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Title: Examining the Influence of Policy Stance on Trading Behaviour of US Politicians

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Introduction

This paper delves into the voting patterns and investment activities of House Representatives in the 117th Congress to uncover trends and potential connections. The decision to focus on the House Representatives was driven by the availability of data. By examining both voting and investment behaviours, the aim is to explore the behavioural dynamics, assuming an absence of insider trading activities. The presentation of data and methodologies utilized in this analysis will elucidate the connections between voting patterns and investment behaviour. The paper will analyse the impact of voting patterns on investment decisions using both graph-analytical and statistical methods. The analysis involves the utilization of incidence matrices representing invested firms and votes, which are then transformed into proximity matrices using the one-mode projection method. Visualization techniques will be employed to identify general patterns, and the data will be further analysed through rudimentary regression equations. Finally, the paper will discuss the findings and address potential limitations of the analysis.

While extensive literature exists on how legislators' personal financial interests influence their policy decisions and voting behaviour, there has been a noticeable gap in research regarding how their beliefs, which govern their voting behaviour on roll call votes, are reflected in their personal lives, specifically in their investment behaviour. This paper aims to fill this gap by exploring how legislators' investment decisions serve as a manifestation of their beliefs outside of legislative duties.

Data and Methodology

In my graph-analytical approach, I focus on pairs of House Representatives as the unit of analysis. I calculate both investment and voting proximities for these pairs. In regression analysis, I utilize the voting proximity data as the explanatory variable, while the investment proximity serves as the dependent variable.

I derive politicians' votes on bills from the official congressional database of voting records. Specifically, I focus solely on House bills, which are legislative pieces that shape the legal code. As part of my analysis I will go through all bills deliberated by House representatives during the first session of the 117th Congress, spanning from January 2021 to December 2021.

This timeframe is convenient for understanding trends, as it allows us to analyse data without being influenced by the force majeure of the Russian invasion of Ukraine. This event may affect the proximities of Congress members due to unified responses against Russia.

I select bills that are related to the industries the House Representatives have invested in, excluding unrelated bills which would affect the accuracy of the proximity.

I create a 32 x 14 matrix. This matrix represents a bipartite graph, where one set of vertices represents the 32 House representatives, and the other set represents the bills directly relevant to the required industries.

$B_{32\times 14} = \left(b_{ij}\right)$, $b_{ij} \epsilon \{-1,0,1\}$, with i being the House Representative and j the bill

I generate incidence matrices with House Representatives represented as one type of vertex and bills as another. Each element of the matrix corresponds to a Representative's vote, with 1 indicating a vote in favour, -1 indicating a vote against, and 0 indicating an abstention.

After this, I turn them into proximity matrices through the one-mode projection.

I proceed to convert the incidence matrix into a voting proximity matrix using the one-mode projection method. This involves multiplying the transpose of the incidence matrix by the original matrix:

$$P_{32\times 32} = B \cdot B^T$$

The one-mode projection reflects the extent to which a pair of House representatives agrees in the legislative process. To mitigate negative proximities among pairs within the matrix, I utilize a normalization method called min-max normalization. This technique serves to standardize the values within the matrix, ensuring a consistent scale across all entries while preserving their relative differences. (Gupta, 2021) Initially, I determine the minimum and maximum values present in the matrix, signifying the lowest and highest possible scores, respectively. Subsequently, I adjust the values by subtracting the minimum value from each entry, effectively setting the minimum value to 0. Following this, I scale the adjusted values to fit within the range from 0 to 1 by dividing each value by the difference between the maximum and minimum values. The resulting normalized matrix facilitates fair comparison and analysis by placing all values on a uniform scale, thereby eliminating negative proximities and enhancing interpretability. The process is:

$$P^{norm} = \frac{P+14}{28}$$

The data that has been calculated serves as the basis for the independent variable of interest in the following regression analysis.

For the investment-related information, I use the data provided by Barchart.com which is a website that provides comprehensive financial information, including data on stocks, options, futures, forex, funds, and cryptocurrencies. It offers a variety of tools and analysis for traders and investors, such as real-time and historical data, technical analysis, charts, and trading strategies. I focus on the firms whose shares have been bought by the House Representatives. I could alternatively focus on examining firms whose shares have been sold by politicians, which would also address the research question. However, I have chosen to concentrate specifically on analysing the buying activities. Although the data is in form of panel data, I use it cross-sectionally. It may prove challenging to entirely eliminate the profit motive inherent in investments, as their primary objective is financial gain. However, I aim to mitigate this aspect by concentrating on instances where politicians purchase shares without subsequent sales. My reasoning is that when politicians or people frequently engage in buying and selling stocks, it often indicates that their primary goal is to achieve financial gain, however cases when politicians or public figures buy shares and hold onto them, it can be perceived as a sign of confidence in the long-term prospects of a company or an industry. This act could be seen as aligning with a belief in the firm's future potential and its role in broader economic or social advancements. It reflects a commitment rather than a quick financial gain. In this context, the specific timing of a politician's investment is less relevant. The mere act of investing at any point can be seen as a demonstration of confidence in the industry, regardless of whether it was necessary to invest to express this sentiment. Therefore, employing panel data with cross-sectional analysis is a justified approach, as it allows for an examination of these investment behaviours over time without focusing on the exact moments of investment. I analyse investments made by the politician as well as those made by individuals closely associated with them, such as their spouse.

I selected the top-10 firms most candidates have invested in during the first session of the 117th Congress. With this information I create a 32 x 10 incidence matrix. This matrix corresponds to a bipartite graph where one set of vertices represents the 32 House representatives, and the other set represents the relevant firms:

$$A_{32\times10} = \left(a_{ij}\right), \textit{where } a_{ij} \in \{0;1\},$$

i is the House representative and j is the firm invested in

Table 1: Investment in Firms by House Representatives Incidence Matrix (Layout Applicable to all Incidence Matrices Used)

	AT&T Inc	Microsoft Corp	Amazon.com Inc	Walt Disney Co	Visa Inc
Harold Rogers	1	0	0	0	0
Deborah Ross	0	0	0	1	0
David Rouzer	0	0	0	0	0
Peter Sessions	1	1	1	0	0
Blake Moore	0	1	0	1	0

Table 1 displays a subset of the incidence matrix. I adopt the presence approach in constructing the matrix, restricting elements to either 0 or 1. This methodology accentuates shared investment points among House representatives in subsequent analyses.

Using the one-mode projection method, I convert the incidence matrix into an investment proximity matrix:

$$P_{32\times32} = A \cdot A^T$$

This step shows the number of common top-10 firms invested in among a pair of Representatives. I normalize this proximity matrix of the undirected, weighted graph by multiplying every element by $\frac{1}{10}$ to obtain

$$P^{norm} = (pij), pij \in [0,1]$$

The calculated data is the foundation for the dependent variable in the subsequent regression.

I use the Fruchterman-Reingold algorithm for visualizing all proximity networks. This algorithm generates a force-directed graph, where vertices experience a repelling force, pushing them apart, and an attracting force from neighbouring vertices, influencing their positions. Through an iterative process, vertices gradually settle into an equilibrium state, with similar vertices clustering together. (Koburov, 2013)

Finally, I utilize all the collected data points to construct regression functions using the ordinary least squares method of estimation. The model employed is as follows:

$InvestingProximity_{ij} = \beta_0 + \boldsymbol{\beta_1} \cdot VotingProximity_{ij} + \beta_2 \cdot SameParty_{ij} + \beta_3 \cdot SameState_{ij} + \beta_4 \cdot Female_{ij} + \beta_5 \cdot i.politician1 + \beta_6 \cdot i.politician2 + u_{ij}$

where i and j are House Representatives, β_0 a constant, the coefficients the effect of the relevant variables and $u_{ij}$the error term that captures unobservable factors that should not correlate with the explanatory variables.

While the primary aim of the research is to ascertain the correlation between politicians' investments and their voting behaviour on roll call votes, there's a rationale behind selecting *VotingProximity* as the independent variable. When *InvestingProximity* is set as the independent variable, the regression analysis elucidates the extent to which an elevation in *InvestingProximity* corresponds with a rise in *VotingProximity*. This scenario implies that politicians may harbour financial objectives, as the alignment in investment strategies influences their voting patterns. Conversely, when *VotingProximity* assumes the role of the independent variable, the regression unveils the degree to which an augmentation in *VotingProximity* coincides with an increase in *InvestmentProximity*. This outcome suggests that politicians' investment choices are potentially swayed by personal beliefs or ideologies within specific industries or firms.

The coefficient of interest in our analysis is $\boldsymbol{\beta_1}$, the effect voting proximity has on investing proximity. To better isolate the effect of voting proximity, I include three control variables, which take binary values, 1, if the effect is present and 0 if it is not.

Party affiliation can influence politicians' perspectives through two avenues: firstly, it can serve as an indication of pre-existing beliefs that align with the party's platform; secondly, it can directly shape an individual's conduct through interactions with like-minded party members. Party affiliation may introduce multicollinearity due to its influence on roll call vote decisions. Multicollinearity occurs when an independent variable shows high correlation with one or more other independent variables in a multiple regression model. This phenomenon poses a challenge as it diminishes the statistical significance of the affected independent variables. (Stock & Watson, 2020) One of the assumptions of ordinary least squares regression is the absence of multicollinearity. When this assumption is violated, the regression may produce inaccurate estimations of coefficients, thereby compromising the accuracy of the study. In table 2 we can see the results of running a regression to estimate the effect of party affiliation on Voting Proximity. Even though the coefficient of the *SameParty* variable is significant, a low R-squared value of 0.07 suggests minimal concern for multicollinearity.

The second control variable concerns the state the House Representatives represent. Every state has an individual number of House Representatives, however given that they have to cater to a similar electorate, it may be the case that this could lead to converging voting patterns without the additional influence of personal beliefs.

Finally, a control variable for gender is included to ascertain if both House Representatives in a pair are female. This accounts for gender-specific issues and beliefs. Given that women’s issues play an important role in the U.S. one could expect that women in the Congress may have some common voting intentions, making their proximities on average closer to each other. However, as it becomes apparent in the regression analysis, this control did not display any statistical significance, and considering that it did not have any effect on the adjusted R-squared, I removed it from the framework.

I also add 2 indicator variables for politicians, i.politician1 and i.politician2. The indicator variables take the value of 1 if the observation corresponds to the respective politician and 0 otherwise. The coefficients β_5 and β_6 represent the additional effect on the dependent variable when the observation corresponds to those politicians, compared to the reference politician, whose indicator variable is omitted from the model. Indicator variables are useful because they allow to estimate the unique effect of each House Representative on the dependent variable, *InvestingProximity*, and as it will be proven later, they greatly improve the fit of the model.

Table 2: The Percentage Point Effect of being in the same party on the Proximity in Voting

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Linear regression                               Number of obs     =        992
                                                F(1, 990)         =      79.84
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0702
                                                Root MSE          =     .12633
```

votingprox~y	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
party	.072951	.0081643	8.94	0.000	.0569297	.0889722
_cons	.8034066	.0051285	156.66	0.000	.7933426	.8134705

The table presents estimations of the factors influencing voting proximity within the realm of House bills. These estimates were derived by utilizing data sourced from congressional voting records. The quantification process adopts the Ordinary Least Squares (OLS) method for estimation.

Analysis and Interpretation of the Matrices

Figure 1: Investing Similarities

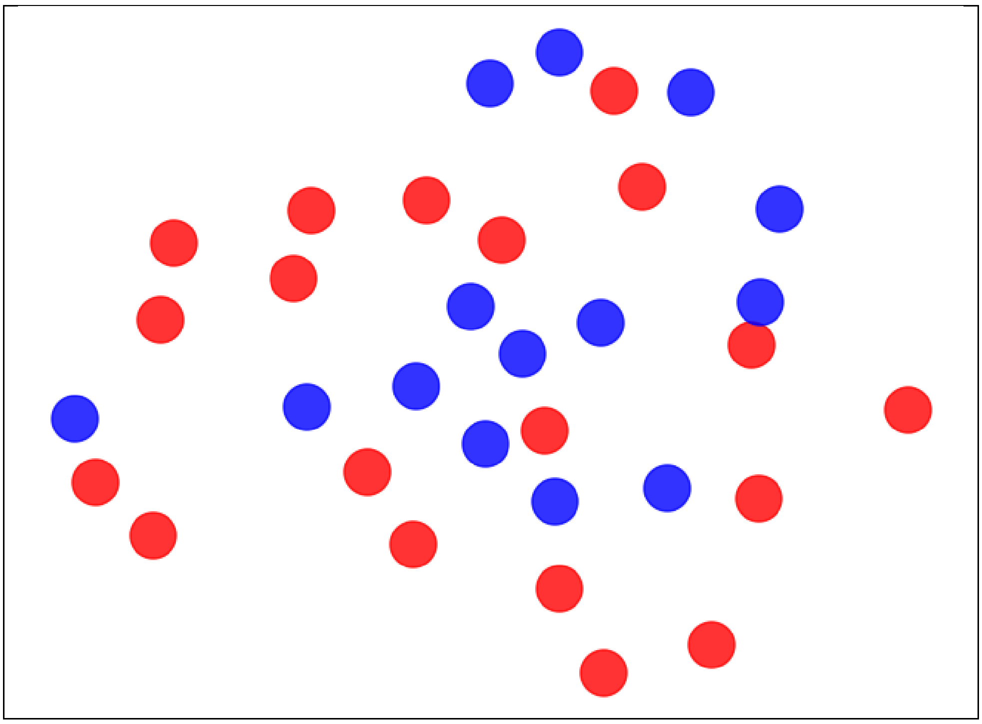

Figure 1 shows the visualization of the investment proximity network via the Fruchterman-Reingold algorithm. Republican House Representatives are coded as red and Democratic House Representatives as blue.

While the dots exhibit some mixing, there is a faint clustering effect: red dots loosely group together, hinting at closer investment proximities among Republican House Representatives, while blue dots also loosely cluster, suggesting some similarity in investment patterns among Democratic House Representatives. The similarity in investment patterns among House Representatives of the same party can be attributed to shared policy preferences, party ideologies, and political goals. Additionally, party leadership, committee assignments, and intra-party communication may further reinforce these investment tendencies. External factors such as economic trends may also contribute, but the cohesive political identity within each party seems to remain an important driving force behind the observed investment similarities. However, as the regression will later show, *SameParty* variable is insignificant, which means there is no basis for believing that party affiliation can influence investment decisions, despite the initial impression of clustering based on political alignment.

Figure 2: Voting Similarities

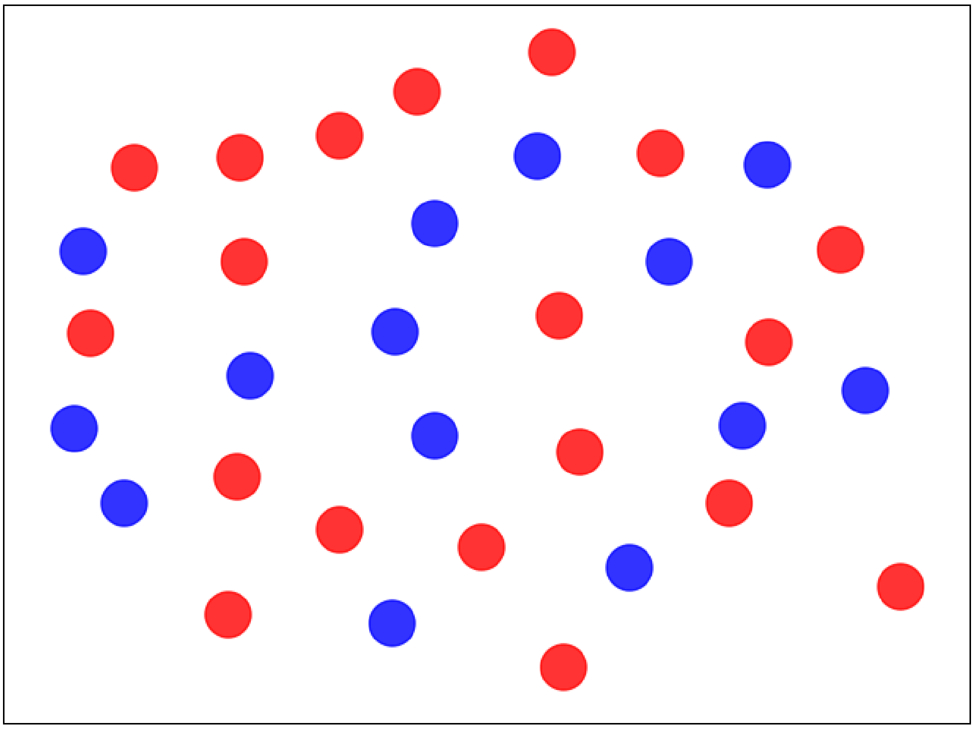

Figure 2 presents the proximities of the House-introduced bills. It seems there is no obvious pattern of clusters, which could imply that the party affiliation of House Representatives may not exert a substantial influence on their opinions regarding these matters. This observation can be seen as advantageous for the scope of the study, as it indicates that the investment decisions and voting behaviours of House Representatives may be less driven by party considerations in this particular context, which leaves room for personal beliefs to influence decisions on these matters.

Quantification of the Effect of *VotingProximity* via Regressions

Table 3: The Percentage Point Effect of the Proximity in Voting on the Proximity in Investing

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
VotingProximity	-0.098***	-0.108***	-0.074*	-0.073*
SameParty	-	0.012**	0.019	0.019
SameState	-	-0.019***	-0.023***	-0.024***
Female	-	0.007	-0.005	-
i.politician1	-	-	Indicators used	Indicators used
i.politician2	-	-	Indicators used	Indicators used
Constant	0.115***	0.118***	0.047	0.048
N	992	992	992	992
adj. R^2	0.052	0.064	0.281	0.281

The table presents estimations of the factors influencing investing proximity within the realm of House bills. These estimates were derived through graph-analytical computations involving the one-mode projection of incidence matrices, utilizing data sourced from Barchart.com and congressional voting records. The quantification process adopts the Ordinary Least Squares (OLS) method for estimation. Additionally, binary control variables were introduced to enhance the clarity of isolating the voting effect. The inclusion of coefficients for the indicator variables has been omitted due to space constraints and their non-essential nature within the scope of the study.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3 shows the regression results. Model 1 shows that even without any control variable, voting proximity does not have a large effect on investing proximity. According to the results, an additional percentage point increase in voting proximity would lead to a 0.098pp fall in investing proximity. Worth mentioning it was unexpected for the sign of the coefficient to be negative. After including the control variables except the indicator variables in Model 2, the marginal effect of a percentage point increase in voting proximity on investing proximity increases in absolute terms, from -0.074 to -0.108 and is still significant at the 0.1% level. The adjusted R-squared also increases slightly from 0.052 to 0.064. After including the indicator variables in Model 3, the marginal effect of a percentage point increase in voting proximity on investing proximity becomes -0.074 and is less significant. The biggest improvement is the increase in the adjusted R-squared, from 0.064 to 0.281, which means that Model 3 can explain 28.1% of the variation in investing proximity observations. Although this R-squared may still be seen as low, it can still be argued that model 3's coefficient is more accurate in capturing the effect voting proximity has. Although both the *SameParty* and *Female* variables were found to be insignificant, I opted to only remove the *Female* variable. This decision was made because while the *SameParty* variable marginally increased the adjusted R-squared and rendered the *VotingProximity* significant, the Female variable did not demonstrate similar effects. Despite not all coefficients of the indicator variables being significant, their inclusion led to a significant increase in the adjusted R-squared value. This underscores the importance of retaining them in the regression model. Even after removing the

Female variable, the values of the coefficients in the regression barely changed. It is worth mentioning that even though the absolute value of the *SameState* variable is lower than that of the *VotingProximity* (0.073 > 0.024), *SameState* has a higher level of significance, which suggests that we are more confident in the effect of the *SameState* variable than of the *VotingProximity*.

Conclusion

My analysis of the voting and investing patterns within the U.S. Congress revealed a noteworthy finding: a weak negative correlation between *VotingProximity* and *InvestingProximity*. Politicians might intentionally opt for investments in varying assets or industries compared to their peers to sidestep any perception of collusion or impropriety, especially if they share close affiliations or voting tendencies. By diversifying their investment portfolios and selecting distinct opportunities, politicians aim to demonstrate independence and prevent accusations of acting in concert for personal gain. This strategic differentiation helps to mitigate suspicion about their motives and intentions, preserving their reputation and public image. However, it is notable that within the study, the highest number of individuals recorded investing in the same firm was four, which implies that that even if multiple politicians invest in the same firm, it may not necessarily imply collusion, as the number of individuals involved is constrained.

On the other hand, it is important to acknowledge the possibility of a missing variable that could explain this relationship, potentially diminishing the significance of *VotingProximity*. This analysis merely offers one interpretation, indicating that voting may not be the sole driver of congressional investment behaviour, and its significance could be diminished when additional factors are considered. The presence of insider trading could also significantly affect the accuracy of these results. My research may be constrained by the timeframe I've utilized, as it focuses exclusively on House Representatives who have purchased shares without subsequently selling them within the specified period. However, it is plausible that shares could have been sold after the timeframe considered, rendering this assumption invalid. Another method to enhance the precision of the results would involve incorporating Senate data, thereby expanding the sample size. This augmentation could potentially bolster the accuracy of the findings.

The empirical isolation of funding as a primary influence becomes challenging due to potential reverse causality: politicians invest in firms based on personal beliefs reflected in voting patterns, then advocate for these firms through legislative actions. My work aimed to explore potential connections, but further investigation, such as examining the presence of insider trading within the 117th Congress, could provide deeper insights into the relationship between *VotingProximity* and *InvestingProximity*.

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