 8/19/2014: He purchased Thermo Fisher Scientific (ticker=TMO; NAICS=33; a life science research company).

[5] https://www.congress.gov/bill/113th-congress/house-bill/4701

TMO daily ret = 0.91%

- 9/2/2014: He disclosed this purchase record.
  TMO daily ret = 2.09%
- 9/8/2014: The bill passed the Committee on Energy and Commerce.
  TMO daily ret = 0.28%
- 9/9/2014: The bill passed the House.
  TMO daily ret = -0.78%

The timing and sequence of these events, specifically along with the positive stock return following the trade disclosure, are consistent with our interpretation: that congressional disclosures may reflect forward-looking fiscal expectations and act as informative signals to the market.



5 Conclusion

Legislative Trades: Stock market responds to the disclosure of congressional trades, and interprets it as a fiscal information shock.

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Filing ID #20009718

Periodic Transaction Report

Clerk of the House of Representatives • Legislative Resource Center • 135 Cannon Building • Washington, DC 20515

Filer Information

Name: Hon. Barbara J Honorable Comstock
Status: Member
State/District: VA10

Transactions

ID	Owner	Asset	Transaction Type	Date	Notification Date	Amount	Cap. Gains > $200?
		iShares Exponential Technologies ETF (XT) [ST] Filing Status: New	S	06/05/2018	06/07/2018	$50,001 - $100,000	☐
		Mastercard Incorporated (MA) [ST] Filing Status: New	P	06/07/2018	06/11/2018	$50,001 - $100,000	☐
		Microsoft Corporation (MSFT) [ST] Filing Status: New	P	06/05/2018	06/07/2018	$15,001 - $50,000	☐
		Vanguard FTSE Emerging Markets ETF (VWO) [ST] Filing Status: New	S	06/05/2018	06/07/2018	$50,001 - $100,000	☐

☑ I CERTIFY that the statements I have made on the attached Periodic Transaction Report are true, complete, and correct to the best of my knowledge and belief.

Digitally Signed: Hon. Barbara J Honorable Comstock, 06/11/2018

Figure 1: **A Periodic Transaction Report Sample: Information, and Report Date.**

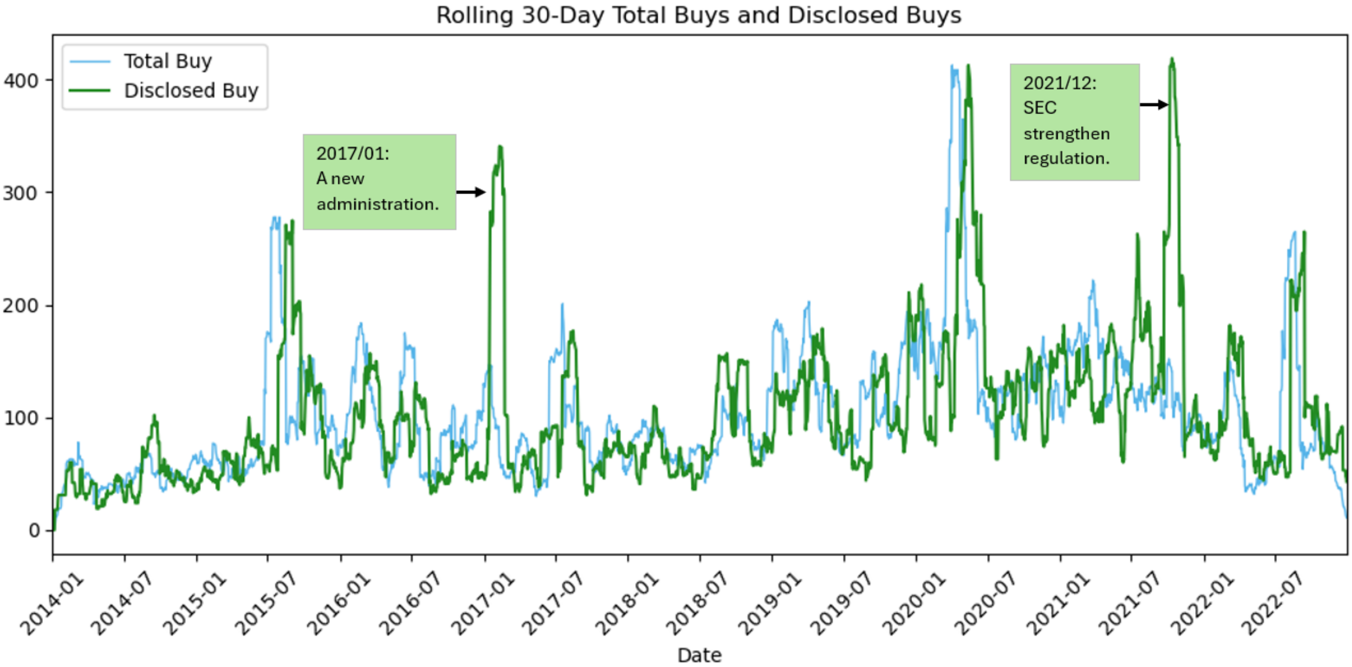


Figure 2: **Time variation in the total actual and disclosed stock purchases (or buys) from all House Representatives in a 30-day rolling window.** Appendix Figure A1 provides the sell counterpart, which exhibits quite different patterns.

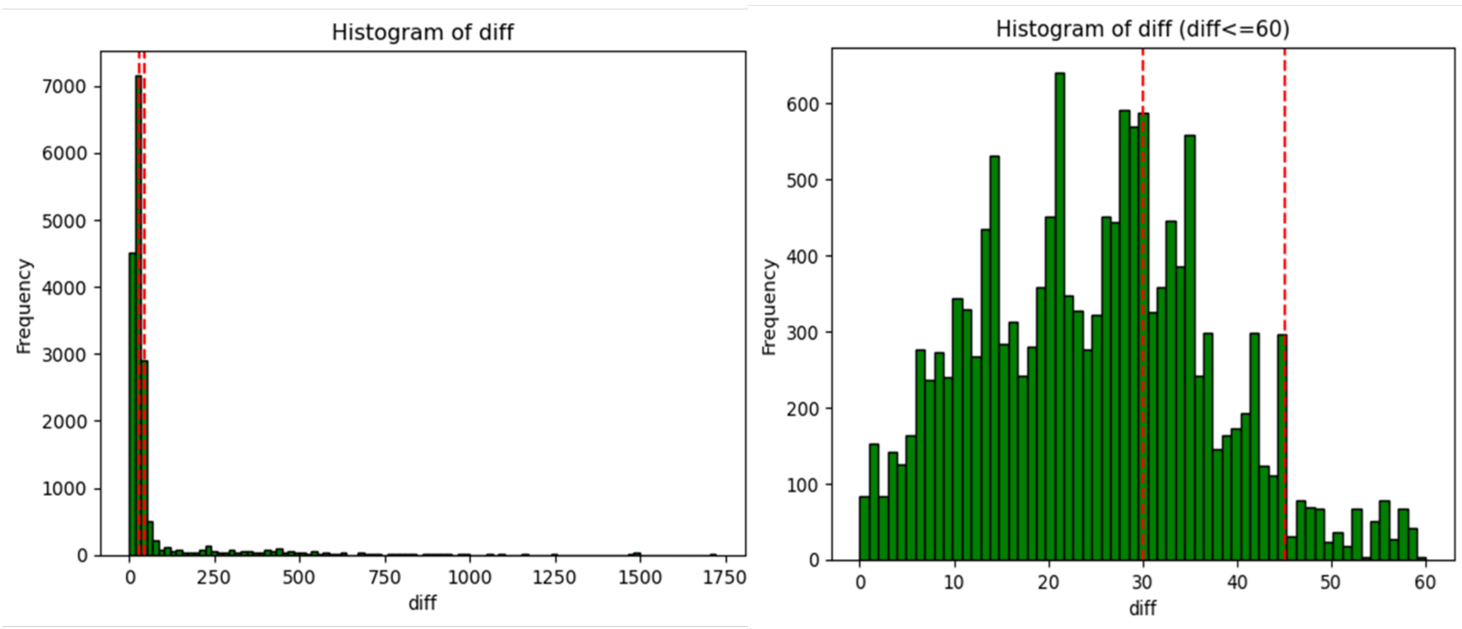
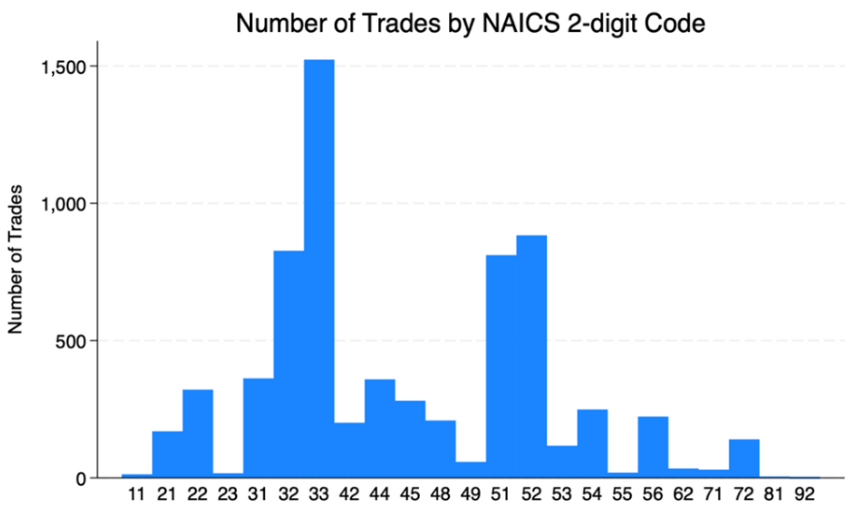


Figure 3: **Distance between disclosure date and transaction date.** This histogram shows the frequency of date differences at the report-ticker level. The left plot shows the full histogram, and the right plot zooms in the histogram. The two red lines correspond to Day 30 and Day 45, respectively.



NAICS	Sector Name
11	Agriculture, Forestry, Fishing and Hunting
21	Mining, Quarrying, and Oil and Gas Extraction
22	Utilities
23	Construction
31-33	Manufacturing
42	Wholesale Trade
44-45	Retail Trade
48-49	Transportation and Warehousing
51	Information
52	Finance and Insurance
53	Real Estate and Rental and Leasing
54	Professional, Scientific, and Technical Services
55	Management of Companies and Enterprises
56	Administrative and Support and Waste Managemen
61	Educational Services
62	Health Care and Social Assistance
71	Arts, Entertainment, and Recreation
72	Accommodation and Food Services
81	Other Services (except Public Administration)
92	Public Administration

Figure 4: **Stock trades across industries.** This bar chart shows the total number of purchases by NAICS-2 digits.

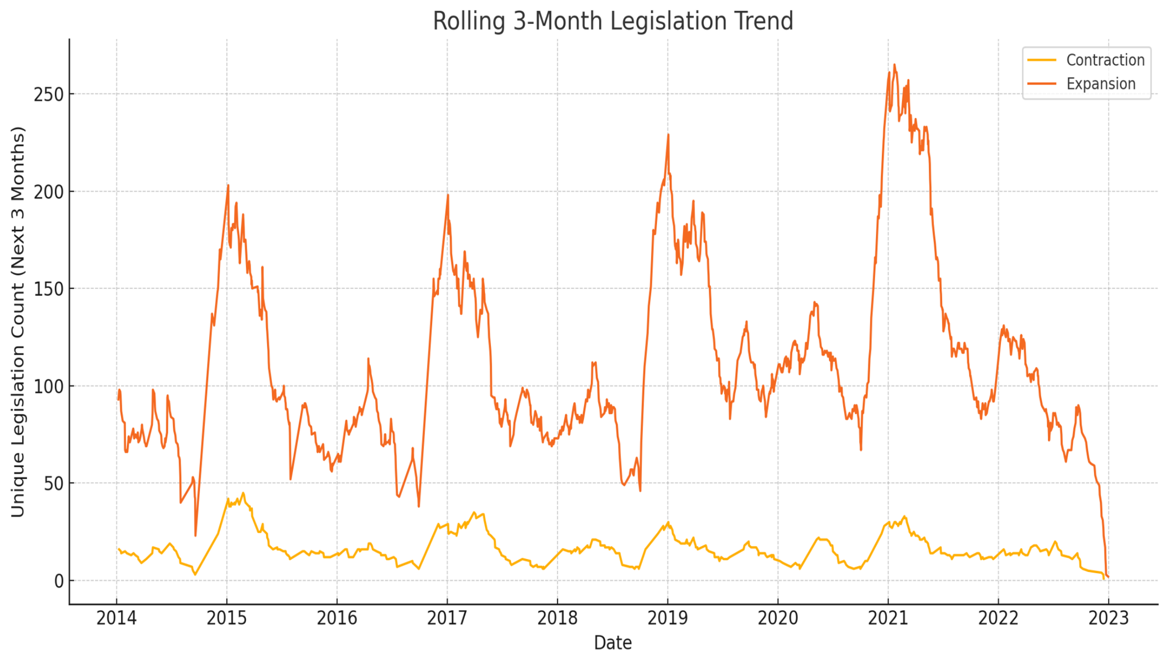


Figure 5: **Expansionary or contractionary nature of a bill.**

Table 1: **Exogeneity test: Do disclosure dates appear strategic?**
This table test whether recent monetary policy event, fiscal policy event, or stock past performances have predictive power of whether a ticker i purchase record is reported on day t. Double-clustered standard errors are reported in parentheses. ***, p-value <1%; **, <5%; *, <10%.

DV:	ReportBuy_1; {i,t}			
Stock FE:	X	X	X	X
Double cluster:	X	X	X	X
$I_{FOMC,[-3,1]}$	0.000772	0.000741	0.000762	0.000776
	(0.000871)	(0.000869)	(0.000872)	(0.000872)
$I_{BillPassing,[-3,1]}$	0.000160	0.000355	0.000259	0.000195
	(0.000498)	(0.000491)	(0.000490)	(0.000483)
ret_1			-0.007820	-0.007660
			(0.006376)	(0.006384)
ret_5			-0.003216	-0.003502
			(0.006619)	(0.006722)
illiq_5			6.059866	-28.330960
			(42.085424)	(45.081106)
volatility_5			0.001978	0.000876
			(0.005058)	(0.005732)
ret_10				0.002131
				(0.006025)
illiq_10				74.740095
				(92.725586)
volatility_10				0.002584
				(0.005030)
$EPU_{ym(t)}$		0.000019***	0.000018***	0.000017***
		(0.000006)	(0.000006)	(0.000006)
Constant	0.004934***	0.002801***	0.002790***	0.002751***
	(0.000381)	(0.000707)	(0.000706)	(0.000710)
Observations	1264597	1264597	1238872	1226969
R-squared	0.0097	0.0100	0.0096	0.0094

Table 2: **Stock Market Effects of Trade Disclosures.** This table xx. Double-clustered standard errors are reported in parentheses. ***, p-value <1%; **, <5%; *, <10%.

DV:	Daily stock returns				
Double cluster:	X	X	X	X	X
Firm controls:	X	X	X	X	X
Macro controls:		X		X	X
Stock FE:			X	X	X
YM FE:					X
	(1)	(2)	(3)	(4)	(5)
			Panel A		
ReportBuy_1	0.002000***	0.001791***	0.001965**	0.001756***	0.001671***
	(0.000769)	(0.000632)	(0.000769)	(0.000631)	(0.000633)
Constant	-0.000149	-0.000110	-0.000286	-0.000233	-0.000255
	(0.000266)	(0.000262)	(0.000313)	(0.000306)	(0.000310)
Observations	929262	929262	929262	929262	929262
R-squared	0.0013	0.0129	0.0012	0.0128	0.0241
			Panel B		
ReportBuy	0.001494***	0.00135***	0.001469**	0.001332***	0.001266***
	(0.000579)	(0.000476)	(0.000579)	0.000474	(0.000484)
Constant	-0.000148	-0.000109	-0.000285	-0.000232	–0.000254
	(0.000266)	(0.000262)	(0.000313)	(0.000306)	(0.000310)
Observations	929262	929262	929262	929262	929262
R-squared	0.0013	0.0129	0.0012	0.0128	0.0241

Table 3: **Robustness tests to Table 2.**
***, p-value <1%; **, <5%; *, <10%.

DV:	Daily stock returns					
Double cluster:	X	X	X	X	X	X
Firm controls:	X	X	X	X	X	X
Macro controls:	X	X	X	X	X	X
Stock FE:	X	X	X	X	X	X
YM FE:	X	X	X	X	X	X
	Pre-2020 only	Drop Tech	Drop weekend disclosures	Drop majority leaders	Control for ret(1)	Control for report sells
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
ReportBuy_1	0.000942**	0.001318**	0.001671***	0.001622**	0.001657***	0.001639***
	(0.000470)	(0.000575)	(0.000632)	(0.000638)	(0.000630)	(0.000617)
ReportSell_1						0.000418
						(0.000536)
Constant	-0.000360	-0.000305	-0.000255	-0.000254	-0.000263	-0.000256
	(0.000279)	(0.000319)	(0.000310)	(0.000310)	(0.000310)	(0.000310)
Observations	645021	698039	929262	929262	929262	929262
R-squared	0.026	0.024	0.025	0.025	0.025	0.025
Panel B						
ReportBuy	0.000856**	0.000967**	0.001266***	0.001238**	0.001256***	0.001258***
	(0.000374)	(0.000429)	(0.000484)	(0.000487)	(0.000482)	(0.000473)
ReportSell						0.000081
						(0.000387)
Constant	-0.000361	-0.000304	-0.000254	-0.000254	-0.000263	-0.000254
	(0.000279)	(0.000319)	(0.000310)	(0.000310)	(0.000309)	(0.000310)
Observations	645021	698039	929262	929262	929262	929262
R-squared	0.026	0.024	0.025	0.025	0.025	0.025

Table 4: **Heterogeneity tests to Table 2.**
This table conducts four heterogeneity tests to results in Table ??. To conserve space, we only report relevant coefficient estimates. ***, p-value <1%; **, <5%; *, <10%.

Panel A: Heterogeneity by split congress or not					
DV:			Daily stock returns		
Double cluster:	X	X	X	X	X
Firm controls:	X	X	X	X	X
Macro controls:	X	X	X	X	X
Stock FE:	X	X	X	X	X
YM FE:	X	X	X	X	X
Congress:	113th 2013-2014	114th 2015-2016	115th 2017-2018	116th 2019-2020	117th 2021-2022
Split congress?	Yes	No	No	Yes	No
ReportBuy_1	0.002808**	0.001243	-0.000672	0.002686***	0.001665
	(0.001245)	(0.000954)	(0.000626)	(0.000898)	(0.001418)
ReportBuy	0.002534***	0.001035	-0.000306	0.002130***	0.000945
	(0.000890)	(0.000692)	(0.000586)	(0.000643)	(0.000938)

Panel B: Heterogeneity by relevant committee roles or not				
DV:		Daily stock returns		
Double cluster:	X	X	X	X
Firm controls:	X	X	X	X
Macro controls:	X	X	X	X
Stock FE:	X	X	X	X
YM FE:	X	X	X	X
Individual:	Committee	Non-Committee	Committee	Non-Committee
ReportBuy_1	0.002554**	0.001476**		
	(0.001012)	(0.000664)		
ReportBuy			0.002048***	0.001082**
			(0.000754)	(0.000513)

Panel C: Heterogeneity by relevant committee roles or not				
DV:		Daily stock returns		
Double cluster:	X	X	X	X
Firm controls:	X	X	X	X
Macro controls:	X	X	X	X
Stock FE:	X	X	X	X
YM FE:	X	X	X	X
Heterogeneity	High FD	Low FD	High FD	Low FD
ReportBuy_1	0.002197***	0.001204**		
	(0.000840)	(0.000577)		
ReportBuy			0.001733***	0.000793*
			(0.000618)	(0.000470)

Panel D: Heterogeneity by budgetary uncertainty period or not				
DV:		Daily stock returns		
Double cluster:	X	X	X	X
Firm controls:	X	X	X	X
Macro controls:	X	X	X	X
Stock FE:	X	X	X	X
YM FE:		X		X
ReportBuy_1	0.001467**	0.001395**		
	(0.000663)	(0.000671)		
ReportBuy			0.001136**	0.001081**
			(0.000503)	(0.000515)
Debt Ceiling Change	-0.000688		-0.000677	
	(0.005724)		(0.005723)	
Interaction	0.025676**	0.024597**	0.018927**	0.017939**
	(0.011073)	(0.010278)	(0.008421)	(0.007862)
Constant	-0.000224	-0.000255	-0.000224	-0.000254
	(0.000309)	(0.000310)	(0.000309)	(0.000310)
Observations	929262	929262	929262	929262
R-squared	0.014	0.025	0.014	0.025

Table 5: **Predict bill passing using actual buys.**
***, p-value <1%; **, <5%; *, <10%.

DV:			$BillPass_{b,j}$			
Double cluster:	X	X	X	X	X	X
Industry FE:		X		X	X	X
Day FE:			X	X	X	X
	(1)	(2)	(3)	(4)	(5)	(6)
$DecisionLength_b$	0.000930***	0.000900***	0.000837***	0.000818***	0.000812***	0.000811***
	(0.000242)	(0.000228)	(0.000135)	(0.000129)	(0.000128)	(0.000128)
$I_{SameParty,b}$	0.061924***	0.061322***	0.035597***	0.036001***	0.036008***	0.035996***
	(0.010241)	(0.009562)	(0.006519)	(0.006282)	(0.006322)	(0.006325)
$ActualBuy_{t(b)-1,t(b)-21,j}$					0.011826***	0.010775***
					(0.003457)	(0.003204)
$ActualSell_{t(b)-1,t(b)-21,j}$						0.001827
						(0.001804)
Constant	0.024885***	0.026986***	0.046345***	0.047171***	0.045545***	0.045360***
	(0.007347)	(0.005879)	(0.009065)	(0.008306)	(0.008300)	(0.008331)
Observations	60970	60970	60858	60858	60858	60858
R-squared	0.12	0.15	0.54	0.55	0.55	0.55

Table 6: **Predict bill passing using actual buys: By economic nature of a bill.**

DV:	$BillPass_{b,j}$	
Double cluster:	X	X
Industry FE:	X	X
Day FE:	X	X
Bill Type:	Expansion	Contraction
$DecisionLength_b$	0.000563***	0.000241
	(0.000168)	(0.000202)
$I_{SameParty,b}$	0.046900**	0.044564
	(0.017190)	(0.043171)
$ActualBuy_{t(b)-1,t(b)-21,j}$	0.020086**	-0.003329
	(0.007128)	(0.002716)
Constant	0.065267***	0.076608**
	(0.014313)	(0.034709)
Observations	7901	1178
R-squared	0.74	0.94

Table 7: **Conditional results.**

DV:	Daily stock returns [-21, +21] of a ReportBuy Event			
Double cluster:	X	X	X	X
Firm Control:		X		X
Stock FE:			X	X
Scenario 1: Purchase, Bill passing, Disclosure				
ReportBuy_1	0.015461***	0.013230***	0.016029***	0.013696***
	(0.003373)	(0.003421)	(0.003411)	(0.003365)
Constant	0.000809	0.000240	0.000779***	0.004782
	(0.000851)	(0.001320)	(0.000184)	(0.003127)
Observations	1333	1147	1333	1147
R-squared	0.017	0.030	0.055	0.059
Scenario 2: Purchase, Disclosure, Bill passing				
ReportBuy_1	0.023478***	0.020281***	0.023424***	0.019723***
	(0.004042)	(0.004570)	(0.004056)	(0.004436)
Constant	0.001427**	0.003704***	0.001430***	0.005051***
	(0.000646)	(0.001037)	(0.000241)	(0.001747)
Observations	1416	1280	1416	1279
R-squared	0.043	0.036	0.063	0.064

Paper Appendix

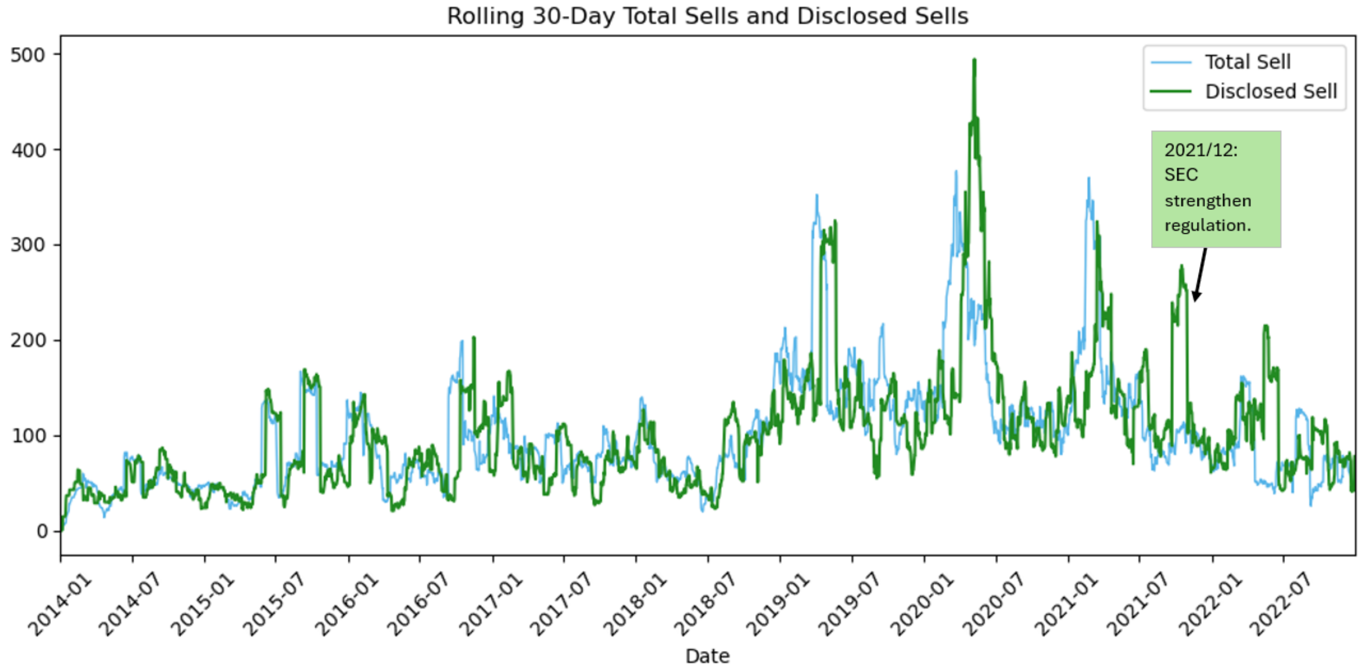


Figure A1: **Time variation in the total actual and disclosed stock sells from all House Representatives in a 30-day rolling window.** Figure 2 is the purchase counterpart.

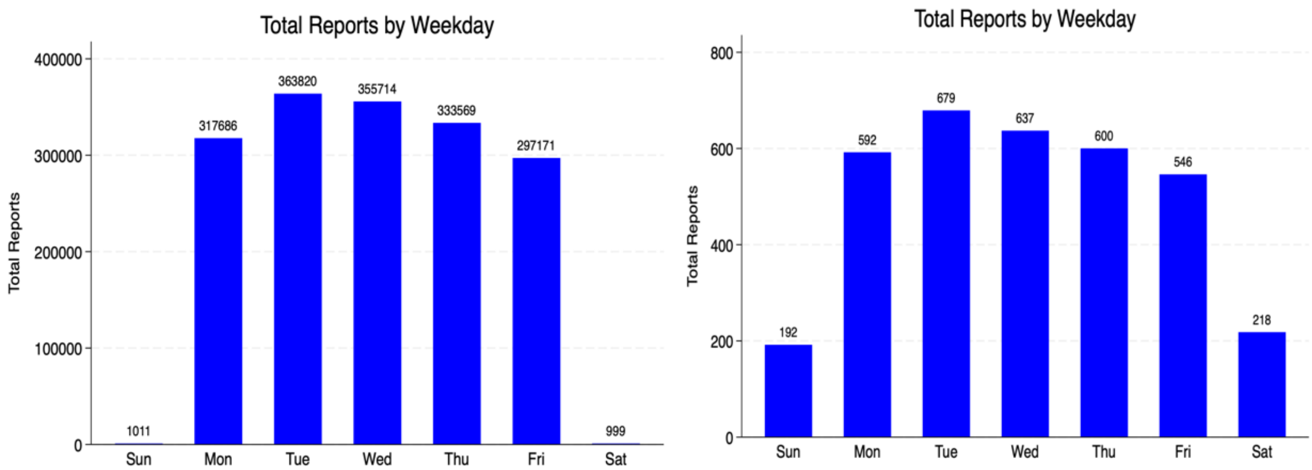


Figure A2: Frequencies of reports by week days.

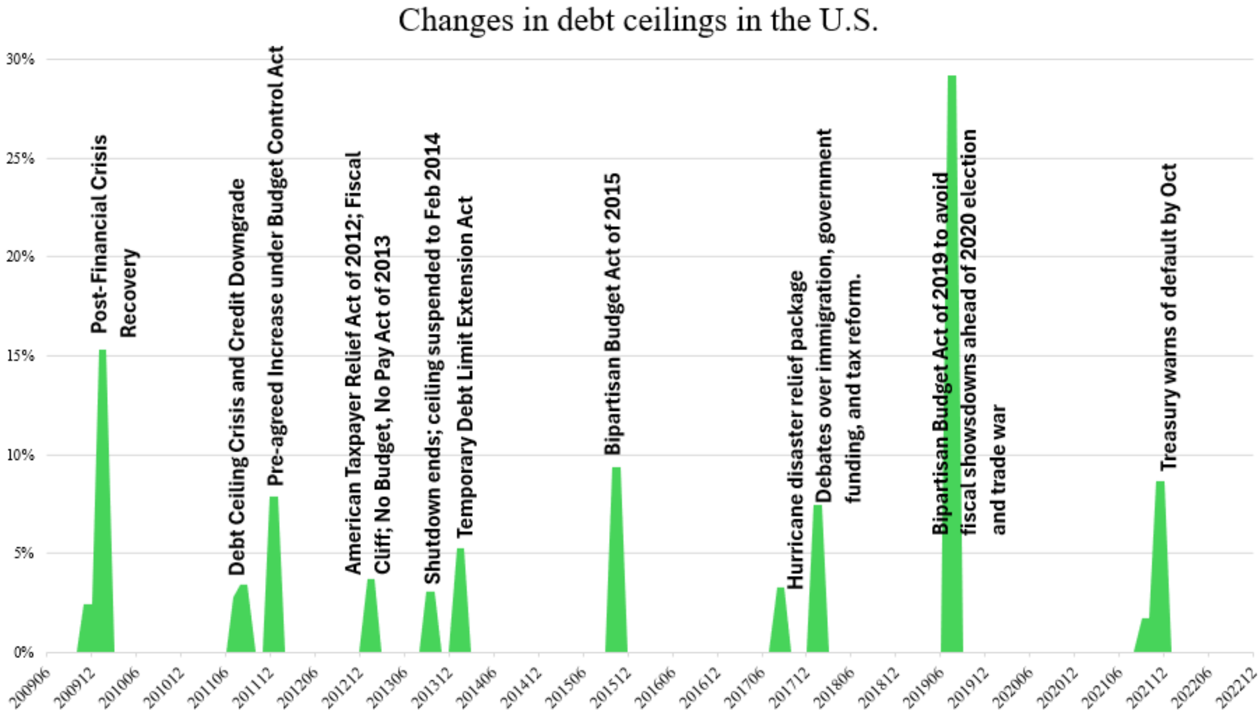


Figure A3: Debt Limit Change

Table A1: Actual transaction day.

DV:	Daily stock returns	
Double cluster:	X	X
Firm controls:	X	X
Macro controls:	X	X
Stock FE:	X	X
ym FE:		X
Buy_1	-0.000448	-0.000471
	(0.000622)	(0.000580)
Constant	-0.000224	-0.000245
	(0.000306)	(0.000309)
Observations	929262	929262
R-squared	0.013	0.025
Buy	-0.000312	-0.000298
	(0.000519)	(0.000493)
Constant	-0.000225	-0.000245
	(0.000306)	(0.000309)
Observations	929262	929262
R-squared	0.013	0.025

Table A2: **Robustness tests to Table 5: Alternative horizons.**

DV:	$BillPass_{b,j}$			
Double cluster:	X	X	X	X
Industry FE:	X	X	X	
Day FE:	X	X	X	X
History:	[-25,-1]	[-30,-1]	[-35,-1]	[-40,-1]
$DecisionLength_b$	0.000811***	0.000808***	0.000810***	0.000809***
	(0.000128)	(0.000127)	(0.000128)	(0.000128)
$I_{SameParty,b}$	0.035972***	0.035938***	0.035905***	0.035894***
	(0.006325)	(0.006338)	(0.006324)	(0.006322)
$ActualBuy_{t(b)-1,t(b)-n,j}$	0.011561***	0.012836***	0.007655*	0.007385*
	(0.003088)	(0.002667)	(0.003712)	(0.003845)
Constant	0.045493***	0.045155***	0.045727***	0.045698***
	(0.008269)	(0.008222)	(0.008344)	(0.008353)
Observations	60858	60858	60858	60858
R-squared	0.55	0.55	0.55	0.55

Internet Appendices

IA Data Appendix