Unveiling the Influence of Industry-Level Information and Committees on Congressional Stock Trading with Graph Data, GNNs, and LLM Agent

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Abstract

In this study, I delve into the dynamics of congressional stock investments, revealing abnormal and asymmetrical excess returns. This suggests the potential influence of privileged information. Contrary to prior studies, I found that a congressperson's stock portfolio significantly mirrors stocks tied to their committee assignments, leveraging a novel graph-structured dataset. By employing a graph neural network, I discovered that committee assignments and firms' lobbying activities are predictive of congresspersons' stock choices. Furthermore, the use of GNNExplainer provided interpretative insights into these predictions. This research prompts a reevaluation of the motivations underpinning congressional service, indicating that personal financial gains could significantly influence decision-making. Additionally, it uncovers intriguing behavioral variations in stock trading among congresspersons. These variations could reflect individual characteristics or systemic factors within our political and financial systems, offering an intriguing avenue for further research.

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1 Introduction

In democratic societies, electoral accountability is a central mechanism through which politicians, vested with the power to make significant public decisions, remain answerable for their actions (Besley, 2006; Fearon, 1999; Ferejohn, 1986). However, the intermingling of public service and personal financial interests can blur the lines of accountability. A key question arises: how closely intertwined are a politician's personal financial gains and their public service role? Are these two realms neatly partitioned, or do they bleed into each other?

The theory of moral hazard is particularly relevant when examining the actions of individuals who are shielded from the consequences of their decisions, as they may behave differently than if they were to bear the full brunt of their actions (Holmström, 1979). This issue assumes critical importance in the political sphere, specifically in the context of congressional stock trading. Elected officials, due to their privileged access to non-public information and regulatory power, could potentially leverage this advantage for personal financial gains through strategic stock trades. Such behavior may lead to potential conflicts of interest and raises questions about the fairness and transparency of our political and financial systems. This dynamic underscores the necessity for a rigorous theoretical and empirical exploration of the stock trading behaviors of politicians, to ensure the accountability and integrity of those serving in public office.

Public choice theory, in addition, posits that it is unrealistic to presume a clear-cut divide between the public and private domains of a politician's life (Buchanan and Tollison, 1984). The theory suggests that individuals aim to maximize their personal utility in both their public and private roles. Building on this, we must consider that the actions of politicians are not solely influenced by their public roles and responsibilities, but also by their personal interests and ambitions. The public service that elected officials provide and their private financial gains are not separate spheres, but interconnected dimensions of their life. In fact, they might leverage their public role to augment their personal finances. Building on this perspective, our research taps into the broader literature in American politics that investigates the motivations of congresspersons. The prevailing wisdom holds that elected representatives primarily seek re-election (Mayhew, 1974). They typically strive to achieve this goal by crafting effective public policies and securing influence within Congress (Fenno, 1977). However, our study underscores that the realm of personal financial gain, although often less examined, can be an important facet of a congressperson's

behavior.

Given these motivations, the financial behavior of politicians, particularly their stock trading activities, warrants closer examination. The trading activities of U.S. Congresspersons offer a unique opportunity to investigate the relationship between public service and personal financial interests. By analyzing the stock trading patterns of Congresspersons and their legislative activities, we can gain valuable insights into the potential conflicts of interest and the implications for electoral accountability.

So far, this issue of financial behavior among politicians has been explored from various angles. Legal scholars have examined the use of political intelligence for profit and the potential for insider trading within the political sphere (Jerke, 2010; Bainbridge, 2010). These studies highlight the challenges of designing legal and enforcement structures to prevent and deter such behavior. While these legal studies provide valuable insights, there has also been attention given to anecdotal approaches that explore specific instances of insider trading by politicians. For example, Schweizer (2011) presents a series of case studies that highlight how politicians and their associates have profited from insider stock tips, land deals, and cronyism. These accounts, while informative, underscore the need for a more systematic and empirical investigation of stock trading behavior among politicians, moving beyond individual anecdotes to a broader analysis of patterns and trends.

Recognizing this need to a broader analysis of patterns and trends, researchers have turned to the excess return approach, which has been used in the broader literature on insider trading, to assess whether politicians achieve abnormal returns on their investments. The excess return approach provides a foundation for understanding how informational advantages may lead to excess returns in financial markets (Jeng et al., 2003; Ivković and Weisbenner, 2005; Seasholes and Zhu, 2009). Building on this excess-return approach, several studies have specifically examined the stock trading activities of U.S. Congresspersons. Ziobrowski et al. (2004) and Ziobrowski et al. (2011) conducted pioneering research in this area, analyzing the common stock investments of members of the U.S. Senate and House of Representatives, respectively. Their findings suggest that members of Congress achieve abnormal returns on their stock investments, raising questions about the potential use of privileged information in their trading decisions.

However, the notion that members of Congress achieve excess returns on their investments has been challenged by other researchers. Eggers and Hainmueller (2013) call into question the consensus that members of Congress trade with an information advantage. They reinterpret existing studies of congres-

sional stock trading between 1985 and 2001 and conduct their own analysis of trades in the 2004–2008 period. Their findings challenge the notion of "widespread" insider trading" in Congress, concluding that in neither period do members of Congress trade with an information advantage. Furthermore, they conduct the first analysis of members' portfolio holdings, showing that between 2004 and 2008, the average member of Congress would have earned higher returns in a passive index fund.

The studies that employ the "excess return" approach to analyze congressional stock trading in the U.S. typically focus on the "average" performance of Congresspersons as a whole. This approach aggregates the stock trading activities and returns of all members of Congress, calculating an average excess return for the entire group. While this methodology provides insights into the overall trading performance of Congress as a collective entity, it may not fully capture the individual-level behavior of specific politicians. By aggregating the data and calculating average returns, the approach may mask variations in the trading behavior of individual members of Congress. As a result, instances of potentially unethical trading behavior by specific politicians, who may leverage privileged information for personal financial gain, could be obscured within the average calculations. This limitation is particularly relevant in light of anecdotal findings, such as those presented by Schweizer (2011), which highlight case studies of individual politicians who have allegedly profited from insider stock tips. These accounts underscore the need for a more granular examination of stock trading behavior at the individual level, moving beyond the analysis of average excess returns for the entire group of Congresspersons.

Additionally, the excess return approach on congressional stock trading mostly adopts a calendar time-based synthetic portfolio approach (Shanken, 1996; Annaert et al., 2009), which involves buying and selling stocks according to the Congressperson's decisions and then selling them a year later. This methodology obscures the importance of the "timing" aspect of such Congresspersons' stock trading, an aspect already well-highlighted by researches like Schweizer (2011) and Tahoun (2014). By focusing on calendar time and ignoring the timing of trades, these studies may miss critical insights into the potential exploitation of non-public information by individual politicians. This underscores the need for further research and alternative methodologies that take into account both the individual-level trading behavior and the timing of trades to provide a more comprehensive understanding of congressional stock trading practices.

In this regard, my research aims to delve deeper into the stock trading activities of individual Congresspersons, estimating the excess return of each Congressperson-ticker level transaction for buy-sell

cycle of such transactions. Throughout this estimation, the findings of this study lend further support to the conclusions drawn by Eggers and Hainmueller (2013). Their research found no widespread evidence of excess returns among Congresspersons, suggesting that insider trading is not a pervasive issue within the U.S. Congress. However, they noted that certain anomalies did exist, implying that a few individual Congresspersons could potentially be generating excess returns on specific tickers. In line with these observations, my estimation also shows a positively skewed distribution of excess returns. While negative excess returns are limited, positive excess returns span a wider range and include some notable outliers. This pattern suggests that while most Congresspersons do not achieve significant excess returns, a small number of individuals may be generating substantial positive returns on trade of specific tickers.

In addition, the breadth and depth of political connections, and their financial implications for both firms and politicians, have been extensively examined across a wide range of literature. Political connections have been shown to significantly impact firm value (Roberts, 1990; Khwaja and Mian, 2005; Goldman et al., 2009), and politicians have been found to derive financial benefits from them (Diermeier et al., 2005; Lenz and Lim, 2009; Querubin and Snyder, 2013). Boller (1995) even demonstrated that members of the United States Congress regularly purchase common stock in companies that they regulate through legislation, highlighting the direct intersection between political activities and financial decision-making. Following this line of inquiry, Eggers and Hainmueller (2014) delved further into the topic, attempting to understand why congressional stock transactions generally appeared to be low in profitability. Their research suggested that transactions with a "political connection", such as local ties or connections from campaign contributions, performed better than transactions without such connections.

However, Eggers and Hainmueller (2014) also found that "we find no evidence that members disproportionately invest in companies to which they are connected through their committee assignments", despite finding such behaivors in local-connection or campaign finance connections. This introduces "a new puzzle", which stands in contrast with the well-established findings regarding committees' specialization in various topics within their authority conferred by statutory jurisdiction (Myers, 2009) or by their bill referral (King, 1994). Moreover, congressional members are known to specialize in such topics (Asher, 1974), leveraging their unique knowledge and expertise to influence legislative outcomes (Boros and Fenno, 1968; Gilligan and Krehbiel, 1989; Kiewiet and McCubbins, 1991; Krehbiel, 1992; Curry, 2019). Thus, the conflicting findings surrounding the link between committee assignments and members' stock trading activities warrant further exploration, enriching our understanding of congressional stock

trading.

In this regard, I re-examine the relationship between legislative activities and their stock transactions, using graph-structured data. This approach is motivated by the nature of the data we collected, which shows that 60% of the Senators' stock transactions are mostly ETFs or mutual funds, which are typically targeted at specific industries, not individual firms. Previous research, such as the study conducted by Eggers and Hainmueller (2014), focused on estimating the impact of firm-level lobbying or committee-assignment of bills lobbied by specific firms on the increase of that specific firm's weight in a congressperson's portfolio. However, this approach does not account for a congressperson's specialization in "industry-level" knowledge, gained through their committee assignments, and the potential utilization of such industry-level knowledge in shaping their personal investment portfolio.

To address this gap, I collected data that captures diverse aspects of legislative activities - such as firms' lobbying on specific bills, bills' assignment to specific committees, and committee membership of congresspersons - alongside with congresspersons' stock trading data. I sourced this data from various relevant platforms, such as Lobbyview (Kim, 2018), Senate & House's financial disclosures, and Congress. In order to investigate the relationship between a congressperson's portfolio and the industry-level specialization of the committees they are assigned to, I utilized a graph-structured data format. This facilitated an analysis capable of revealing a clear resemblance between the two. To substantiate this relationship statistically, I conducted a one-sided paired t-test (Hsu and Lachenbruch, 2014) aimed at determining whether the mean cross-entropy value measuring the similarity between the industry distribution of a congressperson's stock transactions and the industry distribution of their assigned committees was significantly smaller than that of their unassigned committees.

The result of the one-sided paired t-test shows that a congressperson's stock trading pattern significantly resembles the industry distribution of their assigned committees more than that of non-assigned committees. This finding is in stark contrast to the conclusions drawn by Eggers and Hainmueller (2014), highlighting one of the novel contributions of this research in understanding the relationship between committee assignments and stock trading behavior among Congress members.

One possible explanation for the significant similarity between a congressperson's stock transactions and the industry specialization of their assigned committees may lie in the intersection of personal expertise and the congressional committee assignment process. Congresspersons often have backgrounds or interests in specific industries, leading to committee assignments that reflect these specializations

(Boros and Fenno, 1968; Gilligan and Krehbiel, 1989; Kiewiet and McCubbins, 1991; Krehbiel, 1992; Curry, 2019). This could naturally extend to their financial investments, with a congressperson who has a background or vested interest in, for example, technology being more likely to invest in technology-related stocks. Additionally, serving on a committee gives congresspersons privileged access to industry-specific information and insights, potentially informing and influencing their investment decisions in those sectors.

However, it is crucial to consider alternative explanations and potential confounding factors. The concept of homophily, which suggests that people with similar characteristics are more likely to associate with each other, could play a role here. The congressperson might have been drawn to both their committee assignment and specific industry investments due to inherent interests or external factors such as the dominant industries in their district. It's also possible that both committee assignments and investment decisions could be influenced by external factors like market trends, policy interest, or campaign contributions from certain industries. Thus, while the observed correlation is intriguing, further research and rigorous controls are required to ensure these alternative explanations are adequately accounted for.

While this research arrives at a conclusion that is diametrically opposed to that of Eggers and Hainmueller (2014) regarding the importance of committee assignments in shaping a congressperson's investment portfolio, it aligns with the broader trend in the study of congressional stock trading. The work of Eggers and Hainmueller (2014) is valuable in that it moves beyond the traditional excess return approach and instead seeks to identify meaningful associations between various factors that could influence a congressperson's choice of stocks, such as PAC donations, district-level connections, or committee assignments.

In a similar vein, this study emphasizes the need to understand how legislative activities in general, which encompass a vast and complex network of information flows and interactions, can impact a congressperson's choice of specific stocks. These activities include firms lobbying on bills of particular interest to them, the referral of these bills to specific committees based on statutory and historical jurisdiction, and the assignment of congresspersons to these committees based on their expertise.

This approach is further justified by public choice theory, which posits that Congresspeople possess hybrid identities as both public and private entities (Buchanan and Tollison, 1984). Given that individual investors often experience failures (Barber and Odean, 2000; Barberis and Thaler, 2003), it is reasonable

to assume that Congresspeople may also face similar failures when investing as individuals, rather than utilizing privileged information as public figures. This underscores the importance of studying the direct relationship between congressional activities and stock trading patterns, rather than relying solely on tests of excess returns.

In this regard, this research proposes a more fundamental approach to study these behaviors, directly tackling the problem from an information perspective. The aim is to test whether congressional activities, which are often centered around legislative activities, provide information to predict each Congressperson's specific ticker transactions. To achieve this, a predictive model is designed that takes into account a variety of factors tied to each Congressperson's legislative activities. This will include elements such as the committees they are assigned to, the bills being legislated through those committees, and the potential interests of various firms or industries related to those bills. The goal is to ascertain whether these factors can reliably predict a Congressperson's transaction with a specific ticker at a specific time.

In order to effectively capture the complex nature of congressional activities, I have collected and organized data using a heterograph, a type of graph structure that incorporates different types of nodes and edges. This graph-structured data is particularly useful for representing various entities and their relationships, which are inherent in the legislative process. These relationships include firms lobbying on bills of particular interest to them, the referral of these bills to specific committees, and the assignment of congresspersons to these committees.

Pursuing the approach of Eggers and Hainmueller (2014), this research endeavors to predict the specific stock transactions of given congresspersons. If these transactions can be forecast using the graph-structured data, it implies that congressional activities contain vital information that can explain their stock trading patterns. Such a finding is significant as it highlights a potentially strong association between a congressperson's legislative activities and their stock transactions.

In conducting this prediction task, the research successfully trained a Graph Neural Network (GNN) model (Zhou et al., 2020; Wu et al., 2020; Scarselli et al., 2008; Zhang et al., 2019), achieving an accuracy of 0.81 and an AUC-ROC score of 0.89. These results indicate that congressional activities provide substantial information to explain the stock choices of congresspersons, further supporting the hypothesis of a significant correlation between legislative activities and stock transactions.

To understand the varying contribution of different types of edges in the heterograph to the prediction task, an ablation study was also conducted. It systematically removed particular edge types from the

training and calculated the Shapley values (Winter, 2002; Hart, 1989; Littlechild and Owen, 1973), which measure the contribution of each edge type to the prediction. This study found that a congressperson's committee assignments and firm-level lobbying on bills were the most important factors contributing to the model's predictive power. Interestingly, this finding contradicts Eggers and Haimuller's (2014) conclusion, which argued that there's no significant evidence that firm-level lobbying on bills and a congressperson's committee assignments explain the weight of specific stocks in their portfolio.

Furthermore, to address the black-box nature of GNN predictions (Dayhoff and DeLeo, 2001; Buhrmester et al., 2021; Olden and Jackson, 2002), this research incorporates the use of GNNExplainer (Ying et al., 2019). This tool allows for the identification of the most critical nodes and edges for each prediction, which in turn enhances the interpretability of the model. It provides a clearer understanding of the reasons behind the model's prediction regarding the existence of an edge (transaction) between the congressperson and the ticker nodes. I will provide examples illustrating this interpretive capability, demonstrating how it brings greater transparency to the decision-making process of the GNN model. This step is crucial in reinforcing the trustworthiness and understandability of the model, and in promoting its practical applicability in real-world scenarios.

To summarize, this research contributes to the field in several significant ways. First, it corroborates the findings of Eggers and Hainmueller (2013) by affirming the absence of widespread excess returns in congressional stock trading. Second, it reveals the presence of asymmetrically high excess returns when congresspersons earn, as opposed to when they incur losses. Fourth, this study emphasizes the application of graph-structured data and implements a predictive analysis using a Graph Neural Network (GNN). The adoption of GNN enables a richer understanding of the relationship between congressional activities and stock transactions. Unlike conventional predictive modeling that merely relies on independent feature vectors, this approach integrates the topological properties of the network into the prediction task. Finally, the research underscores the significance of a congressperson's committee assignments and firm-level lobbying in explaining the choice of stock transactions. This conclusion contradicts some previous studies, but aligns more closely with traditional literature on the influence of committee specialization and firm-level lobbying. In addition, this investigation redirects the traditional discourse on congressional motivation. Traditional research predominantly emphasizes the public career aspirations of congresspersons, such as re-election and the pursuit of sound public policies. However, the findings of this study reveal a marked similarity between a congressperson's legislative activities and their stock

transaction patterns. This correlation necessitates an expansion of the current understanding of congresspersons' motivations, acknowledging the potential influence of personal financial success on their legislative behavior.

2 Estimating Excess Returns of Congressional Stock Trading

[1]The broader literature on insider trading has long explored the information advantages that certain individuals, such as corporate insiders or well-connected investors, may possess when trading in the stock market. For example, Jeng et al. (2003) estimated returns to insider trading from a performance-evaluation perspective, while Ivković and Weisbenner (2005) studied the information content of the geography of individual investors' common stock investments. These studies highlight the importance of understanding the impact of information asymmetry and potential insider trading in financial markets.

Despite the extensive research on insider trading in general, the application of this approach to congressional stock trading has been limited. In the context of congressional stock trading, previous studies, such as those conducted by Ziobrowski et al. (2004), Ziobrowski et al. (2011) and Eggers and Hainmueller (2013), have predominantly used calendar-time based portfolio approaches (Hoechle and Zimmermann, 2007) to estimate excess returns. This involves creating synthetic buy and sell portfolios (Shanken, 1996; Annaert et al., 2009) that mimic congresspersons' stock purchases and sales but sell or buy such stocks after a year. This approach, however, neglects the importance of transaction timing, which is a crucial aspect of insider trading (Tahoun, 2014; Schweizer, 2011). It does not account for the short-term fluctuations in stock prices that congresspersons might anticipate based on their access to privileged information. Congresspersons could potentially profit from these expected fluctuations by strategically timing their transactions using their privileged knowledge. This presents a severe limitation in understanding the true extent of potential insider trading among U.S. members of Congress.

In addition, averaging excess returns across congresspersons may not capture the full extent of insider trading within the inner circle of Washington D.C. politics. Schweizer (2011) provided anecdotal evidence of politicians and their friends profiting from insider stock tips, while Lenz and Lim (2009) studied corruption and wealth accumulation in Congress, and Jerke (2010) and Bainbridge (2010) examined the use of political intelligence for insider trading with several anecdotes. These case studies suggest that

[1]Reproducible code for this section is available at `https://github.com/syyunn/efd/blob/main/anlys/cashout/fifo-rd-fed-pppsss-include-etf.py`

certain congresspersons might engage in insider trading with specific firms or industries, which would be overlooked in an aggregate analysis.

In this section, therefore, I aim to address these limitations by estimating the excess returns at the congressperson-ticker level, with a focus on the life cycle of each buy/sell chain of specific tickers consecutively transacted by a congressperson. This approach offers a more granular analysis of potential insider trading among U.S. members of Congress, allowing us to better evaluate whether widespread insider trading exists at the congressperson-ticker level. By doing so, we build upon both the general insider trading literature and the existing research on congressional stock trading, contributing to a more comprehensive understanding of the potential information advantages leveraged by politicians in the stock market and the importance of transaction timing.

2.1 Data

To estimate excess returns at the congressperson-ticker level, I first needed to compile comprehensive data on the stock transactions of U.S. members of Congress. I obtained this data by scraping the Senate Financial Disclosure website[2], which provides detailed information about the stock transactions made by congresspersons, including the date, ticker symbol, and the amount of each transaction.

The resulting dataset consists of 25,023 transactions, spanning a period from January 1, 2014, to August 5, 2022. These transactions involve 74 distinct Senators and 2,114 distinct tickers. Among these tickers, around 40% (832) are individual company-level tickers, such as AAPL for Apple Inc. and AMAT for Applied Materials Inc., while the remaining 60% (1,282) are ETFs or mutual funds, like QQQ for Nasdaq-100 index funds or IHI for U.S. Medical Devices ETF. This prevalence of industry-level security transactions suggests that Congresspersons often trade based on broader industry trends, rather than focusing solely on specific firms. This observation urges a recalibration of current literature (Ziobrowski et al., 2011, 2004; Eggers and Hainmueller, 2013, 2014), which tends to focus predominantly on firm-level stock trading behavior. Instead, it highlights the necessity of broadening our perspective, embracing a more comprehensive unit of analysis that extends beyond the firm-level, to include industry or theme-level stock trades.

For each transaction, I added the Volume Weighted Average Price (VWAP) in USD acquired from a commercial stock data API [3]. VWAP is a widely used trading benchmark (Madhavan, 2002; Białkowski

[2] `https://efdsearch.senate.gov/search/home/`
[3] `https://polygon.io/stocks`

et al., 2008; Duffie and Dworczak, 2021) that represents the average price at which a security is traded throughout the day, weighted by the volume of each trade. By using VWAP, I obtained a representative price for each stock transaction, taking into account the varying trading volumes and prices during the entire trading day. However, the Senate Financial Disclosure data is range-censored in terms of the "amount", which represents the value of the stock transaction for that date. The amount is reported as one of the following ranges in Table 1.

Amount Range (USD)
1,001 - 15,000
15,001 - 50,000
50,001 - 100,000
100,001 - 250,000
250,001 - 500,000
500,001 - 1,000,000
1,000,001 - 5,000,000
5,000,001 - 25,000,000

Table 1: Range of the min-max amount of each stock transaction.

first_name	last_name	ticker	asset_name	trans_date	amount_min	amount_max	vwap
John	Hoeven	QCOM	QUALCOMM Incorporated	2017-03-02	100,001	250,000	[NULL]
David A	Perdue , Jr	[NULL]	Alliant Energy Corp CMN	2015-10-21	15,001	50,000	[NULL]
Benjamin L	Cardin	VO	Vanguard Mid-Cap ETF	2021-07-23	1,001	15,000	238.6192
Pat	Roberts	BAC	Bank of America Corporation	2018-07-05	1,001	15,000	27.9392
Patrick J	Toomey	IWF	iShares Russell 1000 Growth ETF	2021-01-14	1,001	15,000	241.4834
Timothy M	Kaine	ODVYX	Oppenheimer Developing Markets Y	2015-07-13	1,001	15,000	[NULL]
Kamala D	Harris	BSV	Vanguard Short-Term Bond ETF	2017-02-28	1,001	15,000	[NULL]
Steve	Daines	[NULL]	AMERICAN TAX EXEMPT BOND FUND	2014-10-22	1,001	15,000	[NULL]
Sheldon	Whitehouse	PANW	Palo Alto Networks, Inc.	2017-01-11	1,001	15,000	[NULL]
Mark R	Warner	ANGIX	Angel Oak Multi-Strategy Income Instl	2017-05-01	15,001	50,000	[NULL]
A. Mitchell	McConnell, Jr.	VFIAX	Vanguard 500 Index Fund Admiral Shares	2018-03-23	15,001	50,000	[NULL]
Sheldon	Whitehouse	TRBCX	T. Rowe Price Blue Chip Growth Fund	2018-05-07	15,001	50,000	[NULL]
Mark R	Warner	DBLTX	DoubleLine Total Return Bond Fund Class I	2018-06-01	15,001	50,000	[NULL]
Ron L	Wyden	BLL	Ball Corporation	2020-05-07	50,001	100,000	65.1487
John W	Hickenlooper	QRTEA	Qurate Retail, Inc. - Series A Common Stock	2021-05-10	250,001	500,000	14.2215
Mark R	Warner	AGG	iShares Core U.S. Aggregate Bond ETF	2021-03-05	1,001	15,000	114.2362
Christopher A	Coons	MSAIX	Invesco American Value Fund Class Y	2020-09-10	15,001	50,000	[NULL]
Robert J	Portman	WCMIX	WCM Focused International Growth Fund Institutiona	2019-07-11	1,001	15,000	[NULL]
Christopher	Murphy	[NULL]	Aggressive Managed Allocation Age 4-7	2015-12-21	1,001	15,000	[NULL]
A. Mitchell	McConnell, Jr.	PRSCX	T. Rowe Price Science & Tech	2017-12-15	1,001	15,000	[NULL]
Rick	Scott	SHV	iShares Short Treasury Bond ETF	2019-03-21	250,001	500,000	110.4938

Figure 1: **Senator's Stock Transactions Data (Compiled)** The table shows the compiled stock transactions data which includes the name, ticker, date, amount min/max, and VWAP for each transaction.

It is important to note that not all of the transactions have a clear ticker because some assets are not publicly traded on an exchange (See "NULL" values in ticker field in Figure 1). Additionally, not all transactions have VWAP values, as not all tickers or asset names have available stock price data from the data provider (See "NULL" values in vwap column in Figure 1). This may lead to some limitations in the analysis, but the dataset still provides a rich source of information for understanding potential insider trading among U.S. members of Congress. An excerpt of a few rows of such compiled transaction data is provided in Figure 1.

2.2 Uncanny Timing of Congressional Stock Trading

Firstly, I gained insights into the mechanisms behind their trading decisions by reviewing news articles. For example, there were several media reports[4][5] regarding Ron Wyden's semiconductor stocks trading. I searched for Senator Ron Wyden's stock transactions with a NAICS code beginning with 334, which indicates computer and electronic product manufacturing. I found that three different tickers (AMAT, AVGO, KLAC) of the transactions that met this condition have a commonality in that they all started on the same date, April 6th, 2020, and ended on either April 6th or April 16th, 2021. Furthermore, all of them follow a similar pattern of multiple purchases followed by sales after certain critical points, such as $Purchase - Purchase - \ldots - Purchase \mid Sales - Sales - \ldots - Sales$ as shown in Fig 2.

	fi	la	ticker	trans_type	trans_date	trans_type	amount_min	amount_max
1	Ron L	Wyden	AVGO	Purchase	2020-04-06	Purchase	15,001	50,000
2	Ron L	Wyden	AVGO	Purchase	2020-04-06	Purchase	15,001	50,000
3	Ron L	Wyden	AVGO	Purchase	2020-04-06	Purchase	15,001	50,000
4	Ron L	Wyden	AVGO	Purchase	2020-04-06	Purchase	15,001	50,000
5	Ron L	Wyden	AVGO	Purchase	2020-04-06	Purchase	15,001	50,000
6	Ron L	Wyden	AVGO	Purchase	2020-04-06	Purchase	15,001	50,000
7	Ron L	Wyden	AVGO	Purchase	2020-06-04	Purchase	15,001	50,000
8	Ron L	Wyden	AVGO	Purchase	2020-06-04	Purchase	15,001	50,000
9	Ron L	Wyden	AVGO	Purchase	2020-06-04	Purchase	15,001	50,000
10	Ron L	Wyden	AVGO	Purchase	2020-06-04	Purchase	15,001	50,000
11	Ron L	Wyden	AVGO	Purchase	2020-06-04	Purchase	15,001	50,000
12	Ron L	Wyden	AVGO	Purchase	2020-06-04	Purchase	15,001	50,000
13	Ron L	Wyden	AVGO	Purchase	2020-06-23	Purchase	15,001	50,000
14	Ron L	Wyden	AVGO	Purchase	2020-06-23	Purchase	15,001	50,000
15	Ron L	Wyden	AVGO	Purchase	2020-06-23	Purchase	15,001	50,000
16	Ron L	Wyden	AVGO	Purchase	2020-06-23	Purchase	15,001	50,000
17	Ron L	Wyden	AVGO	Purchase	2020-06-23	Purchase	15,001	50,000
18	Ron L	Wyden	AVGO	Purchase	2020-06-23	Purchase	15,001	50,000
19	Ron L	Wyden	AVGO	Purchase	2021-03-04	Purchase	1,001	15,000
20	Ron L	Wyden	AVGO	Purchase	2021-03-04	Purchase	1,001	15,000
21	Ron L	Wyden	AVGO	Purchase	2021-03-04	Purchase	1,001	15,000
22	Ron L	Wyden	AVGO	Purchase	2021-03-04	Purchase	1,001	15,000
23	Ron L	Wyden	AVGO	Purchase	2021-03-04	Purchase	1,001	15,000
24	Ron L	Wyden	AVGO	Sale (Partial)	2021-03-30	Sale (Partial)	1,001	15,000
25	Ron L	Wyden	AVGO	Sale (Partial)	2021-03-30	Sale (Partial)	1,001	15,000
26	Ron L	Wyden	AVGO	Sale (Partial)	2021-03-30	Sale (Partial)	1,001	15,000
27	Ron L	Wyden	AVGO	Sale (Partial)	2021-03-30	Sale (Partial)	1,001	15,000
28	Ron L	Wyden	AVGO	Sale (Partial)	2021-03-30	Sale (Partial)	1,001	15,000
29	Ron L	Wyden	AVGO	Sale (Full)	2021-04-06	Sale (Full)	100,001	250,000
30	Ron L	Wyden	AVGO	Sale (Full)	2021-04-06	Sale (Full)	100,001	250,000
31	Ron L	Wyden	AVGO	Sale (Full)	2021-04-06	Sale (Full)	100,001	250,000
32	Ron L	Wyden	AVGO	Sale (Full)	2021-04-06	Sale (Full)	100,001	250,000
33	Ron L	Wyden	AVGO	Sale (Full)	2021-04-06	Sale (Full)	100,001	250,000

Figure 2: **Senator Ron Wyden's stock transactions for Broadcom Inc. (Ticker: AVGO)** The transactions exhibits a pattern of multiple purchases followed by sales after certain critical points, spanning from April 6th, 2020 to April 6th, 2021.

On April 1st, 2021, President Biden announced a plan to invest $50 billion to boost the U.S. chip

[4]Theo Wayt, "US Sen. Ron Wyden boosts chipmakers while his wife buys their shares", New York Post, May 20, 2021, https://nypost.com/2021/05/20/us-sen-ron-wyden-boosts-chipmakers-while-his-wife-buys-their-shares/

[5]Alicia Parlapiano, Adam Playford, and Kate Kelly, "These 97 Members of Congress Reported Trades in Companies Influenced by Their Committees", The New York Times, Sept. 13, 2022, https://www.nytimes.com/interactive/2022/09/13/us/politics/congress-members-stock-trading-list.html

industry[6]. After this announcement, Senator Ron Wyden sold all of his semiconductor stocks. This suggests that members of Congress may have access to not only legislative information but also the publicization of such information that can potentially move the stock market beforehand. This enables them to not just design their portfolio, but also determine when to buy and when to sell, with some anticipation of specific events and their impact on the market.

As shown in the example of Ron Wyden, importance of timing in the context of political insider trading is emphasized by scholars like Tahoun (2014) and Schweizer (2011). Accordingly, this research proposes to integrate such timing considerations into the analysis of excess returns. Specifically, we will adopt an approach that recognizes the life-cycle of transactions, starting from consecutive purchases and ending with consecutive sales. This methodology will be detailed further in Section 2.3, ensuring that our analysis is cognizant of both the decision to invest in specific stocks and the timing of these decisions.

2.3 "Purchsaes-then-Sales": Sub-sequences of Congressional Stock Transactions

Based on the observation introduced in Section 2.2, I partitioned each transaction sequence into sub-sequences, where each sub-sequence consists of consecutive purchase transactions followed by consecutive sale transactions, all arranged in chronological order as illustratively shown in Figure 3. This kind of sub-sequence partitioning is based on the assumption that if congressional investments involve insider trading—using privileged knowledge—there should be a timing of both the beginning and end of the investment that is driven by a certain event (Cziraki et al., 2021; Sivakumar and Waymire, 1994). Specifically, the event of interest would be one that, upon being publicized, moves the stock market into a different phase. In the case of insider trading, we would expect to see a pattern where a congressperson accumulates a long position in a stock ahead of a positive event and subsequently monetizes that position by selling the stock after the event becomes public and positively impacts the stock price. Conversely, a congressperson may sell a stock ahead of a negative event and avoid losses when the event becomes public and negatively impacts the stock price.

It is important to note that in this analysis, we are only considering the case of congresspersons taking long positions and subsequently selling those positions, as this is the type of transaction that is

[6]Alex Leary and Paul Ziobro, "Biden Calls for $50 Billion to Boost U.S. Chip Industry", The Wall Street Journal, March 31, 2021, https://www.wsj.com/articles/biden-urges-50-billion-to-boost-chip-manufacturing-in-u-s-11617211570

reported in Financial Disclosure reports. In these reports, there are no "stock-shorting" transactions, which involve betting against a stock and profiting from its decline. As such, our partitioning approach focuses on identifying sub-sequences of consecutive purchases followed by consecutive sales, which may reflect the use of privileged knowledge to take advantage of market-moving events and realize profits from long positions.

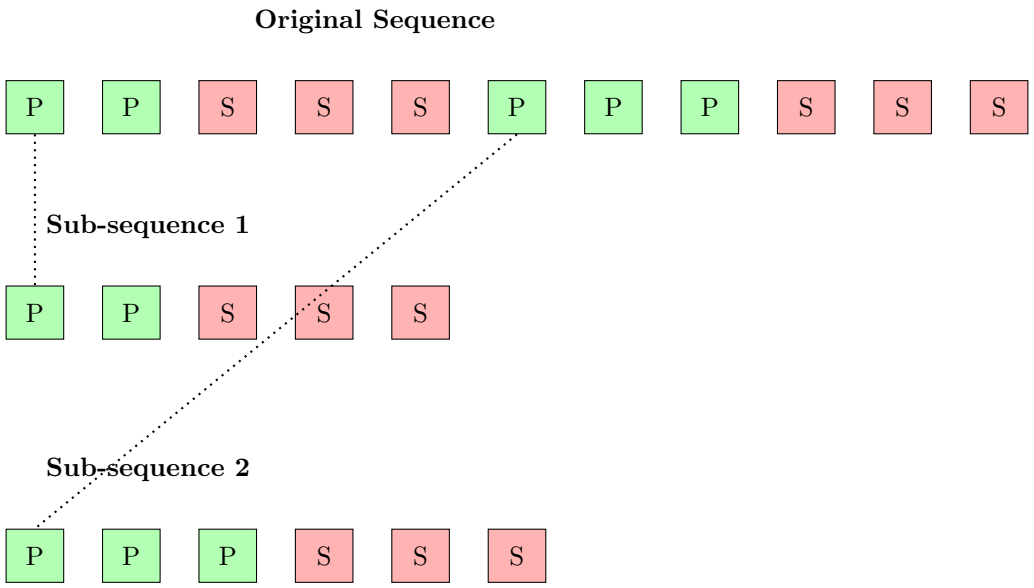


Figure 3: Partitioning of transaction sequences into sub-sequences based on consecutive purchase and sale transactions.

Through the partitioning process, I obtained a total of 435 sub-sequences spanning across 358 unique combinations of Senator-Ticker pairs. Each sub-sequence represents a long position taken by a senator in a specific stock and is characterized by a start date and an end date. The start date corresponds to the date of the first purchase transaction in the sub-sequence, and the end date corresponds to the date of the last sale transaction in the sub-sequence. The duration of each sub-sequence, measured in days, represents the length of time the senator held the long position. On average, senators held such long positions for approximately 340 days, and around 65% of these positions were held for less than a year. The frequencies of durations for all subchains are illustrated in Figure 6.

2.4 Estimating Excess Returns of Sub-sequences

Estimating the excess return of the 435 sub-sequences, which were acquired following the procedure described in Section 2.3, presented a methodological challenge due to the nature of the Finance Disclosure data. The data provides only the "minimum and maximum" range of amounts spent on purchasing or

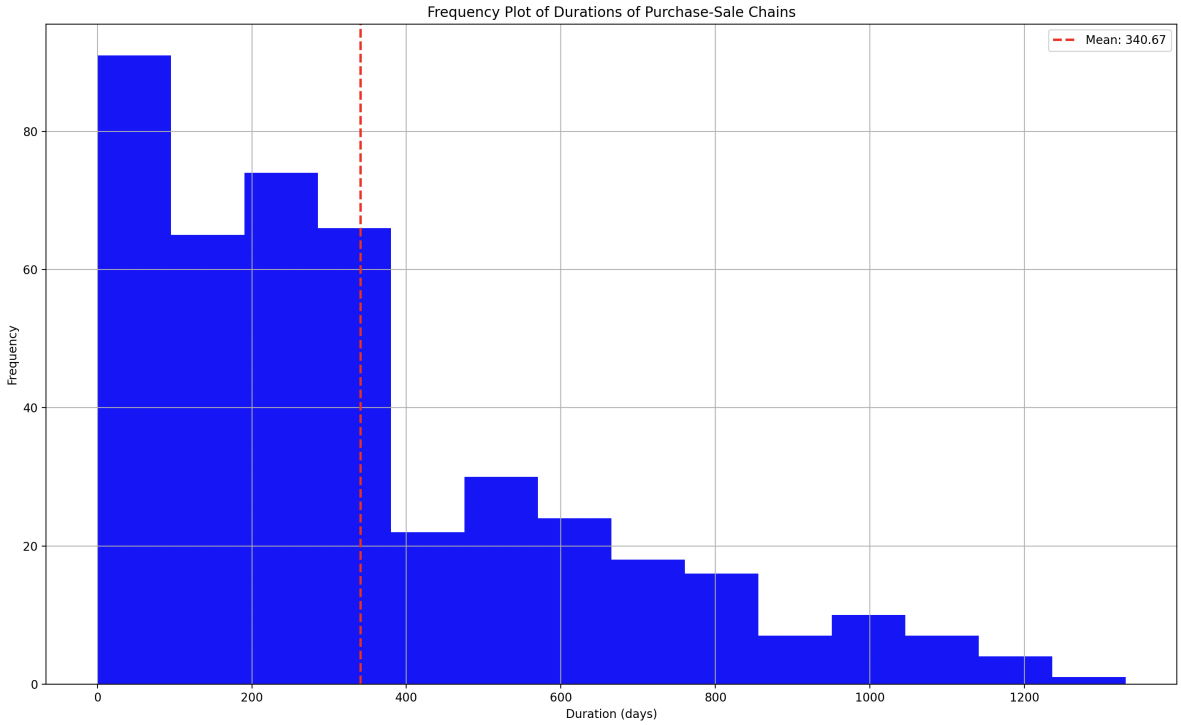


Figure 4: **Frequencies of durations of long positions held by congressmen at the Senator-Ticker level** The durations are measured in days and represent the length of time between the start and end dates of each subchain. The mean duration of holding such long positions is approximately 340 days. Notably, around 65% of these long positions are held for less than a year

selling each ticker on a specific day as illustrated in Table 1, rather than exact transaction amounts. To address this challenge and estimate the excess returns for each Purchase-Sale sub-sequence, the following approach was taken:

1. **Random Sampling of Transaction Amounts**: For each transaction (purchase or sale) within a sub-sequence, an amount was randomly sampled from a uniform distribution with support equal to the minimum and maximum range of the transaction amount provided in the data.

2. **Estimation of Shares Bought or Sold**: The sampled amount was divided by the volume-weighted average price (VWAP) of the stock on the corresponding transaction date to estimate the number of shares bought or sold by the congressperson.

3. **Creating Settled Pairs**: Within each sub-sequence, settled pairs of buy-sell transactions are identified. A settled pair consists of one unit of a buy transaction matched with one unit of a subsequent sell transaction. The pairing process is based on a first-in/first-out principle, meaning that stocks purchased earlier are matched first to sales, before those bought later. This ensures that the sale always occurs after the purchase. Multiple settled pairs can be created within a single sub-sequence.

4. **Computing Profit Return Rate for Each Settled Pair**: For each settled pair, the profit return rate is calculated as the relative profit or loss from the buy-sell transaction. The profit return rate is computed using the formula:

$$\text{Profit Return Rate} = \frac{\text{Sale Price} - \text{Purchase Price}}{\text{Purchase Price}} * 100$$

where "Sale Price" is the price at which the stock was sold, and "Purchase Price" is the price at which the stock was purchased.

5. **Penalizing the Profit Return Rat with Fed Reserve Rate**: The profit return rate for each settled pair is then penalized by the average Federal Reserve Rate during the holding period of that specific pair. The holding period is defined as the time interval between the purchase date and the sale date of the settled pair. The penalized return, or "excess return" for each pair is calculated as:

$$\text{Excess Return } = \text{Profit Return Rate} - \text{Average Federal Reserve Rate}$$

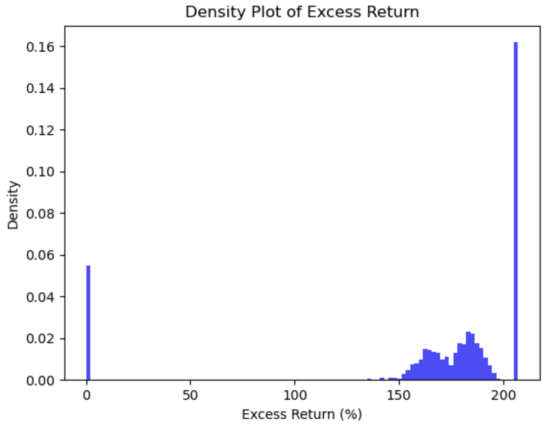
The Average Federal Reserve Rate represents the risk-free rate of return that could have been earned from a risk-free investment during the same holding period.

6. **Averaging Excess Returns**: The final excess return for the entire sub-sequence is computed by averaging the excess returns of all the individual pairs of settled buy-sell transactions within the sub-sequence. This approach provides a comprehensive measure of the excess return for the sub-sequence, accounting for profit ratio above the risk-free rate of return for each holding period.

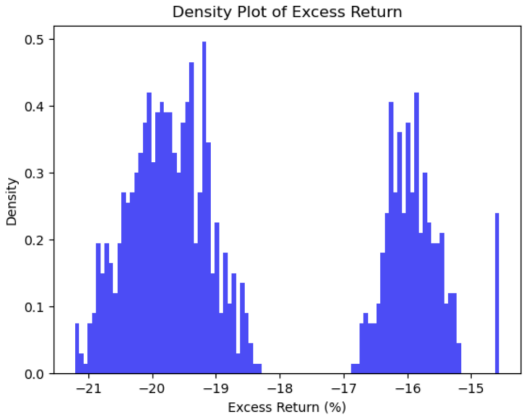
By following this approach, the excess return of each sub-sequence was estimated while accounting for the limitations of the available data. Using the Federal Reserve Rate as the baseline for comparison is a more conservative approach because it represents a risk-free rate of return (Bauer and Rudebusch, 2014; Sarno and Thornton, 2003) that is typically higher than the interest rates offered by most savings accounts. As a result, the excess return is measured against a higher baseline, potentially lowering the final estimation result and providing a more cautious assessment of the excess return earned by the congressperson.

To assist in understanding the concepts explained previously, I am presenting the estimated excess return distributions for Senator Ron Wyden's sub-sequences involving two different companies: Applied

Materials Inc. (AMAT), which provides manufacturing equipment, services, and software to the semiconductor industry, and Marriott International Inc. (MAR), a global hotel brand. These distributions were computed using the random sampling method explained earlier, where the randomness is inherited from the uniform random sampling of transaction amounts from the provided minimum and maximum ranges. It is important to note that each sub-sequence is uniquely identified not only by the congressperson-ticker level but also by the start and end dates of the sub-sequence.



(a) Ron Wyden's excess returns from transactions involving Applied Materials Inc. (AMAT) from April 2020 to April 2021.



(b) Ron Wyden's excess returns from transactions involving Marriott International Inc. (MAR) from May to August 2020.

Figure 5: Estimated Excess return distributions of Senator Ron Wyden's transactions for AMAT and MAR

In Figure 5, the mean of the excess return distributions for Senator Ron Wyden's sub-sequences involving AMAT and MAR are 166.30% and -18.43%, respectively. As we can see, even the same senator sometimes achieves great excess returns while also experiencing failures. In a similar vein, I collected the mean values of the excess return distributions for all 435 subsequences, which are presented in Figure 6.

In Figure 6, among the mean estimated excess returns, Ron Wyden's semiconductor-related stocks like Applied Materials Inc (AMAT), KLA Corp. (KLAC), and Broadcom Inc. (AVGO) are highly ranked, scoring from 80% to 166% of excess returns. These transactions have already been spotlighted by the media, as introduced in Section 2.2. This suggests that this method can reveal such dubious transactions spotlighted by the media, ranking them as acquiring high-performing excess returns.

What is noticeable is that the cumulative density of the excess return distribution reaches 0.5 when the excess return is 0. It means that not all transactions of Senators are always successful, but it's more like random whether they actually acquire positive excess profit. This finding aligns more with the results from Eggers and Hainmueller (2013) than those of Ziobrowski et al. (2004) and Ziobrowski et al. (2011),

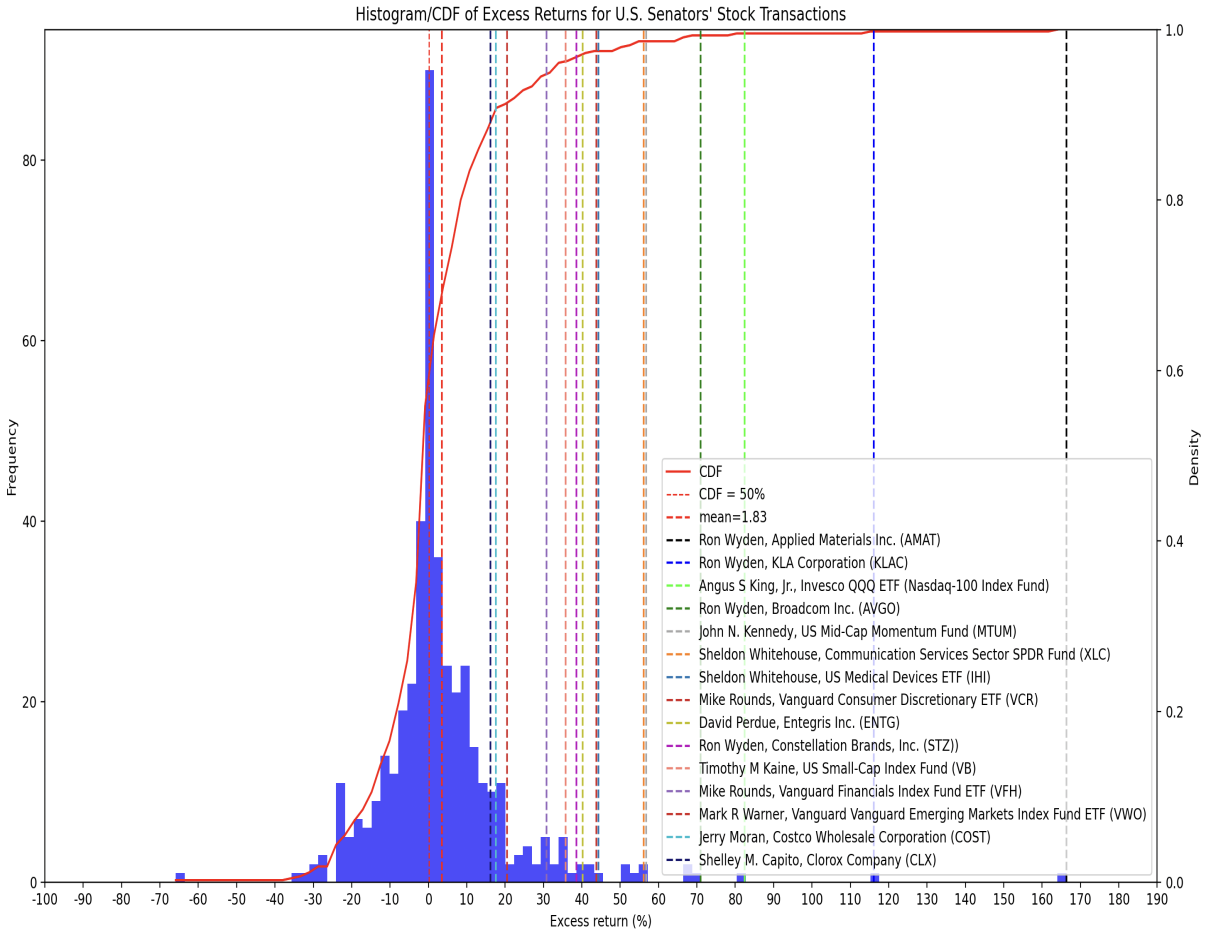


Figure 6: Distribution of Senators' Mean of Estimated Excess Returns Distribution.

suggesting that Senators are more like mediocre investors who align with the literature about failing individuals as investors, as explained in broad finance literature such as Barberis and Thaler (2003), and Barber and Odean (2000).

However, one thing that is important to notice is that the distribution in Figure 6 scores a skewness of 2.804, which means the tail on the right side of the distribution is longer. This indicates that compared to the case of Senators losing money, at least in situations where they are acquiring excess return from it, they may be more related to some privileged knowledge that can back up the performance of such stock transactions. The presence of the long tail suggests that, in some cases, Senators might be involved in transactions that benefit from privileged knowledge, as Eggers and Hainmueller (2014) suggest, which could be originating from their political connections, including connections established through Political Action Committee (PAC) donations or district-level affiliations with the firms in question.

While the current findings provide valuable insights into the nature of congressional stock trading, it is essential to delve deeper into the fundamental relationship between congressional activities and

stock transactions. In order to gain a better understanding of the underlying factors that drive congressional stock trading behavior and the potential impact of privileged information on investment decisions among lawmakers, we need to explore an approach that quantifies the predictive power embedded in the congressional activities and assesses the extent to which these activities are associated with stock transactions.

It is worth noting that this approach is not entirely novel, as Eggers and Hainmueller (2014) have already studied the connections between congressional-related activities and the specific firm's stock transactions of a congressperson. Their research examined factors such as PAC contributions, lobbying and geographical connections based on district, and congressperson's committee membership and firm-level lobbying, to determine whether these factors could predict a congressperson's stock transactions.

Given that the innate difficulty in identifying the intention behind such transactions (Ziobrowski et al., 2011, 2004; Eggers and Hainmueller, 2013, 2014), due to the limited information available or the more fundamental challenge of distinguishing between a congressperson's private and public life (Buchanan and Tollison, 1984), it is essential to examine how dynamically these transactions are connected with congressional activities in terms of information.

One possible avenue for this exploration is to represent congressional activities as a graph, which can effectively capture the complex relationships between various actors and actions (Henaff et al., 2015; Kaushik et al., 2002) within the legislative process. Graph-based representations are well-suited for modeling the interconnected nature of congressional activities, taking into account not only the individual actions of Congress members but also the broader context of committee memberships, lobbying efforts by firms on specific bills of their interest, the referral of bills to specific committees, and the assignment of Congresspersons to certain committees.

Eggers and Hainmueller (2014) studied the impact of such factors, particularly committee membership and firm-level lobbying on bills, on stock transactions at a binary level, considering whether or not this information existed for each congressperson-stock pair. However, congressional activities are more complex and interconnected, with various entities involved in these relationships simultaneously rather than in isolation. For example, multiple firms in the semiconductor industry, such as Intel, Qualcomm, Broadcom, Apple, and IBM, participate in lobbying efforts for bills related to their sector, like the CHIPS Act (H.R.4346 117th Congress) or FABS Act (S.2107 117th Congress). These activities are governed by specific congresspeople within particular committees, and all this information collectively can forms the

detailed context in which a congressperson transacts stock.

In addition, as explained in Section 2.1, a congressperson's securities transactions are not limited to individual firm levels. In fact, 60% of these transactions involve exchange-traded funds (ETF) or mutual funds that target a wide range of specific industries such as wireless communication, medical devices, or mid-cap or small-cap companies. Therefore, the full context of a congressperson's stock transactions extends beyond individual companies to encompass broader industry trends and movements.

In light of this, the next section will introduce a newly compiled dataset that captures congressional activities as a whole, in the form of graph-structured data. I will then demonstrate how this graph-structured data can be useful, for example, by directly computing the similarity between a committee's industry-level specialization and the industry-level distribution of a congressperson assigned to that committee in Section 5. Additionally, I will present a method for modeling the predictive task, which can directly take graph-structured data as input using Graph Neural Networks in Section 6. An array of analyses using graph-structured data will enhance our comprehension of the intricate relationships between congressional activities and stock transactions. This approach will offer more profound insights into the potential influence of privileged information acquired through congressional activities on lawmakers' investment decisions.

3 Graph-Structured Data for Representing Congressional Activities

[7] The data utilized in the following sections forms a large, complex network that is categorized as a heterograph or heterogeneous graph. This structure captures congressional activities through different types of nodes and edges, thereby encapsulating the multi-faceted nature of these activities. This heterograph encompasses information on congressional activities, such as committee assignments, bills being lobbied by firms, bill assignments to committees, and firms classified under specific NAICS codes. The detailed specifications of the node types can be found in Table 2, while the edge types are described in Table 3. Different types of nodes and their relationships, captured by different types of edges, are provided in Figure 7. The process of data collection from disparate sources and the subsequent disambiguation and merging of entities are elaborated upon in Appendix A. Additionally, Appendix B provides a detailed

[7] Reproducible code for this section is available at `https://github.com/syyunn/gnnex/blob/main/data/graph.ipynb`

explanation of a more modern approach to extracting structured data from collected financial disclosure PDFs. In this approach, I utilized a Large Language Model (LLM) to aid in the extraction process. The specifics of how the LLM was employed are discussed in detail within the appendix.

Table 2: Heterograph (Nodes)

Node Type	N	Period	Source
Firm (Ticker)	4,202	-	Lobbyview & Finance Disclosure
Bills	47,767	110-117th Congress	Lobbyview
Congressperson	2,431	113-118th Congress	Lobbyview & Finance Disclosure
Committee	556	-	Lobbyview
NAICS code	744	-	naics.com
Total	55,700	-	-

Table 3: Heterograph (Edges)

Edge Types	N	Period	Source
Congressperson- Buy/Sell- Firm (Ticker)	24,675	[2013-01-24, 2023-03-08]	Finance Disclosure
Firm (Ticker) - Lobby On - Bill	148,487	[2016-01-02, 2022-02-24]	Lobbyview
Ticker- Classified as - NAICS Codes	4,147	-	Finance Disclosure & naics.com
Bill- Referred to - Committee	75,626	[2016-01-05, 2021-12-17]	Lobbyview
Congressperson- Assigend to - Committee	11,698	115-117th Congress	Finance Disclosure & Lobbyview
Total	264,633	-	-

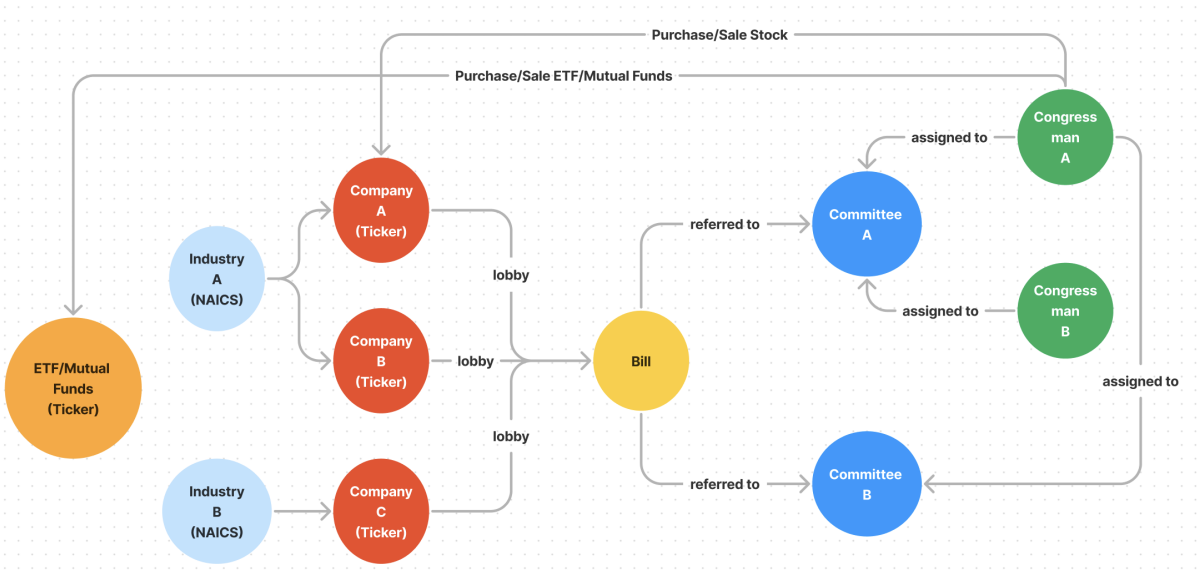


Figure 7: The network data includes various types of nodes and edges that represent different entities and interactions within the congressional activities and investment behavior of Congresspersons.

To provide a more concrete understanding of the data, Figure 8 displays a subgraph related to Senator Ron Wyden's transaction in Trip Advisor stock (Ticker: TRIP). This subgraph illustrates the relationships between Senator Ron Wyden's congressional activities, including his membership in the

Senate Finance Committee, his involvement with a specific bill related to airport improvements, and the economic sectors represented by NAICS codes, thereby providing insights into how these activities could potentially influence or be influenced by his stock transactions.

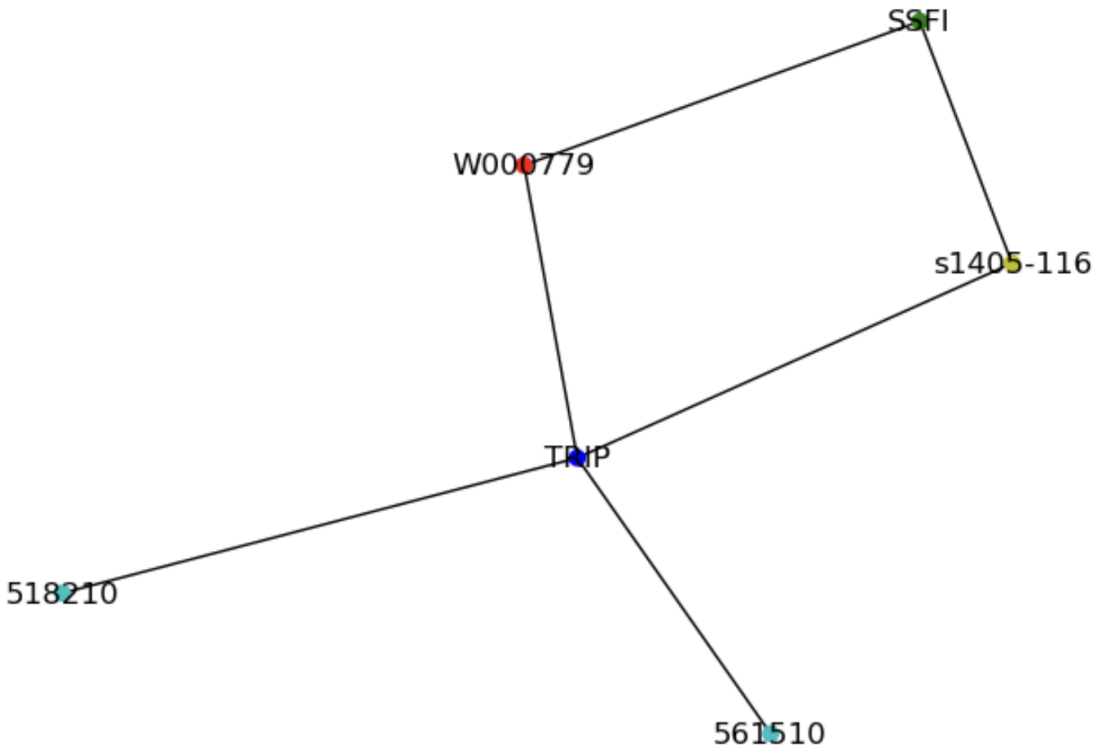


Figure 8: **A subgraph illustrating the congressional network related to the transaction of Senator Ron Wyden's Trip Advisor stock.** The node labeled W000779 corresponds to Ron Wyden's bioguide-id, which is a unique identifier provided by Congress for each senator. SSFI represents the Senate Finance Committee, of which Ron Wyden is a member. S1405-116 is a bill in the 116th Congress that revises requirements for the airport improvement program and pilot program for passenger facility charges at nonhub airports. The node labeled 518210 represents the NAICS Code for Data Processing, Hosting, and Related Services, while 561510 represents Travel Agencies.

4 Identifying Informative Predictors in Congressional Stock Trading Using an LLM Agent

This section delves into the design of a link prediction task aimed at identifying key features and information within network data that are informative for predicting congressional stock trading. We employ an emerging tool - a Large Language Model (LLM) agent - notable for its ability to reason and act autonomously. By tasking this LLM agent with performing link prediction tasks across various legislator-

ticker pairs, we assess the likelihood of transactions based on available network data. This approach leverages the agent's advanced reasoning capabilities to analyze connections within the graph structured data explained in Section 3, providing insights into the dynamics of congressional stock trading behavior.

4.1 High-Dimensional Complexity and Theorization in Network Data

In this section, I justify the use of a Large Language Model (LLM) agent in our study. The primary motivation for employing an LLM agent is to identify important features that can explain congressional stock trading behaviors in an interpretable manner. This task becomes particularly challenging with high-dimensional data, a common characteristic of graph-structured data. Unlike traditional tabular data, graph-structured data often involves large adjacency matrices that are highly dimensional, scaling as N^2 with N being the number of nodes (Ward et al., 2011). This high dimensionality poses distinct challenges in data analysis and theorization, particularly when analyzing networks that capture societal phenomena (Tang and Liu, 2012; Thi and Nguyen-Hoang, 2013).

In political science, handling high-dimensional data for tabular datasets has primarily been addressed using two methods: tree-based models and LASSO. Tree-based models, as discussed in Montgomery and Olivella (2018), are effective for detecting nonlinearities and interactions in datasets with many covariates. These models are valued for their flexibility and ability to uncover complex relationships within data. LASSO, on the other hand, as exemplified in Mauerer et al. (2015), is particularly beneficial for reducing model complexity. It systematically identifies relevant predictors, simplifying the interpretation of complex electoral analyses that involve multiple parties.

However, for network data in political science, there is a noticeable gap in the methodology. The field currently lacks a widely agreed-upon approach to manage the high dimensionality inherent in graph-structured data (Lazer, 2011; Ward et al., 2011). The challenge of managing high dimensionality in graph-structured data is further intensified when using heterographs as predictors. Heterographs, characterized by their diverse node and edge types, offer a comprehensive data representation format for social phenomena. Despite this, they are infrequently employed in social network analysis. This underutilization is notable given their potential as a general framework for capturing the complexities of social interactions.

To address the challenges associated with the high dimensionality of graph-structured data, particularly when using heterographs as predictors in political science, this study introduces a novel method that

leverages a Large Language Model (LLM) agent. The primary motivation behind employing an LLM agent is to effectively identify key features within the network—such as specific types of connections and combinations thereof—that can explain congressional stock trading behaviors in an interpretable manner. The LLM agent's role in this context is to sift through the complex network data, pinpointing potential predictors that might otherwise be overlooked due to the data's high dimensionality. For example, it could be hypothesized that if a legislator assigned to a committee handles a significant number of bills targeted at a particular industry, this could be a strong predictor of whether that legislator engages in transactions of certain stock tickers related to the same industry. The following sections will delve into a comprehensive explanation of what Large Language Models (LLMs) and LLM agents are, and the specific design of the theorizing agent being proposed.

4.2 Large Language Models (LLMs) and LLM Agents

Large Language Models (LLMs) are advanced AI systems capable of understanding, generating, and engaging with human language (Zhao et al., 2023). These models are trained on vast amounts of text data, allowing them to grasp a wide array of language patterns, nuances, and contexts. LLMs like OpenAI's GPT-3.5 and GPT-4 exemplify this technology's pinnacle (Radford and Narasimhan, 2018), demonstrating near-human-like reasoning abilities. These models can make decisions based on a complex understanding of language, context, and, to some extent, the logic and knowledge embedded in their training data (Lampinen et al., 2022).

One key characteristic of LLMs is their ability to generate coherent and contextually relevant text, making them particularly useful for a range of applications, from content creation to data analysis. In the realm of predictive modeling, LLMs stand out for their ability to process and interpret complex data structures in a way that mimics human cognitive processes (Kojima et al., 2022; Hayashi et al., 2019). This capability makes them highly valuable in fields like political science (Luitse and Denkena, 2021), where interpreting intricate relationships within data is crucial.

Continuing from the foundational understanding of Large Language Models (LLMs), a notable trend in their application is the shift from using them as mere one-time question-answering systems to leveraging them in a more dynamic and interconnected manner. Expanding on this concept, the proposed approach seeks to enhance the problem-solving capabilities of LLMs by enabling them to dissect complex problems into a sequence of interconnected steps. This methodology facilitates a more detailed and systematic

exploration of solutions, where each step builds on the insights gained from the previous one. By breaking down problems in this manner, LLMs can provide a more nuanced and comprehensive understanding of each component of the problem, leading to a potentially more effective and holistic solution (Wei et al., 2022; Yao et al., 2023a).

In addition to the aforementioned step-by-step approach, there is an emerging trend of augmenting Large Language Models (LLMs) with a variety of tools, thereby enhancing their problem-solving capabilities. These augmented LLMs, or "LLM Agents", are empowered to utilize these tools based on their own discretion and reasoning, choosing the most appropriate tool for a specific situation (Yao et al., 2023b). For instance, an LLM augmented with search capabilities can effectively invoke this tool as a part of its problem-solving process whenever it deems necessary. Since LLM Agents are designed with an awareness of their own data cut-off points, recognizing the limitations in their training data up to a certain point in time. This self-awareness enables them to identify situations where their existing knowledge base may be insufficient. In such scenarios, an LLM Agent can decide to refer to external sources of data, such as the web or apis, to acquire more current and accurate information (Qin et al., 2023; Patil et al., 2023).

Then, how can we leverage these LLM Agents for theorizing and explaining complex phenomena such as congressional stock trading by letting them traverse over graph-structured data? This question opens up a new realm of possibilities in the application of LLM Agents. In the following section, I will propose a novel architecture that merges traditional machine learning techniques with the capabilities of LLM Agents. This hybrid approach aims to empower LLM Agents to not only analyze and interpret intricate data structures like graphs but also to generate their own explanations and hypotheses.

4.3 Advancements in Designing Self-Learning LLM Agents

The academic community and industry have shown considerable interest in exploring new applications of Large Language Models (LLMs), encountering unique challenges along the way. One significant issue is that LLMs, due to their immense parameter size and often proprietary nature, are difficult to fine-tune. While OpenAI offers fine-tuning options for the last few layers of models like GPT-3.5 and GPT-4, with user-prepared supervised input-output pairs, this process incurs additional costs and complexities.

Consequently, the focus has shifted towards designing learning experiences for LLMs that do not require traditional weight updates or parameter adjustments. This approach, known as "no-derivative learning", has rapidly evolved into a significant field of study (Yang et al., 2023; Zhu et al., 2023; Wang

et al., 2023). It involves crafting system architectures that enable LLMs or LLM Agents to learn and achieve specific goals without altering their underlying LLM model weights.

A prime example of this method is the "LLM as optimizer" (OPRO) concept (Yang et al., 2023), which proposes no-derivative learning by creating a meta-prompt that is iteratively updated. The achievement of the task is scored, and this scoring is also performed by another LLM. This method demonstrates that prompts can evolve through self-evaluation or self-reflection, effectively allowing the LLM to function as an optimizer. This approach has been successfully applied to solve linear regression problems, showcasing the LLM's ability to operate in an optimizer-like capacity.

Furthermore, from the perspective of optimizing actions, Shinn et al. (2023) introduced a verbally reflecting agent that generates task feedbacks. These feedbacks are then maintained in an episodic memory buffer, aiding the agent in making better decisions in subsequent trials. This concept of self-evaluation or self-reflection, through designing a meta-prompt that allows the agent to assess its own performance and store these reflections for future reference, has become another cornerstone of no-derivative learning.

Additionally, the Wang et al. (2023) presented a novel approach where embeddings of these reflections are stored in a database. This enables the utilization of similarity searches over vector space, enhancing the agent's ability to recall and act upon past experiences effectively. For instance, Wang et al. (2023) taught LLM Agents to play Minecraft by storing environment information as embeddings with corresponding skills as key-value pairs. These environment-skill pairs are retrieved based on the current environment, allowing the LLM Agent to augment its reasoning process with previously effective skill sets.

4.4 Predictive Theorization with Self-Learning LLM Agents

To analyze the dataset introduced in Section 3, a complex heterograph with 55K nodes and 264K edges featuring five distinct types of nodes and edges, we face a substantial challenge. This dataset, encapsulating a variety of congressional activities, offers insights into how these activities might influence the stock trading behavior of congresspersons. The central inquiry revolves around the impact of these activities on stock trading, aiming to develop theories or hypotheses about such behaviors. This endeavor is complicated by the dataset's high dimensionality and the dense interconnections of its heterograph structure, which markedly deviates from the simplicity of traditional tabular data formats.

As discussed in Section 4.3, self-learning Large Language Model (LLM) Agents emerge as a promising solution to this challenge. By engaging these agents in iterative predictive tasks focused on the existence of links between legislator-ticker pairs, they can self-evaluate their performance. This process involves the agent assessing which observations within the dense graph data and which specific aspects of its topology or structure were pivotal in their problem-solving approach.

In this context, I propose an innovative methodology where the traditional task of link prediction, commonly used in Graph Neural Networks (GNN), is approached through a self-learning LLM Agent. This method entails having the Agent predict the presence or absence of a link for a given legislator-ticker pair. Following each prediction, the agent engages in self-reflection or evaluation, analyzing the reasons behind its success or failure in comparison to the ground truth.

This approach not only leverages the advanced capabilities of LLMs in handling high-dimensional data but also introduces a novel dimension of self-assessment and learning. It allows the LLM Agent to progressively refine its understanding and approach to the data, potentially uncovering significant insights about the relationship between congressional activities and stock trading behaviors. This method represents a significant step forward in the application of AI in political science, particularly in analyzing complex, graph-structured data.

5 Industry-level Similarities between Congresspersons and Committees

In this section[8], I aim to examine the relationship between committee assignments and stock trading behavior among congress members, addressing the puzzle arising from Eggers and Hainmueller (2014)'s findings. Despite their discovery of the role that political connections play in profitable transactions, they found no evidence that committee membership influenced investment decisions. This observation is strikingly contrary to the preponderance of literature highlighting the importance of committee assignments and the specialized knowledge they confer.

Numerous studies, such as Patterson (1970), King (1994), and Asher (1974), have focused on the role of committee assignments in shaping legislative outcomes, the impact of bill referral on committee specialization, and members' specialization in topics related to committees' jurisdiction, respectively. Further

[8]Reproducible code for this section is available at `https://github.com/syyunn/efd/blob/main/anlys/cycle/main9-transactions-desc-house-included.ipynb`

research reinforces this notion of committee assignments as platforms for leveraging congressperson's knowledge and expertise, as shown in Boros and Fenno (1968); Gilligan and Krehbiel (1989); Kiewiet and McCubbins (1991); Krehbiel (1992); Curry (2019). The results of Egger and Hainmueller (2014) thus present a unique counterpoint, as they seem to contradict this prevailing understanding of committee roles in the legislative process.

Committee assignments provide congresspersons with unique access to information and resources related to specific industries and policy areas. As members of these committees, they are privy to the latest policy developments (Price, 1978), market trends, and regulatory changes (Weiss, 1989) that could potentially affect the performance of companies in the industries they oversee. The specialized knowledge and insights gained from participating in committee activities could inform their investment decisions and potentially influence their stock trading behavior. For example, they might be more inclined to invest in companies within their committee's jurisdiction due to their deeper understanding of the industry dynamics and future prospects. Furthermore, their committee roles could enable them to establish connections with industry stakeholders and gain access to non-public information that could potentially offer them an edge in making investment decisions.

This section aims to provide a more robust statistical examination of the correlation between committee specialization and the stock trading patterns of Congress members. Specifically, it probes the degree to which committee specialization mirrors the industry distribution of a Congress member's stock portfolio. This industry-focused analysis is justified by several observations and hypotheses:

1. As evidenced in Section 2.1, approximately 60% of the stock transactions by Senators involve ETFs or Mutual Funds. This indicates that congressional trading doesn't merely operate at the firm-level but extends to the industry-level, suggesting a possible connection between industry-specific knowledge and transaction behaviors.

2. On the data side, the graph-structured data introduced in Section 3 allows for the direct aggregation of industry-level committee specialization by tracing the link from firms lobbying on bills to the committees these bills are assigned to.

3. As shown in Figure 6, many of the investments with high excess returns are industry-specific ETFs or Mutual funds. For instance, Senator Ron Wyden's collection of semiconductor stocks like AMAT, AVGO, and KLAC; Senator Mike Rounds' Financial Sector ETF; and Senator Sheldon Whitehouse's Medical Device ETFs. These observations underscore the need for an industry-level analysis that goes

beyond firm-level stock trading.

In addition, the legal framework also favors an industry-level analysis. Following the STOCK Act 2012 and the corresponding Senate Ethics manual (Boxer et al., 2012), Congress members are prohibited from trading based on information obtained through their official duties. This suggests that leveraging not just firm-specific, but industry-level information garnered from congressional activities for trading is legally restricted. This study will hence scrutinize whether there exists a discernible pattern between committee specializations and industry-level stock transactions.

5.1 Measuring Industry-level Specialization

In this subsection, I will discuss the measurement of committee specialization in terms of industry-level specialization. By aggregating NAICS codes for the bills lobbied by various industries and those bills being referred to specific committees, I aim to quantify the industry-level specialization of each committee.

As an example, we can expect the Senate Banking Committee to have a higher degree of jurisdiction over banking-related issues, such as regulations tied to LIBOR (London Interbank Offered Rate) rates. This, in turn, would influence firms associated with NAICS codes related to banking (e.g., 52) to lobby the bills assigned to this committee more actively. This industry-level specialization can be effectively captured using the graph-structured data discussed in Section 3.

To capture this industry-level specialization, I aggregate the North American Industry Classification System (NAICS) codes of each firm that is lobbying on each bill. These codes categorize each firm according to its primary business activity. I then look at the bills assigned to each committee. This allows to identify which industries - as represented by their NAICS codes - are most active in lobbying bills that fall under the purview of specific committees. For instance, if a significant number of firms with the NAICS code for banking (52) are lobbying on bills assigned to the Senate Banking Committee, this would suggest a high degree of industry-level specialization of Senate Banking Committee on financial industry. This method of analysis, leveraging graph-structured data, allows us to explore the relationships between committee assignments, industries, and lobbying activities.

To represent the committee-level specialization, I create a discrete probability distribution for each committee by aggregating the NAICS code distributions of firms that lobby bills assigned to those committees. Specifically, I count the occurrences of each NAICS code associated with firms that lobby

bills referred to a particular committee. This method highlights the committee's industry focus, as it captures the concentration of lobbying efforts by firms within specific industries. Once we have the count-based frequency plot for each committee, we can easily convert it into a probability distribution function (PDF) by normalizing the counts with the total occurrences of all NAICS codes.

Similarly, to aggregate the NAICS code distribution of firms involved in each congressperson's stock transactions, we can simply count the occurrences of NAICS codes associated with all stock transactions executed by the congressperson (both purchases and sales). This provides a clear picture of the industries in which they invest, as the NAICS codes are derived from the firms whose stocks are being bought or sold by the congressperson in their stock transactions. We then normalize the count-based frequency plot with the total occurrences of all NAICS codes to obtain a PDF representing the congressperson's industry preferences.

As we've seen in Section 2.4, the data used for estimating Senator's excess return shows that around 60% of tickers are Exchange-Traded Funds (ETF) or mutual funds, which are not single firms but representing certain industries or the stock market in general. For example, in Figure 6, one of the highest excess returns, like the 45% profit shown by Sen. Sheldon Whitehouse, is the ticker IHI, which is an ETF that invests in the US medical device market. Sen. Sheldon Whitehouse supported the Biden plan to fully utilize the Defense Production Act, increase the supply of necessary medical equipment and supplies[9]. As shown, Senators do not always reflect their knowledge gained from congressional activities at the firm level but at the industry level. In either case, this measurement can effectively capture their level of specialization in certain industries in terms of their transaction patterns. By comparing the similarity between the two distributions, one from the committee and one from the congressperson, we can statistically test how similar they are to each other.

Subsequently, we measure the similarity between a congressperson's stock transactions' industry preference and a committee's industry specialization. This similarity can be quantified using cross entropy. Cross-entropy is a useful statistical tool for determining the similarity between two distributions (Wu et al., 2018; Mao et al., 2013), making it an ideal choice for comparing the distributions of NAICS codes for committee assignments and stock transactions. In this regard, for a given congressperson i and committee k, the cross entropy H_{ik} is computed as:

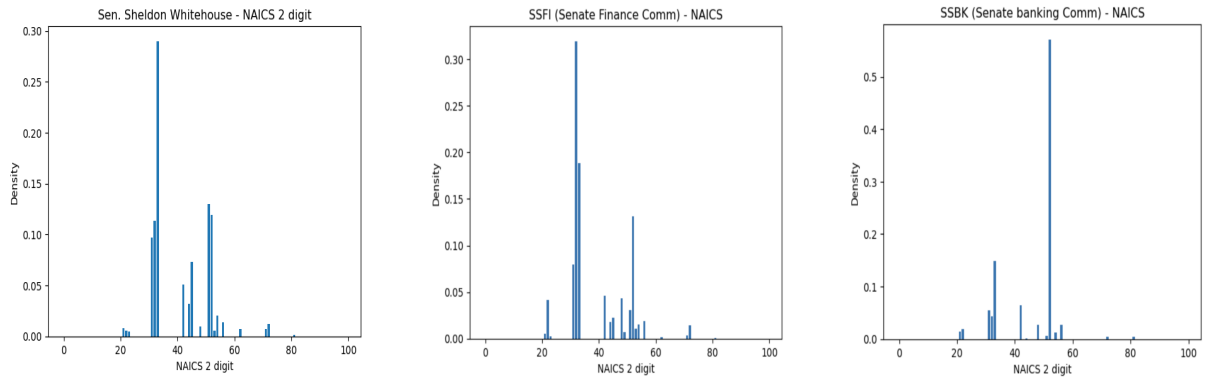
[9]See `https://www.whitehouse.senate.gov/news/release/whitehouse-supports-biden-plan-to-fully-utilize-defense-production-act-increase-supply-of-necessary-medical-equipment-and-supplies`

$$H_{ik} = -\sum_{j} P_{i,j} \log Q_{k,j}$$

Here, $P_{i,j}$ refers to the density of congressperson i's trades in industry j relative to all their transactions, and $Q_{k,j}$ denotes committee k's specialization in industry j.

A lower cross entropy H_{ik} suggests a higher similarity between the industry preference of congressperson i's stock transactions and the industry specialization of committee k. This value is calculated at the congressperson-committee level, thereby providing an industry-level similarity measure between them.

Figure 9 provides an example of this measurement for Sen. Sheldon Whitehouse's case. It displays the NAICS code distributions for Sen. Whitehouse's stock transactions, the Senate Finance Committee (SSFI), and the Senate Banking Committee (SSBK). The figure illustrates that the distribution of Sen. Whitehouse's stock transactions resembles the distribution of the Senate Finance Committee more closely than that of the Senate Banking Committee, highlighting the connection between his transactions and his committee assignments.



(a) Sen. Sheldon Whitehouse's NAICS Distribution

(b) Senate Finance Committee (SSFI) NAICS Distribution

(c) Senate Banking Committee (SSBK) NAICS Distribution

Figure 9: Comparison of NAICS code distributions for Sen. Sheldon Whitehouse, Senate Finance Committee (SSFI), and Senate Banking Committee (SSBK). The figure illustrates how the distribution of Sen. Whitehouse's stock transactions resembles the Senate Finance Committee's distribution more closely than that of the Senate Banking Committee.

In Figure 9, we can calculate the cross-entropy between Sen. Whitehouse's stock transaction distribution and the distributions of Senate Finance Committee (SSFI) and Senate Banking Committee

(SSBK). The results are as follows:

$$\text{Cross entropy (Sen. Sheldon Whitehouse, SSFI)} = 0.816$$

$$\text{Cross entropy (Sen. Sheldon Whitehouse, SSBK)} = 3.311$$

These values indicate that Sen. Sheldon Whitehouse's investment portfolio is more similar to Senate Finance Committee in terms of NAICS code distribution, as a lower cross-entropy value represents a closer resemblance between the distributions. This reflects that Sen. Whitehouse's stock portfolio more closely resembles the industry distribution of his own committee, the Senate Finance Committee (SSFI), compared to the Senate Banking Committee (SSBK), to which he does not belong. Also, this suggests that the cross-entropy measure effectively captures the similarity between the industry-level specialization of a committee and the preferences reflected in a congressperson's stock portfolio.

5.2 Paired T-Test: Comparing Assigned and Unassigned Committees

In this subsection, I investigate whether there is a significant difference in the similarity between the industry distributions of Congress members' stock transactions and the industry distributions of their assigned and unassigned committees. To conduct this analysis, I computed the cross-entropy between the NAICS code distribution of stock transactions and committees for the 115th, 116th, and 117th Congresses. I restricted the stock transaction dates to match each congressional term (e.g., for the 115th Congress, from January 2017 to January 2019) to ensure that only transactions during these periods were considered.

Senators and House Representatives are typically assigned to several committees during each congressional term. For each Congress member i, and for each congressional term t, I calculated the cross-entropy $H^t_{i,k}$ between their stock transactions and each committee k (both assigned and unassigned). The objective is to ascertain whether the industry preferences in a Congress member's stock transactions align more closely with the industry specializations of their assigned committees than those of unassigned committees. To summarize these measurements, I calculated the mean cross-entropy value for each Congress member i across all their assigned committees (denoted as $\bar{H}^t_{i,\text{assigned}}$), and the mean cross-entropy value across all their unassigned committees (denoted as $\bar{H}^t_{i,\text{unassigned}}$) for each congressional term t. The means here are taken over all committees k that each Congress member i is assigned or not assigned to

respectively, for each term t.

To test this, I performed a one-sided paired t-test on the differences in these mean cross-entropy values for each congress member i and congressional year t. The null hypothesis for this test was that the mean cross-entropy of assigned committees is less than or equal to that of unassigned committees for each Congress member and Congressional year ($\bar{H}^t_{i,\text{assigned}} \geq \bar{H}^t_{i,\text{unassigned}}$). The alternative hypothesis was that the mean cross-entropy of assigned committees is greater than that of unassigned committees ($\bar{H}^t_{i,\text{assigned}} < \bar{H}^t_{i,\text{unassigned}}$). A rejection of the null hypothesis would thus provide evidence that congressional activities significantly influence stock transaction behavior, indicating that a Congress person's stock trading pattern significantly resembles the committee's industry-level specialization.

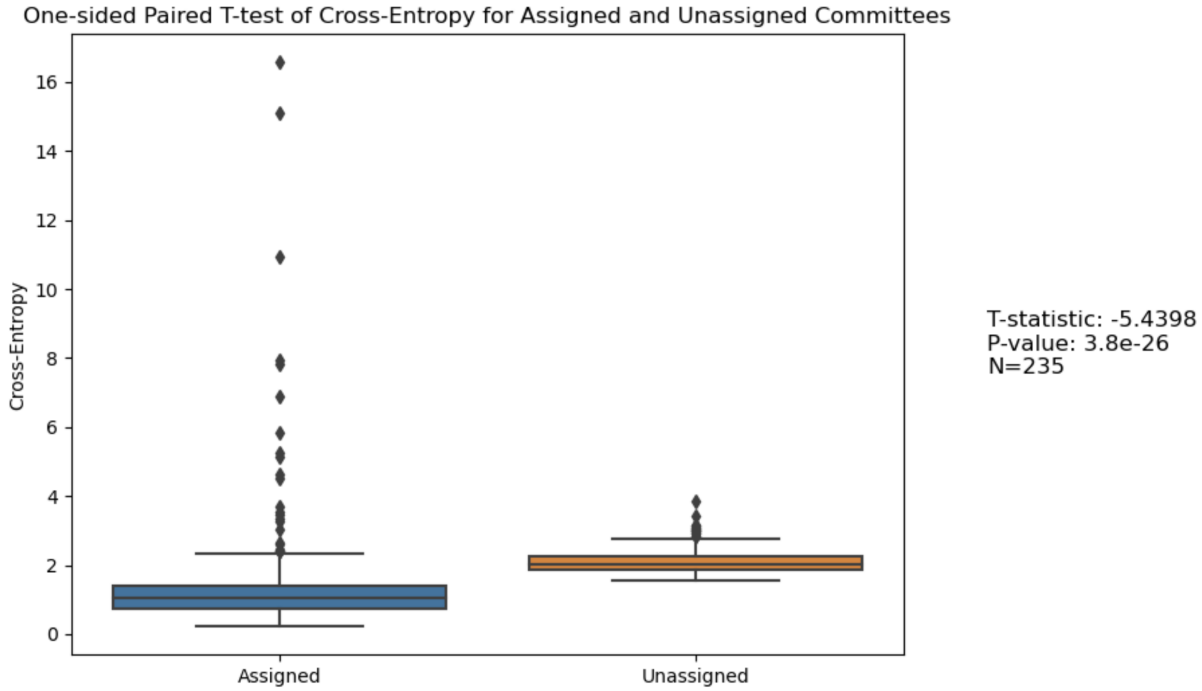


Figure 10: **One-sided Paired t-test results for the cross-entropy of assigned and unassigned committees.** The figure shows the comparison between the average cross-entropy of assigned and unassigned committees, with a sample size of 235 unique pairs of (Congressperson, Congressional year). The significantly lower average cross-entropy for the assigned group suggests that the stock trading patterns of Congress members more closely resemble the industry distribution of their assigned committees compared to unassigned committees.

The results of the one-sided paired t-test are presented in Figure 10, with a sample size of 235 unique pairs of (Congressperson, Congressional year). The statistical test indicates that the average cross-entropy of the assigned committees is significantly lower than that of the unassigned committees. This finding suggests that a Congressperson's stock trading pattern significantly aligns with the industry-level specialization of the committees they are assigned to, supporting the hypothesis that congressional

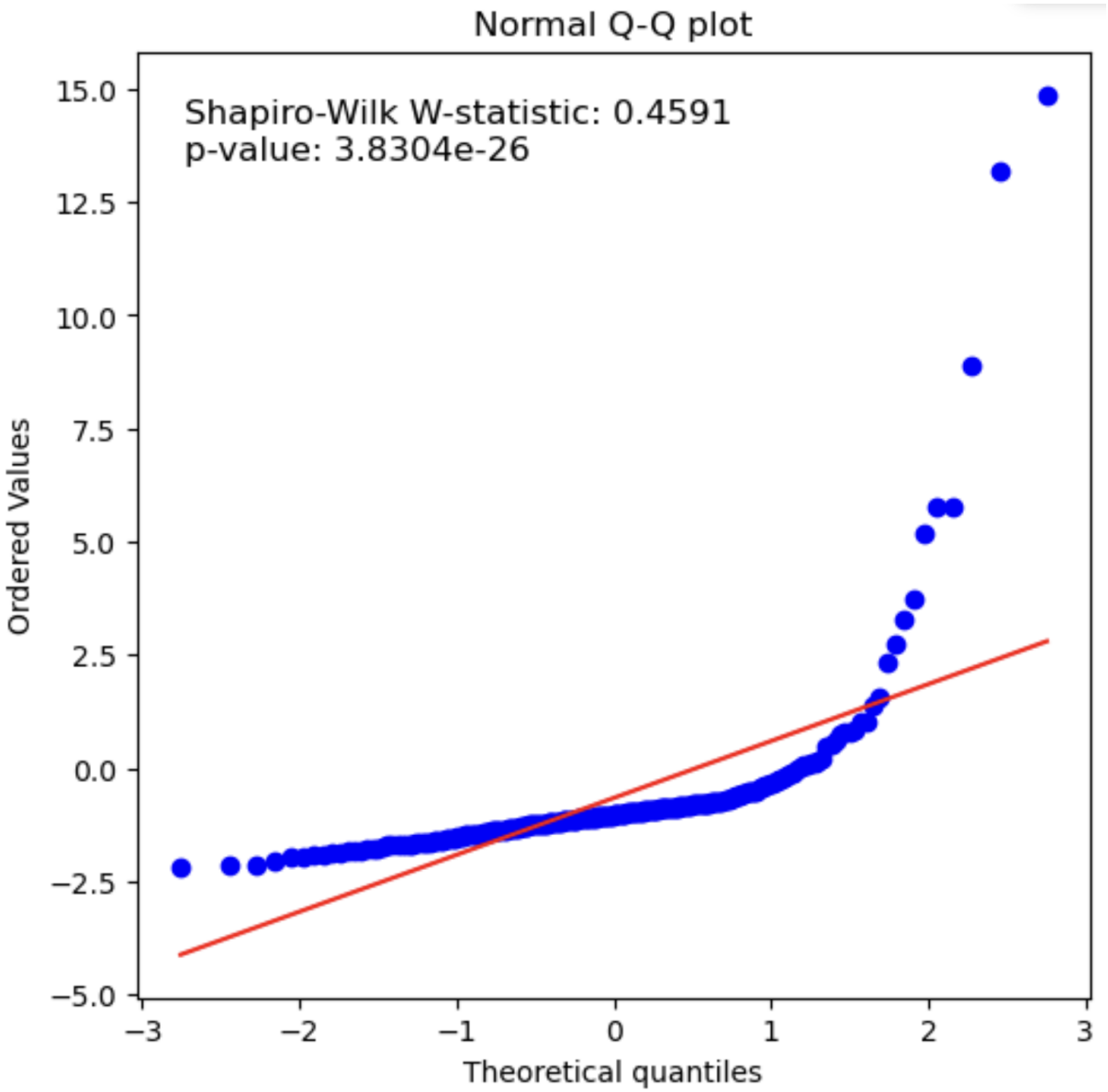


Figure 11: **Normal Q-Q plot of the differences in cross-entropy values:** Significantly small p-value of 3.8304×10^{-26}, decisively rejecting the null hypothesis and suggesting that the differences in cross-entropy are not normally distributed.

activities influence stock transaction behavior.

The paired t-test used in this analysis is based on several assumptions. Firstly, the data must consist of pairs of observations, where each pair represents a particular entity under two conditions or at two time points. In our case, these pairs consist of average cross-entropy values for each Congressperson for each congressional year, under two conditions: assigned and unassigned committees. This pairing is meaningful as it controls for individual-level variation and trends across time, isolating the effect of committee assignment on stock transaction behavior.

Secondly, the paired t-test assumes that the differences between paired observations are independently

and identically distributed. In the context of our study, this would mean that the difference in cross-entropy values between the assigned and unassigned committees for a specific Congressperson in a specific Congressional year should be independent of the differences observed for other Congresspersons or other Congressional years.

However, this assumption could potentially be compromised in our setting. Congresspersons often interact and influence each other, potentially leading to correlated trading behaviors. If one Congressperson's stock trading strategy is influenced by another's, this might induce correlations among the differences in cross-entropy values across pairs, thereby potentially violating the assumption of independence.

Additionally, committee assignments are typically influenced by the specialties and expertise of Congresspersons, which can create a potential confounding effect. Since Congresspersons with similar areas of expertise are likely to be assigned to similar committees, the trading patterns influenced by these assignments could become correlated, posing another challenge to the assumption of independence.

Finally, the paired t-test assumes that the differences between paired observations follow a normal distribution. As illustrated in Figure 11, this assumption appears to be violated in our case, with the differences not closely following the reference line in the Q-Q plot.

Despite the limitations of using a paired t-test, the results indicate that the average cross-entropy for the assigned group is at least descriptively lower than that of the unassigned group. This suggests that the stock trading patterns of Congress members more closely resemble the industry distribution of their assigned committees compared to unassigned committees. This result is directly opposite to the findings of Eggers and Hainmueller (2014), which conclude that "*...In contrast, we find no evidence that members disproportionately invest in companies to which they are connected through their committee assignments...*(p.4)". This result, on the other hand, suggests that there exists a clear resemblance between the industry-level bias in Congresspersons' trading and their committees' industry-level specialization.

There could be several reasons for this discrepancy. For example, the data range is different: Eggers and Hainmueller (2014) consider the period from January 1, 2004, to December 31, 2008, while in this case, we consider the 115th, 116th, and 117th Congresses, which correspond to the years 2017 to 2022. However, more fundamentally, the difference may reside in the measurement approach.

Eggers and Hainmueller (2014) use a binary encoding to indicate whether a specific firm has engaged in lobbying behavior on a certain bill that is referred to a particular congressional committee. They then design a linear regression model to predict the weight of that specific firm's stock in a congressperson's

entire investment portfolio. In this way, they investigate whether there is a relationship between a firm's lobbying activities on bills assigned to a committee and the investment decisions of congresspersons who are members of that committee. However, this approach only captures a specific company's lobbying behavior rather than industry-level information in its entirety. For example, multiple firms can lobby on the same bill assigned to a certain committee, then a congressperson on that committee can evaluate more broadly how this could impact the industry as a whole and selectively redesign their own portfolio. This means that there is no reason to assume that a congressperson would buy a specific stock that is being lobbied for — instead, it is more plausible to understand that such lobbying provides more detailed context about a specific industry, which the congressperson can utilize in their personal financial investment decisions.

Therefore, while the cross-entropy approach, which directly measures the industry-level similarity between a committee's interests and a congressperson's portfolio, provides a more intuitive and comprehensive understanding of the potential influences on a congressperson's investment behavior, it is not without limitations. The approach allows us to discern a relationship between the industry-level specialization of committee assignments and the industry-level bias in Congresspersons' stock trading, which contributes to our understanding of these influences. However, it is important to recognize that confounding factors could affect both committee assignments and the resemblance of stock trading to the committee's industry-level specialization. For example, scholarly consensus suggests that committee assignments are often based on a congressperson's existing knowledge and expertise (Boros and Fenno, 1968; Gilligan and Krehbiel, 1989; Kiewiet and McCubbins, 1991; Krehbiel, 1992; Curry, 2019). Consequently, it's possible that the observed correlation between a congressperson's trading patterns and their committee's industry specialization may not entirely result from knowledge gained through congressional activities, but may also be influenced by pre-existing expertise and interests. This introduces a confounding factor, making it challenging to disentangle the effects of pre-existing expertise from the potential influence of congressional committee assignments on trading decisions. The relationship between a congressperson's industry specialization, their committee assignments, and their stock trading patterns thus warrants further exploration and calls for more nuanced analysis.

Another potential limitation of this analysis is the difficulty in collecting NAICS codes for ETFs and Mutual Funds, which comprise approximately 60% of the stock transactions in our dataset. Although each ETF or Mutual Fund's website provides information about their holdings, it was challenging to

establish a generalizable pattern across different providers to obtain the composition of stocks held by these funds and their corresponding NAICS codes. Consequently, this section focuses on individual stocks and their corresponding NAICS codes, which might not fully capture the reality of Congress members' investments. However, the findings still indicate that the individual stock trading behaviors of Congress members are significantly influenced by their assigned committees.

In addition to our primary findings, it's important to acknowledge an interesting observation from Figure 10: the variance in average cross-entropy for assigned committees is considerably higher than that for unassigned committees. This suggests that the stock trading behavior of a subset of Congresspersons deviates significantly from the industry specialization of their assigned committees. This pattern opens up a fascinating potential interpretation.

The conventional political science theory posits that the primary motivation for congressional members is re-election (Mayhew, 1975; Fenno, 1977). From this perspective, Congresspersons might demonstrate caution in selecting stocks to trade to avoid the perception of conflict of interest with their assigned committees' focus industries. Essentially, they may strive to prevent any appearance of using insider knowledge gained from committee assignments for personal financial gain, which could negatively affect their chances of re-election. This behavior underscores the importance of considering not just direct legislative and financial interests but also political strategy and public perception in understanding the investment behavior of Congresspersons.

6 Predicting Congressional Stock Transactions using Graph Neural Networks

In the previous section, therefore, I discussed the limitations of the linear prediction model used by Eggers and Hainmueller (2014), which employed a binary encoding of lobbying and committee assignments to predict the weight of a specific firm's stock in a congressperson's portfolio. I pointed out that this model did not fully capture the complex interactions between different entities involved in congressional activities, particularly at the industry level. However, I acknowledge that the model was an attempt to explain congressional stock transactions using potentially explanatory components such as district, PAC, lobbying, and committee assignments.

It's important to note that while the cross-entropy approach in Section 5 revealed a clear resem-

blance between Congresspersons' stock trading behavior and their assigned committees' industry-level specialization, this approach does not directly answer whether this resemblance originates from knowledge gained through congressional activities or from the Congresspersons' expertise and experience before their congressional tenure.

In this section[10], I propose to use a graph neural network (GNN) (Zhou et al., 2020; Wu et al., 2020; Scarselli et al., 2008; Zhang et al., 2019) to predict congressional stock transactions using the information embedded in the congressional activities captured in the data explained in Section 3. The GNN approach is uniquely equipped to handle this task because it can model the complex relationships among various entities involved in congressional activities, all of which are naturally structured as a graph.

By using GNN, we can design a model that directly consumes the congressional graph that captures legislative-related activities of different entities, thereby enabling us to test the predictability of congressional trading behavior based on these activities. This will help us isolate the influence of congressional activities on stock trading from pre-congressional expertise and other confounding factors, which is a significant step forward in our understanding of the interplay between committee assignments, congressional activities, and stock transactions. By leveraging a graph representation of the relationships between firms, bills, committees, and congresspersons, we can train a GNN to predict whether a congressperson is likely to buy a particular stock.

The advantage of using a Graph Neural Network (GNN) over a traditional approach such as including industry dummy variables in a regression model can be attributed to several reasons.

Firstly, a GNN can integrate complex interactions between entities along with their inherent attributes simultaneously in a way that traditional regression models can't accomplish. In our case, we have a multitude of entities such as Congresspersons, committees, bills, industries, and stocks, each with their unique characteristics, represented as node-level attributes in the graph. Additionally, their relationships, expressed as edges in the graph, embody another layer of intricate information. By modeling these entities and their interactions as a graph and applying GNN, we can concurrently consider node attributes and graph topology, enabling a more nuanced understanding of the congresspersons' decision-making processes in their stock transactions. This holistic approach of GNN allows us to capture these complex relationships in a more natural and efficient way.

Secondly, GNNs can better handle the heterogeneous and high-dimensional nature of our data. A

[10]Reproducible code for this section is available at `https://github.com/syyunn/gnnex/blob/main/hetero/train_kfold_auto.py`

traditional approach using industry dummy variables is limited in its ability to handle high-dimensional categorical variables. Furthermore, this approach treats each industry as a separate and independent entity, ignoring any potential correlations or dependencies between industries. On the other hand, GNNs can handle high-dimensional data and also account for the interconnectedness of entities.

Finally, GNNs are capable of learning and evolving over time, allowing them to adapt and improve their predictions as new data comes in. This is especially useful in our context, where the behavior and preferences of Congresspersons, the focus of committees, and the performance of industries and stocks can change over time.

In conclusion, using GNNs to predict congressional stock transactions provides a more nuanced and dynamic understanding of the intricate relationships among various entities involved in congressional activities, leading to more accurate predictions.

6.1 Designing a Binary Classifier with Graph Neural Networks

To predict congressional stock transactions using a graph neural network (GNN) approach, I design a binary classifier that takes as input a graph G, a congressperson and a ticker (stock symbol). The classifier, denoted as $f(G, \text{congressperson}, \text{ticker})$, will output a binary prediction of either 0 or 1, indicating whether an edge (a buy or sell relationship) exists between the given congressperson and the ticker.

The hidden representations (Rauber et al., 2016; Das et al., 2020)o f the congressperson and the ticker, denoted as $h_{\text{congressperson}}$ and h_{ticker} respectively, are obtained as outputs of the GNN model. The main task in this approach is to train the GNN model to learn a computational graph that generates "good" representation of the congressperson and the ticker, $h_{congressperson}$ and h_{ticker}, which involves how to effectively encode the information embedded in the network to perform the downstream task of binary classification (Féraud and Clérot, 2002).

To design the classifier, a probabilistic modeling approach is used that comprises of a sigmoid function applied to the logit, which is the output of the model. The logit of the model is obtained by passing the representation learned by the GNN, $h_{congressperson}$ and h_{ticker}, to an MLP (Multi-layer perceptron) (Gardner and Dorling, 1998; Tang et al., 2016) that maps the representations of the congressperson and the ticker to a single logit. In other words, the MLP takes as input the representations of the congressperson and the ticker learned by the GNN, and outputs a logit that will be used to compute the probability of the existence of edge between them. MLP is simply an affine transformation over

the concatenation of two representations, $h_{congressperson}$ and h_{ticker}, follwed by a non-linear activation function (Lu and Lu, 2020), which is ReLU (Agarap, 2018) in this case.

Formally, the logit of the classifier is defined as:

$$\begin{aligned}
\text{logit} &= \text{MLP}\,(x) \text{ where} \\
\text{MLP}(x) &= \text{ReLU}(Ax + b) \\
x &= \text{concat}\,(h_{\text{congressperson}}, h_{\text{ticker}}) \\
A &\in \mathbb{R}^{(d+d)\times 1} \\
b &\in \mathbb{R}^1
\end{aligned}$$

· logit: This is the output of the model. It's a transformed version of the probability that a congressperson would invest in a particular stock. In this binary classification problems, the logit (also known as log-odds) is the logarithm of the odds p/(1-p) where p is the probability of a positive event that congressperson trades such stock.

· MLP: This stands for Multi-Layer Perceptron, a type of artificial neural network. In this case, it's a function that takes the concatenated embeddings of a congressperson and a ticker as input and produces a logit as output.

· $h_{\text{congressperson}}$, h_{ticker}: These are the vector embeddings of a congressperson and a ticker symbol, respectively. Each vector embedding represents the congressperson or ticker in the learned feature space. The embeddings are of dimension d.

· ReLU$(Ax+b)$: This is a Rectified Linear Unit activation function applied to a linear transformation of the input. ReLU is defined as $\text{ReLU}(x) = \max(0, x)$ and is used to introduce non-linearity into the model.

· concat: This is a function that concatenates (joins together) two vectors. Here, it concatenates the embeddings of a congressperson and a ticker symbol into a single vector of shape $1 \times 2d$, where d is the dimension of the individual embeddings. This shape is designed to be compatible with the weight matrix A which is of shape $2d \times 1$.

· A: This is a weight matrix for the linear transformation in the MLP. It's of shape $(d+d)\times 1$, meaning it takes a vector of size $2d$ and transforms it to a vector of size 1.

- b: This is a bias term for the linear transformation in the MLP. It's added to the output of the linear transformation before the ReLU activation is applied.

- d: This represents the dimensionality of the vector embeddings of the congressperson and ticker. $d + d$ is therefore the dimensionality of the concatenated input vector.

The sigmoid function is then applied to the logit to obtain a probability value:

$$\text{prob } = \sigma(\text{ logit })$$

where $\sigma(x)$ is the sigmoid function. The probability value indicates the likelihood of an edge existing between the given congressperson and the ticker. If the probability value is above a certain threshold, we predict that an edge exists between them, otherwise we predict that there is no edge.

Then remaining task is how to design a GNN model that can effectively learn the representations of the congressperson and the ticker, $h_{\text{congressperson}}$ and h_{ticker}, respectively, which can be used to train the classifier. In the following section, I will discuss the design of the GNN model.

6.2 Design of the Graph Neural Network Architecture

To obtain the representations $h_{\text{congressperson}}$ and h_{ticker}, I use a GNN approach that is designed to handle the complexity and dynamics of the congressional graph. The GNN approach is based on the idea of message passing and updating (Zhou et al., 2020; Wu et al., 2020), which is a process of aggregating information from the neighbors and updating the representation of each node accordingly.

In the case of the congressional graph, I use an edge-conditioned convolution GNN model (Gilmer et al., 2017; Simonovsky and Komodakis, 2017), which takes into account the edge attributes, such as the date, to better capture the complex relationships in the graph. The message passing, aggragation and updating in this model is defined as:

$$\mathbf{h}_i' = \mathbf{\Theta}\mathbf{h}_i + \sum_{j \in \mathcal{N}(i)} \mathbf{MLP}\left(\mathbf{e}_{i,j}\right) \cdot \mathbf{h}_j$$

where $\mathbf{h}_i$ and $\mathbf{h}_j$ are the representations of nodes i and j, respectively, $\mathbf{e}_{i,j}$ is the edge attribute between nodes i and j, $\mathcal{N}(i)$ is the set of neighbors of node i, $\mathbf{\Theta}$ is a learnable matrix of size $d \times d$, where d is the dimension of the representation space, and $\mathbf{MLP}$ takes the edge attribute $\mathbf{e}_{i,j}$ as input and outputs a weight matrix of size $d \times d$. This weight matrix is then multiplied with the representation

$\mathbf{h}_j$ of the neighbor node j to obtain a message $\mathbf{m}_{i,j} = \mathbf{MLP}(\mathbf{e}_{i,j}) \cdot \mathbf{h}_j$. In the updating step, the message from each neighbor node is aggregated by summing them up, and the resulting sum is added to the current representation $\mathbf{h}_i$ of node i multiplied by the learnable parameter matrix $\mathbf{\Theta}$ to obtain the updated representation $\mathbf{h}'_i$.

In the case of the congressional graph, the edge attribute $\mathbf{e}_{i,j}$ represents the relationship between nodes i and j at a specific date, which is represented as the elapsed time from a reference date (in this case, January 1, 2016). However, in our case, we have different types of edges, which means that $\mathbf{MLP}(\mathbf{e}_{i,j})$ should be differently defined for different types of edges. This is because parsing the information of start and end dates should be considered differently across different edge types. For example, committee assignments of a congressperson that occurred over a specific congressional year should be considered differently from the date information that a certain firm lobbied on a certain bill. To account for this, I used the expanded version of the above formula:

$$\mathbf{h}_i^{(l+1)} = \mathbf{\Theta}^{(l)}\mathbf{h}_i^{(l)} + \sum_{j \in \mathcal{N}(i)} \mathrm{MLP}_k^{(l)}\left(\mathbf{e}_{i,j}^{(k)}\right) \cdot \mathbf{h}_j^{(l)}$$

Here, l represents a layer, and we can expand the expressivity of such message passing and updating process by stacking up the repeated layers of this operation. This allows the model to learn a more complex representation of each node, which is essential for capturing the intricate relationships in the congressional graph. Experimentally, I found that using 2 layers of message passing and updating was sufficient to learn the best representation of each node and used this configuration for the GNN model.

In conclusion, our GNN aims to learn the optimal parameter set that defines $\mathbf{\Theta}^{(l)}$ and $\mathrm{MLP}_k^{(l)}$ to output the best representations $\mathbf{h}_i^{(l)}$ and $\mathbf{h}_j^{(l)}$, which helps to perform the downstream task successfully. In this case, the downstream task is generating the best logit in the prediction head, $\mathrm{MLP}(\mathbf{h}_{\text{congressperson}}, \mathbf{h}_{\text{ticker}})$. It is important to note that the representations $\mathbf{h}_i^{(l)}$ and $\mathbf{h}_j^{(l)}$ are initialized randomly before they are provided into the first layer of the message passing and updating process. Through multiple rounds of message passing and updating, the GNN is tuned to output the best representation of each node that scores the best performance as possible in binary classification of edge existence.

6.3 Training & Evaluation of the GNN

6.3.1 Dataset Preparation

In the context of our GNN architecture, the goal is to predict the existence of edges between two nodes, a task commonly known as link prediction. To train the GNN for this task, the dataset must be prepared for training and evaluation (test). The dataset consists of a total of 24,675 edges, which represent the relationship (congressperson, buy-sell, ticker).

To create a balanced dataset for the link prediction task, the dataset is divided into a train and test set with an 8:2 ratio, resulting in 19,740 instances for training and 4,935 instances for testing. The network is then trained using the 19,740 instances and its performance is evaluated on the 4,935 test instances.

In addition, to ensure a balanced dataset, the same number of randomly sampled negative edges (Yang et al., 2020) is prepared. These negative edges are created by randomly selecting pairs of nodes (congressperson and ticker) that do not have a connection in the original dataset. This results in a total of 39,480 edges for training and 9,870 edges for testing. Including both positive and negative examples in the training process helps the model to better differentiate between true and false existence of edges between congressperson and tidcker nodes, improving its ability to predict links in the graph.

6.3.2 Training of the GNN

For the training of the GNN, a two-layer GNN architecture, as $l = 2$, is employed. Additionally, node embeddings h_i are represented as vectors in a 64-dimensional space ($h \in \mathbf{R}^{64}$). This hyperparameter is also set experimentally.

In order to measure the performance of the model during the training process, binary cross-entropy loss is used as the loss function. Binary cross-entropy loss is particularly suitable for binary classification problems (Ruby and Yendapalli, 2020), such as link prediction (Zhang and Chen, 2018), where the goal is to differentiate between the presence and absence of a connection between two nodes. This loss function quantifies the difference between the predicted probabilities and the true labels, and penalizes the model for incorrect predictions. Formally, the binary cross-entropy loss for a set of samples is defined as:

$$L = -\sum_{i=1}^{N} \left(y_i \cdot \log\left(p_i\right) + \left(1 - y_i\right) \cdot \log\left(1 - p_i\right) \right)$$

where L represents the total binary cross-entropy loss. N is the total number of samples. y_i is the true label for the ith sample (1 for the presence of a connection, and 0 for the absence of a connection). p_i is the predicted probability of a connection existing between two nodes for the ith sample.

By minimizing the binary cross-entropy loss, the GNN learns to accurately predict the existence or non-existence of links in the network, ultimately improving its performance on the link prediction task. For the minimization, the Adam optimizer (Kingma and Ba, 2014) with stochastic gradient descent (SGD) is utilized. SGD is an iterative optimization algorithm that updates the model's parameters based on a random sample (or minibatch) of training data in each iteration (Amari, 1993). This approach helps in converging faster and reduces the impact of noisy gradients, thus improving the optimization process. Adam is an adaptive learning rate optimization algorithm, combining the advantages of two other popular optimization methods, AdaGrad and RMSProp (Kingma and Ba, 2014). This optimizer is well-suited for large-scale problems and is known for its ability to efficiently handle noisy and sparse gradients, making it a suitable choice for training GNNs.

To obtain a more robust estimation of the model's performance and uncertainty, a 5-fold cross-validation (Hastie et al., 2001) is performed. In this approach, the entire dataset is randomly split into five equal-sized chunks. For each fold, one chunk is used as the test set, while the remaining chunks are combined to form the training set. This process is repeated five times, with each chunk being used once as the test set. This technique allows for a better understanding of the model's performance across different subsets of the dataset and provides uncertainty statistics of overall prediction performance.

6.3.3 Evaluation & Ablation Study

In this study, we conducted a link-prediction (Zhang and Chen, 2018) task to predict the existence of an edge between a congressperson and a ticker, symbolizing the trade relationship - whether the given congressperson would sell or buy a particular stock. This task was performed using a variety of edge types, and the performance was evaluated using two metrics: accuracy and Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

The results of this evaluation are depicted in Figures 12 and 13. With all edge types included, the model achieved an accuracy of approximately 81% and an AUC-ROC of 0.89. These results indicate that the model was generally effective at predicting the stock transactions of congresspersons.

To further understand the importance of each edge type, I conducted an ablation study, where I

systematically removed each edge type from the training and testing data and observed the resulting performance drop. The most significant drop in performance was observed when the edge type ('congressperson', 'assignment', 'committee') was removed. This resulted in a decrease in accuracy from 81% to 67%, and a decrease in AUC-ROC from 0.89 to 0.76. This suggests that the ('congressperson', 'assignment', 'committee') edge type carries significant information for predicting a congressperson's stock transactions.

In comparison, the removal of other edge types, such as ('bill', 'assigned_to', 'committee'), or ('ticker', 'lobbies_on', 'bill'), resulted in less dramatic performance drops. This further underscores the relative importance of the ('congressperson', 'assignment', 'committee') edge type in this prediction task.

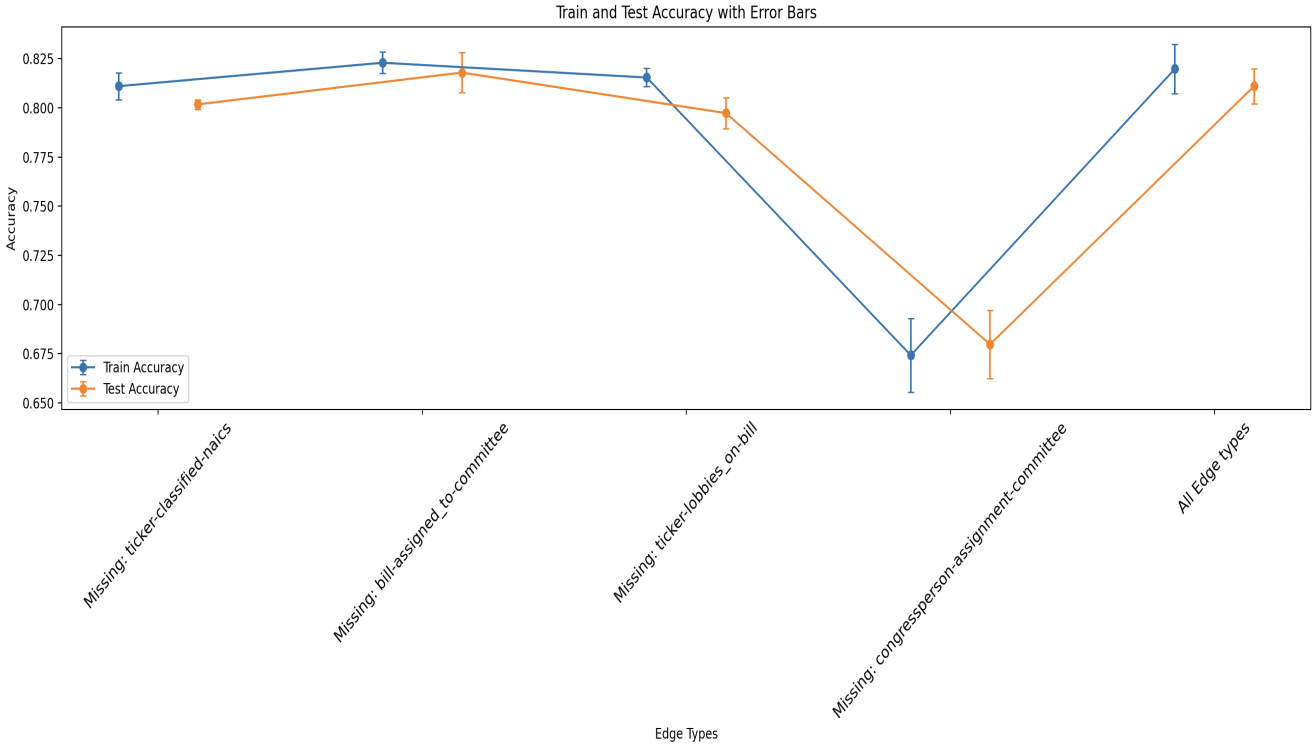


Figure 12: **Accuracy drop for different edge types.** The figure shows the accuracy of the model with all edge types included and with each edge type removed one at a time. With all edge types included, the model achieved an accuracy of approximately 81%. The most significant drop in accuracy, to 67%, was observed when the edge type ('congressperson', 'assignment', 'committee') was removed. This suggests that the ('congressperson', 'assignment', 'committee') edge type carries significant information for predicting a congressperson's stock transactions.

To further quantify the importance of each edge type, I employed the concept of Shapley values (Winter, 2002; Hart, 1989; Littlechild and Owen, 1973), a concept borrowed from cooperative game theory. In this context, each edge type can be considered as a player in a cooperative game, where the "payout" is the performance of the model.

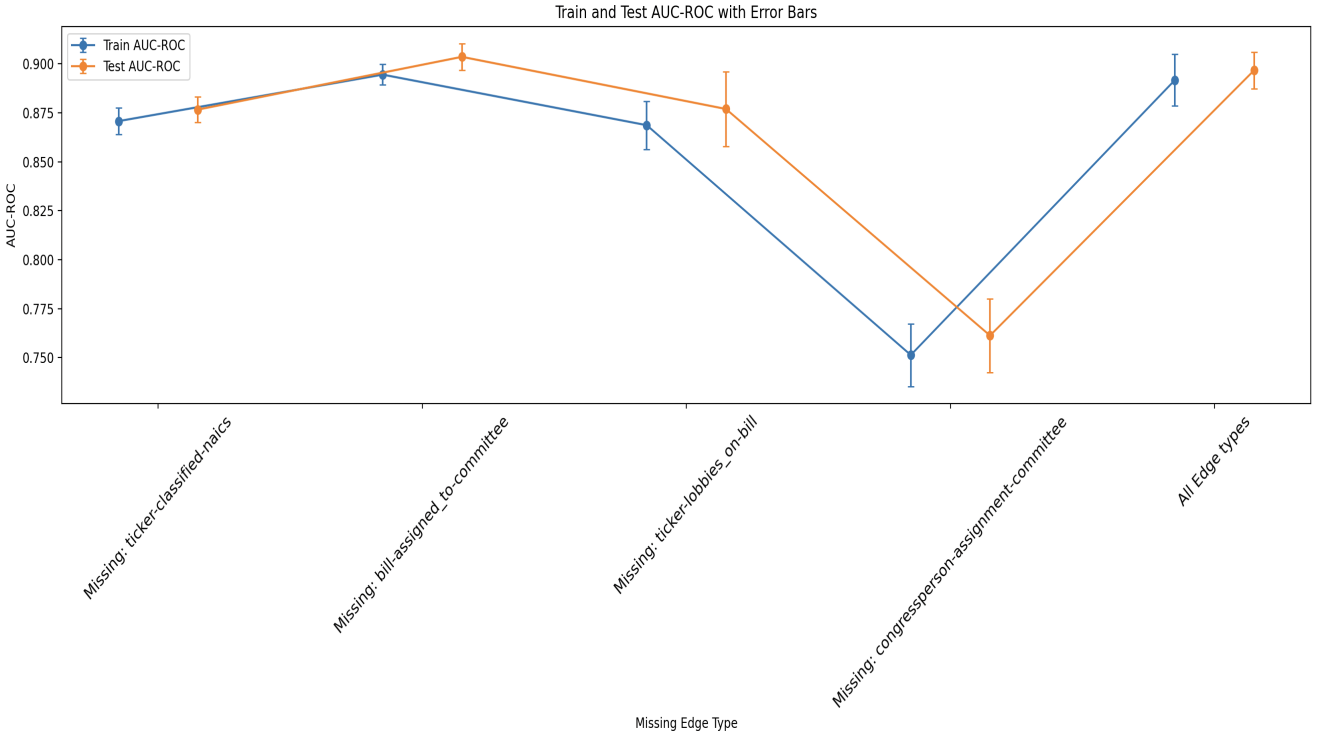


Figure 13: **AUC-ROC drop for different edge types.** The figure shows the AUC-ROC of the model with all edge types included and with each edge type removed one at a time. With all edge types included, the model achieved an AUC-ROC of approximately 0.89. The most significant drop in AUC-ROC, to 0.76, was observed when the edge type ('congressperson','assignment', 'committee') was removed. This suggests that the ('congressperson', 'assignment', 'committee') edge type carries significant information for predicting a congressperson's stock transactions.

$$\varphi_i(v) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(n - |S| - 1)!}{n!} (v(S \cup \{i\}) - v(S))$$

Here, $\varphi_i(v)$ is the Shapley value for edge type i, representing the average marginal contribution of edge type i to the performance of the model, considering all possible combinations of edge types. N is the set of all edge types, not the total number of edges. In our case, there are four edge types, so N is 4. S is a subset of N that does not include edge type i, $|S|$ is the number of edge types in subset S, and n is the total number of edge types. $v(S \cup i)$ and $v(S)$ represent the performance of the model when edge type i is added to and excluded from the subset S of edge types, respectively. This means that the Shapley value indicates how much each edge type contributes to the performance of the model, which in our case is measured by prediction accuracy or AUC-ROC.

The Shapley values were computed over all $16 (= 2^4)$ possible combinations of the four different edge types, with each combination evaluated through a five-fold cross-validation process. The uncertainty associated with each Shapley value, as reflected in the standard deviation across the five folds, provides

an indication of the stability of the Shapley value estimates. The results of this analysis are shown in Figure 14.

These findings indeed underline the crucial role of the (congressperson', assignment', 'committee') edge in predicting congresspersons' stock transactions. Nevertheless, it's worth noting that these results are contextually bound to our graph design. The importance of committee assignments in predicting stock transactions might be somewhat overemphasized due to the absence of other possible edges connecting congresspersons to stocks, such as bill co-sponsorship, business relations, or previous occupation. Including additional edges reflecting other aspects of congressional activities in future work might provide a more nuanced view of the importance of committee assignments and other factors in predicting congresspersons' stock trading behavior."

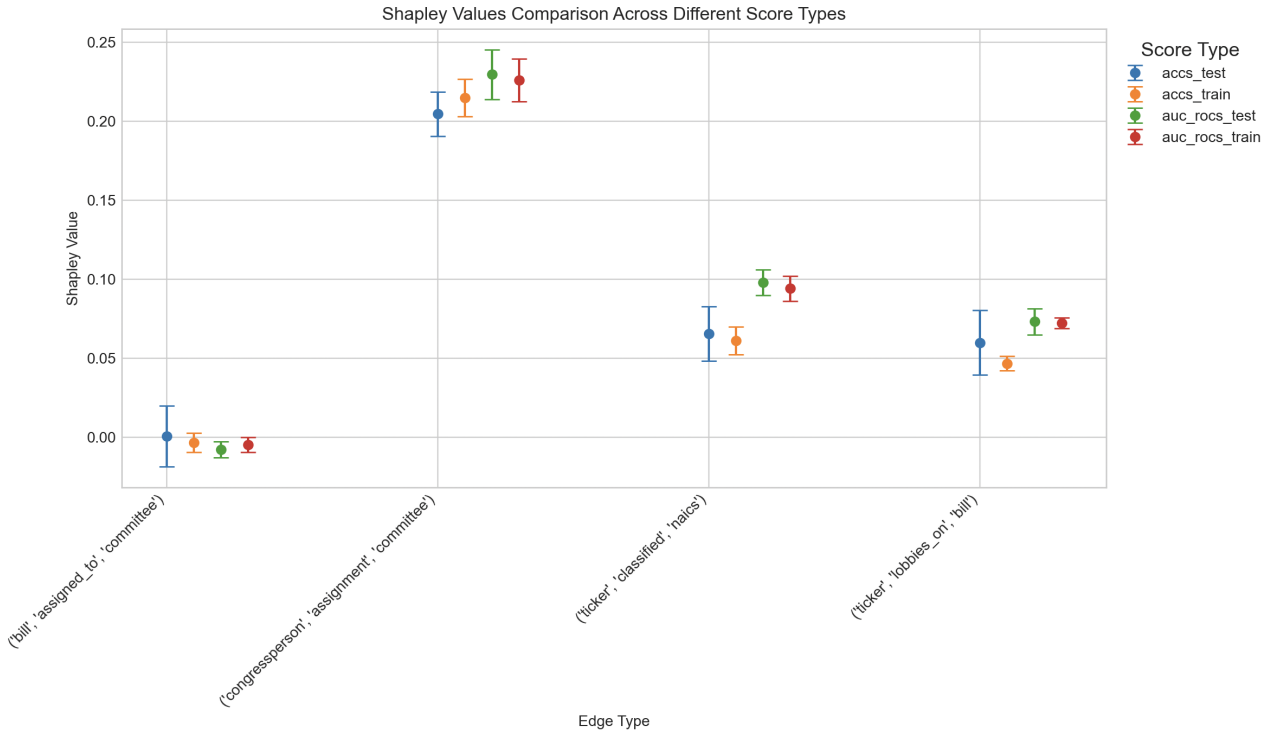


Figure 14: **Shapley values for different edge types.** The figure shows the Shapley values for each edge type, computed over all $16(2^4)$ possible combinations of the four different edge types. The Shapley value for an edge type represents its average marginal contribution to the performance of the model, considering all possible combinations of edge types. The most important feature, according to the Shapley value analysis, was ('congressperson', 'assignment', 'committee'), followed by ('ticker', 'classified_as', 'naics') and ('ticker', 'lobbies_on', 'bill'). This further reinforces the conclusion that the ('congressperson', 'assignment', 'committee') edge type plays a crucial role in predicting congressperson's stock transactions.

In the Shapley value analysis, I observed that the edge type ('bill', 'assigned_to', 'committee') had a Shapley value of zero or even negative. This suggests that this type of edge does not contribute to

increasing the performance of the model. In fact, it appears to harm the performance when included.

The reason for the zero or negative contribution of the edge type ('bill', 'assigned_to', 'committee') is not immediately clear and warrants further investigation. One possible explanation could be that bills can be assigned to different committees, making this information more complex and potentially harder for the model to utilize effectively. In contrast, the firm-level lobbying information and industry-level classification of firms provided by the edge types ('ticker', 'classified_as', 'naics') and ('ticker', 'lobbies_on', 'bill') are more straightforward. These edge types may allow the model to more easily discern patterns in company behavior and use this information to make accurate predictions.

6.4 Interpreting Predictions with GNNExplainer

[11]To further explain which nodes and edges the trained model focuses on to output such predictions, I used GNNExplainer (Ying et al., 2019), which trains soft node and edge masks that can be applied to the original graph to extract the subgraph most relevant to the prediction.

The detailed implementation of GNNExplainer involves modifying the update rule for the node representations in the GNN. The original update rule is:

$$\mathbf{h}_i^{(l+1)} = \mathbf{\Theta}^{(l)}\mathbf{h}_i^{(l)} + \sum_{j \in \mathcal{N}(i)} \text{MLP}_k^{(l)}\left(\mathbf{e}_{i,j}^{(k)}\right) \cdot \mathbf{h}_j^{(l)}$$

In the modified update rule, we introduce soft node and edge masks, denoted by m_i and $m_{i,j}$ respectively, which are element-wise multiplied with the node and edge representations:

$$\mathbf{h}_i^{(l+1)} = m_i \cdot \mathbf{\Theta}^{(l)}\mathbf{h}_i^{(l)} + \sum_{j \in \mathcal{N}(i)} m_{i,j} \cdot \text{MLP}_k^{(l)}\left(\mathbf{e}_{i,j}^{(k)}\right) \cdot \mathbf{h}_j^{(l)}$$

The soft masks are continuous values between 0 and 1, as opposed to hard masks which are either 0 or 1. This allows us to optimize the masks using stochastic gradient descent (SGD).

The objective of the optimization is to minimize the L2 loss between the predictions of the original graph and the masked graph, denoted by y_{original} and y_{masked} respectively:

$$\mathcal{L} = \| y_{\text{original}} - y_{\text{masked}} \|^2 + \lambda \cdot \left(\|m_i\|_1 + \|m_{i,j}\|_1 \right)$$

[11]Reproducible code for this subsection is available at `https://github.com/syyunn/gnnex/blob/main/hetero/explain_edge.py`

Here, λ is a regularization parameter that controls the complexity of the subgraph by encouraging sparsity in the masks. For this study, I used a value of 0.01 for λ.

The masks are trained separately for each prediction, which makes the method less scalable but provides insights into which nodes and edges are important for mimicking the original model's prediction. After training the node and edge masks, I can generate a subgraph by applying the masks to the original graph. The complexity of the subgraph can be controlled by setting a cutoff level for the mask values, or by adjusting the regularization parameter λ. Figures 15 and 16 provide examples of the output from GNNExplainer for specific stock transactions.

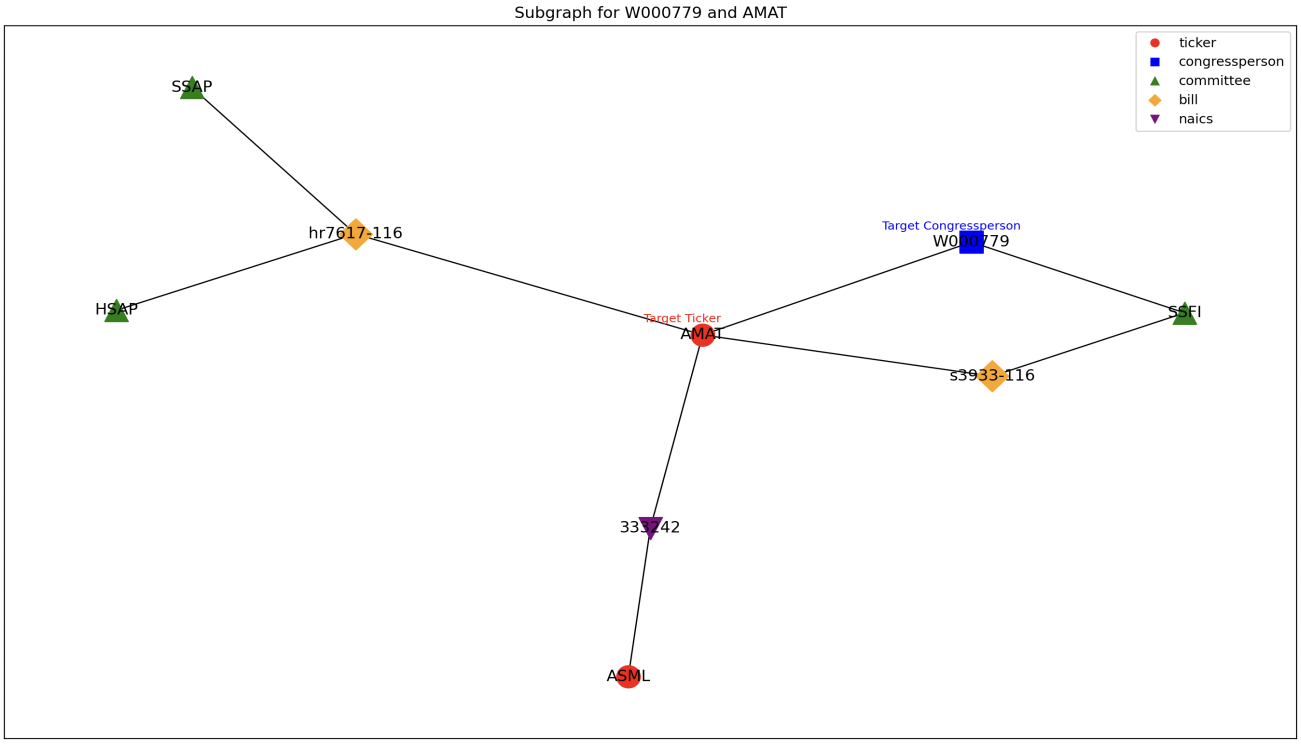


Figure 15: **GNNExplainer output for Senator Ron Wyden's transaction of AMAT's stock.** The figure shows the subgraph extracted from the entire graph using the node and edge masks trained by the GNNExplainer. The GNNExplainer identified S3933-116 (the CHIPS Act) and HR7617-116th among the bills that AMAT lobbied on, NAICS code 333242 (Semiconductor Machinery Manufacturing) among the NAICS code classifications of AMAT, and ASML, among the firms classified as 3333242 as the most influential factors for this transaction.

Figure 15 focuses on Senator Ron Wyden's transaction of Applied Materials Inc. (AMAT)'s stock. To generate the subgraph from the entire graph, I applied the node and edge masks trained by the GNNExplainer. This process involved selecting the nodes and edges with the highest scores from the masks. For instance, among all 56 bills that AMAT lobbied on, I selected the two bills that had the highest scores in the edge mask. Similarly, among the two NAICS code classifications of AMAT, I selected

the NAICS code 333242 (Semiconductor Machinery Manufacturing), which had the highest score in the edge mask.

The GNNExplainer successfully identified the most relevant bill for this transaction, S.3933-116, the CHIPS Act, which subsidizes the US semiconductor industry. Interestingly, the GNNExplainer also highlighted H.R.7617-116, a more general appropriations act, titled "Defense, Commerce, Justice, Science, Energy and Water Development, Financial Services and General Government, Labor, Health and Human Services, Education, Transportation, Housing, and Urban Development Appropriations Act, 2021 ". While this bill may not be directly related to subsidization of the semiconductor industry, it is indicative of the broader legislative environment. It's worth noting that the National Defense Authorization Act (NDAA) for Fiscal Year 2021, which is often associated with appropriations for the semiconductor industry, was also part of the data. However, the GNNExplainer did not identify it as a highest score node for this particular transaction. This could be due to a variety of reasons, such as the complexity of the appropriations process or the indirect relationship between the NDAA and H.R.7617-116.

In addition to identifying relevant bills, the GNNExplainer also provided insights into the industry context of Senator Wyden's transaction of AMAT's stock. The NAICS code 333242, which corresponds to Semiconductor Machinery Manufacturing, includes four different companies: Applied Materials, ASML LLC (ASML), Azenta Inc (AZTA), and Tokyo Electron America Inc (TOELY). The GNNExplainer ranked ASML as the most relevant node for this transaction. This makes sense given the industry dynamics. While Azenta is a semiconductor company, it primarily focuses on bio-related semiconductor products, which may not be as directly relevant to AMAT's business. Tokyo Electron, on the other hand, is a much smaller firm compared to ASML or AMAT. Most importantly, ASML and AMAT are known to have a competitive relationship, with AMAT consistently striving to capture market share from ASML. Therefore, the GNNExplainer's identification of ASML as the most relevant node for this transaction is consistent with the industry context.

As the chair of the Senate Finance Committee (SSFI), Senator Wyden has been a key player in initiatives related to the semiconductor industry. Despite the unexpected selection of H.R.7617-116 by the GNNExplainer, the overall results still highlight the relevance of Senator Wyden's legislative activities and industry context to his stock transactions.

Figure 16 presents another example, focusing on Senator Pat Roberts's transaction of Amazon

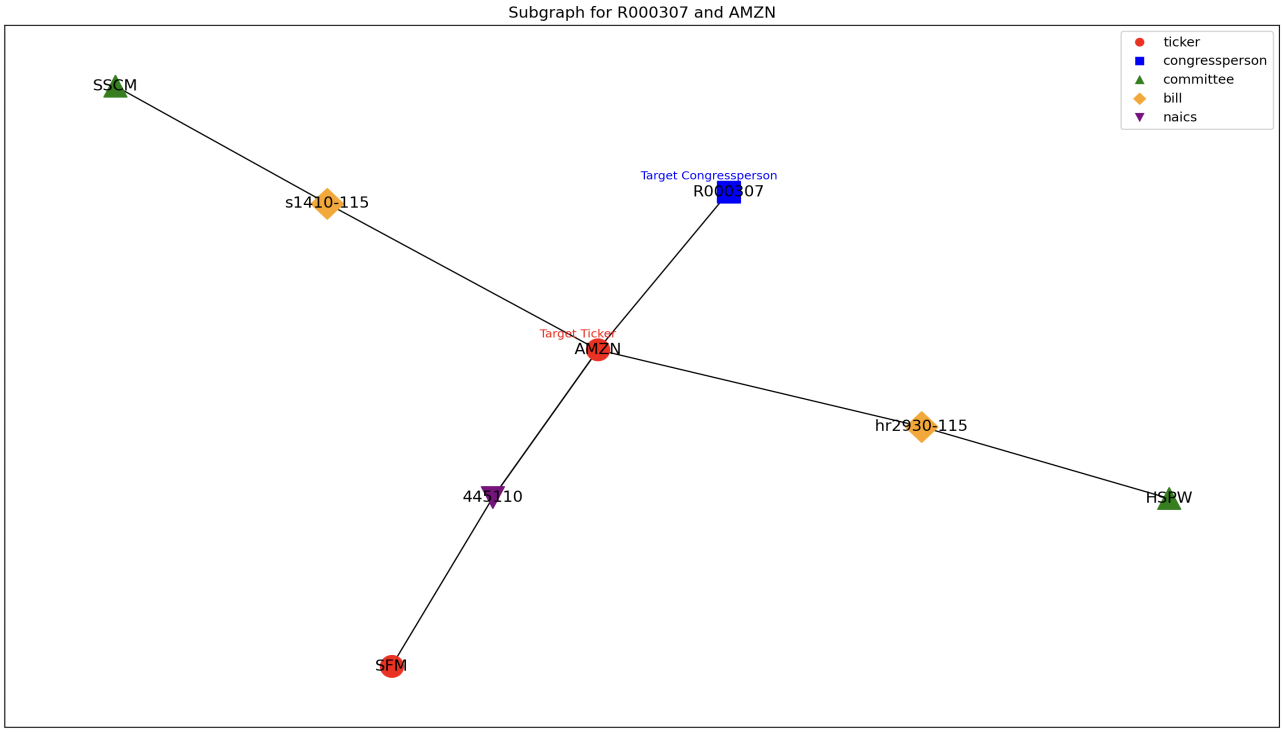


Figure 16: **GNNExplainer output for Senator Pat Roberts's transaction of Amazon's stock.** The figure shows the subgraph extracted from the entire graph using the node and edge masks trained by the GNNExplainer. The nodes and edges in the subgraph were selected based on their high scores in the masks, indicating their relevance to the model's prediction for this specific transaction. The GNNExplainer identified H.R.2930-115 (Drone Innovation Act of 2017) and S.1410 (Safe DRONE Act of 2017) among the bills that Amazon lobbied on as the most influential factors for this transaction. This is particularly interesting given Senator Roberts's known legislative activities related to drone technology.

(AMZN)'s stock. Among the 119 bills that Amazon lobbied on, the GNNExplainer identified H.R.2930-115 (Drone Innovation Act of 2017) and S.1410 (Safe DRONE Act of 2017) as the most relevant bills. This is particularly interesting because Senator Roberts co-sponsored the bill S.2730-116, which establishes a Drone Advisory Committee. Furthermore, 2017 was the year when Amazon started to publicize their plans for drone delivery[12]. Therefore, we can interpret that Senator Roberts's transaction of Amazon's stock was likely influenced by his legislative activities related to drone technology.

Indeed, Figures 16 and 17 were not primarily intended to reinforce the main story that committee membership matters. Rather, they serve as an example of how the GNNExplainer can elucidate the decision-making process of the graph neural network for individual predictions. These figures showcase the ability of GNNExplainer to generate a plausible explanation for each specific prediction case, thereby providing a mechanism to interpret the predictions made by the neural network. The "black-box" nature of neural networks is a common criticism (Shrikumar et al., 2016; Joshi et al., 2021; Castelvecchi,

[12]https://www.businessinsider.com/amazon-takes-critical-step-toward-drone-delivery-2017-5

2016), owing to their complex, high-dimensional, and non-linear decision-making process, which is often challenging to interpret and understand. This makes it difficult to trust their predictions, especially in sensitive contexts where understanding the reasoning behind predictions is essential. GNNExplainer addresses this criticism by providing a tool to interpret the predictions of the GNN, thereby making it more transparent and trustworthy.

These examples demonstrate the ability of the GNNExplainer to highlight relevant legislative and industry context for specific stock transactions. It's noteworthy that the GNNExplainer was able to identify these relationships even without explicit information about bill titles, text, or sponsorship relationships. This suggests that the GNNExplainer is effectively capturing the underlying patterns in the data that are relevant for the prediction task.

7 Conclusion and Future Directions

In this study, I delved into the dynamics of congressional stock investment, exploring what exactly influences these investment choices. My analysis aligned with the traditional financial literature's approach of excess return, which provided a direct estimation of possible excess return. This estimation addressed the range-censored limitation of the financial disclosure at the specific congress-ticker level, considering the life-cycle of transactions - from consecutive purchases to consecutive sales. This reconfirmed the findings of Eggers and Hainmueller (2013), which argued there was no widespread excess return among congressional investments. However, my findings indicate that such excess returns do exist at least abnormally and asymmetrically, more pronounced in the positive skewness compared to the negative returns. This suggests that some privileged information may drive such asymmetry in their excess return overall.

Secondly, I addressed a puzzle originating from the conclusions drawn by Eggers and Hainmueller (2014), who found no clear evidence that congresspersons disproportionately invested in stocks linked to their lobbying and committee assignments. This finding seemed somewhat counterintuitive and diverged from the extensive research on committee assignment and congresspersons' specialization in specific topics governed by committees. Stemming from this, I compiled a novel graph-structured dataset that more comprehensively captures congressional activities. This data utilizes a hetero-graph type, representing the interactions between different types of entities. Leveraging this dataset, I proposed a novel measure using cross-entropy, demonstrating that a congressperson's stock portfolio significantly resembles the

stocks related to their assigned committees, compared to unassigned ones.

Furthermore, I expanded on the work of Eggers and Hainmueller (2014) by using the graph neural network to determine how possibly relevant factors, such as congressional activities captured in the graph data, predict congresspersons' stock transactions. The results showed that, contrary to Eggers and Hainmueller (2014), the committee assignment of congresspersons and lobbying activities of firms are the most important features predicting their stock selections. In addition, to address the black-box nature of predictions leveraging neural networks, I proposed using GNNExplainer (Ying et al., 2019). This type of explainability method complements the evaluation metric to interpret case-by-case predictions and provides a more interpretable and semantically rich explanation of why a particular congressperson may choose certain stocks.

Adding onto these findings, it's worth examining the broader implications of our results. On a macro level, this research invites us to reassess our understanding of the motivations underpinning congressional service. The common perception is that congresspersons are primarily motivated by the goal of reelection, with their actions driven by a desire to serve their constituents and deliver policy outcomes that align with their promises and their party's platform. However, our findings suggest that the picture may be more complex, with financial considerations also playing a significant role. The evidence that some congresspersons are able to achieve outsized returns on their stock investments points to the potential for personal financial gain to be a motivating factor in their decisions and actions. This raises profound questions about the alignment of incentives in our political system and the possibility of conflicts of interest.

On a micro level, the analysis reveals fascinating variations in the behavior of congresspersons when it comes to stock trading. While some closely mirror the stock transactions related to their committee assignments, others diverge considerably. This cautious behavior may be an attempt to avoid the appearance or reality of insider trading, a legal and ethical boundary that all congresspersons must navigate. Unraveling the sources of these behavioral differences presents an intriguing avenue for further research. Are these variations simply a reflection of individual personalities, strategic thinking, and risk tolerance? Or are they indicative of deeper systemic factors within our political and financial systems that are yet to be fully understood?

Could the differences in trading patterns, for instance, be linked to the disparities in the level of scrutiny that different congresspersons face, their connections within the industry, or the financial literacy

they possess? Do congresspersons with certain committee assignments have more access to non-public market-moving information? Uncovering these underpinnings would offer a more nuanced understanding of the complex interplay between politics and finance and could inform policy decisions to improve transparency and fairness in our political system.

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A Data Merging and Entity Disambiguation

One of the key challenges to make this graph-structured data is the effective disambiguation of entities, as the data is collected from multiple sources, including LobbyView, Senate/House Financial Disclosures, and naics.com. In this graph-structured dataset, entities such as Congresspersons and firms may appear under different names or expressions. For example, "Ron Wyden" may also be referred to as "Ron L. Wyden", and "Apple" may appear as "Apple Inc.". To accurately disambiguate these differing text representations of entities, it is essential to establish a unique identifier for each entity, regardless of the variations in their names.

Theoretically, matching entities based on text similarity between two datasets with n and m rows has a computational complexity of $O(nm)$ (Román et al., 2012). Therefore, as the datasets grow larger, this complexity becomes prohibitively expensive. For instance, matching 70,000 firm names from LobbyView to 4,000 firm names appearing in the ticker table would require 280,000,000 times of computations for text similarity. To address this challenge, I developed a novel approach that leverages URLs as unique identifiers for entities.

The approach involves acquiring the corresponding URL for each entity through Google searches, such as `https://en.wikipedia.org/wiki/Ron_Wyden` for Ron Wyden and `https://www.apple.com/`

for Apple, Inc. A key advantage of using URLs as unique identifiers is that they facilitate effective entity disambiguation. For example, if two different expressions, "Ron Wyden" and "Ron L. Wyden" are both assigned the same URL `https://en.wikipedia.org/wiki/Ron_Wyden`, we can confidently recognize that these two expressions refer to the same entity. This approach allows us to accurately consolidate information about entities that may be represented in various ways across different data sources. Additionally, this method reduces the computational complexity to $O(n+m)$, as only one query is required for each row of data. To further scale up this process, I parallelized the URL acquisition process by batching queries and distributing them across multiple servers available through commercial cloud services like AWS.

B Effective Parsing Technique for Financial Disclosures

Financial Disclosures from the House are provided as encrypted PDF files. While text can be extracted from these files, the encryption results in irregular patterns, particularly in the tables that contain information about Congresspersons' stock buying and selling activities. These irregular patterns make it challenging to parse the data using manually coded patterns, as the deviations are difficult to anticipate and account for. To address this challenge, I utilized OpenAI's APIs, specifically the GPT-3.5 Turbo language model, to parse the PDFs into a CSV format that includes information such as when and who bought or sold which ticker, and how much.

The process involves querying the Large Language Model (LLM) with the extracted text from the PDFs and instructing the model to convert the irregularly formatted tables into structured CSV data which includes columns such as the date of the transaction, the name of the Congressperson, the ticker symbol of the stock, the type of transaction (buy or sell), and the amount of the transaction.

By leveraging the capabilities of the GPT-3.5 Turbo language model, I was able to effectively parse information contained in PDF files that would normally require manual human labor. This approach significantly streamlines the data extraction process and ensures the accuracy and consistency of the parsed data.

In summary, this innovative approach to entity disambiguation through URL acquisition and parallelization enables efficient data merging from diverse sources, ensuring the accuracy and scalability of the analysis.