Congressional Stock Trades and Economic Policy Uncertainty

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This Version: November 25, 2023

Abstract

Do congress members trade on insider information? We answer this old question from a new perspective by investigating if there is any relation between the abnormal returns of stock trades by congress members and economic policy uncertainty. Using congressional stock trading data over 2014-2022, we find evidence of a positive relation between economic policy uncertainty and short-term abnormal returns of congress members' stock purchases, after adjusting for S&P 500, size (measured by year-end market capitalization), and Fama-French 12-industry adjustments. Overall, our findings suggest an existence of (short-term) informativeness among stock purchases by congress members. This work is the first to link politician stock trades' performance to an economic indicator that is also closely tied to information privilege politicians attain from their work of policymaking.

Keywords: Economic Policy Uncertainty, Congress members, Congressional stock trades, Cumulative abnormal returns, Politician trading, Government, Federal and State government, Government spending, Fama-French 3-factor, Industry-adjusted, Size-adjusted, Market-adjusted, STOCK Act, COVID-19

JEL Classifications: G14, G18

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[1]All the codes and datasets used in this project are for now (privately) available here https://github.com/yam3moe/CongressionalStockTradesandEPU. Please contact the principal author for access.

[2]This paper is scheduled for presentation at SWFA 2024 Annual Meeting

[3]We thank Brian Baugh, Bingkuan (Bryan) Cao, Richard A. DeFusco, Paul Dion, Donna Dudney, Geoffrey C. Friesen, Jinsook Lee, Stanislava Nikolova, Roberto Stein, Liying Wang, and Julie Wu for their valuable comments and suggestions during our 2nd year paper presentation.

1 Introduction

Should congress members be allowed to trade stocks? This seemingly pretty simple, short, and straightforward question has in actuality been at the center of heated discussions, a spectrum of opinions, and frustrations among the public, lawmakers, and scholars alike. Generally speaking, those in the 'Yes, they should be' camp argue that congress politicians have as much a right to invest in financial products as anyone else and the idea of intentionally closing the doors of financial markets to a specific subset of population is certainly not the hallmark of a free market.[1] This side of the debate may also believe that taking a blanket ban approach is unhelpful, especially when the STOCK Act (Stop Trading on Congressional Knowledge) of 2012 is already in place to rein in unlawful trading behaviors by politicians. Conversely, the opposing side emphasizes less on an individual's right to participation in the financial markets, and more on the ethics, integrity and public perception of elected officials. They contend that legislators are no mere individuals. Lawmakers have a certain power over the stock market since they could simultaneously influence stock market prices by their decisions and have privileged access to valuable information that are predictive of stock price movements. Absent of an environment that effectively deters congress members from generating financial gains by abusing such power, members may be trading on private information to build up their riches unethically and unfairly. The 'they should not be allowed to trade' side of critics concludes that the likelihood of such non-public-information-driven tradings warrants treating congress members as non-corporate insiders. Hence, at the very least, they advocate for stock tradings of elected congress members to be regulated by a more stringent standard than the current problems-plagued STOCK Act,[2] if not the outright ban. This way, the group believes that politicians will be held to the same expectation and standard as their counterparts corporate insiders. Furthermore, the opposing camp also believes that even if insider trading aids in increasing the efficiency of the market (Bhattacharya and Nicodano, 2001), stock trades by government officials with high access to market-influencing information violate ethical standards required of public servants and damage public image of the government (Moore, 1990). One primary reason among many why congress trading elicits such a wide array of opinions could be mixed evidence concerning the alleged informational advantage accrued to politicians. Besides, notwithstanding several media reports about some congress (as well as other branches of government) officials making suspicious extremely timely trades, it is also not entirely right to assume all legislators are adept at converting that prized information advantage into financial gains (C. Eggers and Hainmueller, 2013).

[1]Should Members of Congress Be Banned from Trading Stocks?
[2]Members of Congress Shouldn't Trade Stocks, But Even in Solutions Loopholes Remain

It could be possible that a few bad apples in the congress are ruining the public image of the entire government institution. Adding more anomalies to this issue are academic studies on the performance of politician stock trades which too gives off conflicting results.[3]

We acknowledge that contrary results in academic literature call for more investigation into the matter. Hence, in this study, we attempt to uncover new evidence that could help us identify if congress politicians seem to be using informational advantage in their stock trades. In doing so, we take a different approach wherein we study whether the performance of political stock investments, measured by cumulative abnormal returns, is related to an index tied to politician's activities in policymaking. The index is called economic policy uncertainty index.[4] In answering if politicians may be trading on insider information originated from the walls of the Capitol building, our work is different from many of previous studies that use the following approaches or settings: 1). relying on a change in regulatory environment (for example, the passing of STOCK Act in 2012 or the amendment of the act in 2013) as a shock and using difference-in-difference method (Wilson, 2018; Lenz and Lim, 2009), 2). constructing calendar-time portfolios (Ziobrowski et al., 2004) or holdings-and-transactions-based portfolios (C. Eggers and Hainmueller, 2013), and lastly 3). emphasizing on trading patterns during and around a period marked by high information asymmetry or volatility - for example, 2020 Congressional Insider Trading scandal (Goodell and Huynh, 2020). Our rationale for analyzing politicians' advantage in stock trades by exploiting the index stems from the its design which primarily accounts for uncertainty related to the actions of lawmakers and possibly officials from other branches of the government. The methodology behind the construction of the index ensures that the source of the uncertainty is lawmakers and other government officials. Being the originators of economic policy uncertainty, they may be protected to some degree from negative impacts of the that uncertainty. In other words, lawmakers may be concurrently generating uncertainty through their works and encountering or harvesting information advantage useful to guard against uncertainty generated by them. Because this politician-generated uncertainty index also affects the stock market movement (Baker et al., 2016), it is highly probable that politicians may possess information vests against the bullet of financial market unpredictability caused by policy uncertainty. If the informational edge is utilized by them in trading stocks, we should observe a relation between their stock trades' performance and policy uncertainty. This reasoning is specific to and important for our investigation as it can equip us with the indirect/inferential evidence of politicians using information advantage against uncertainty for financial gains. Conversely, the absence of it possibly signifies that politicians do not exploit the information advantage or fail to cash in

[3]See Karadas (2019), C. Eggers and Hainmueller (2013), Eggers and Hainmueller (2014)

[4]developed by Baker et al. (2016) and is also carried by Bloomberg, Haver, FRED, and Reuters

on it because they don't know how or don't have the expertise to turn the ad.

To test our hypothesis, we put to use the 2014-2022 stock transactions data of both types of congress members, compiled by QuiverQuantitative. It is an online portal which, in addition to offering FinTech services, collects and maintains data related to congressional stock trades, government contracts, and lobbying finances. Employing various specifications formed from utilizing cumulative abnormal return measurement adjusted for three types of benchmark, inclusion of macroeconomic variables, and exclusion of the turbulent 2020 from the sample, our tests overall provide a rather consistent support for the claim that politicians appear to have access to and trade stocks on privileged information (against uncertainty). [5] We find that when uncertainty is higher, abnormal returns of politician stock purchases also tend to go up. The positive effect documented is statistically significant at either 1% or 5% for most of the specifications in our tests. More precisely speaking, our analysis produces five major findings. First, throughout this study, we discovered that the volatile market condition and extremely high values of economic policy uncertainty index values — both triggered by COVID-19 crisis — severely affect the results generated. Since 2020 was an unconventional year, we repeated all our analysis twice: one inclusive of 2020 transactions and one without. In results obtained from regression analysis without transactions made in 2020, we continuously see a strong evidence of positive relation between economic policy uncertainty and abnormal returns of stock purchases transacted by politicians in adjustments using S&P 500, size and Fama-French 12 industry. Second, with or without 2020 transactions, we document that congressional buy trades' abnormal returns over S&P 500 index is always strongly and positively associated with economic policy uncertainty. The fact that the inclusion of 2020 transactions alone nullifies the positive effect documented (for size and industry adjustments) may imply politicians' information advantage in buying stocks may only go to the extent that the policy uncertainty has not become so large as to confuse even those with access to informational edge (We explain further in Section 6.6). Third, we do not observe politicians sales' abnormal returns getting lower with increased policy uncertainty, suggesting that, opposite to buy trades, sell transactions by politicians may not be informed. This is hardly surprising since the parallel literature on corporate insider trading informs us that sales trades are generally less informed than buys (Lakonishok and Lee, 2001; and Wang et al., 2012). Fourth, we document that there is a higher degree of informativeness for politicians' buy trades in stocks of firms belonging to industries which are more highly exposed to economic policy uncertainties. This finding reinforces our hypothesis that politicians informational advantage could be traced to policy uncertainty generated by their actions. Lastly, we find evidence

[5] In an earlier version of this paper, we provided an extensive number of specifications to validate the robustness of results.

that the documented informational edge do not vary with politicians age although this finding could also arise due to sample selection and/or availability of reported data on lawmakers' financial trades (See the Data section). Taken together, our work provides (indirect) evidence of politicians possessing information advantage that could help them generate financial gains even in an environment marked by growing policy uncertainty because they are the very people who are the source of this uncertainty.

Overall, our study contributes to the increasingly important literature on the intersection of politics and finance. The subject of politicians accumulating wealth while in office has very much become a thorny and touchy issue. In light of this, we hope that our work adds to the literature by providing a new insight about politician tradings. Our findings may serve as a new piece of consideration for people on both sides of the debate and thus help to advance the discussion for the betterment of all involved.

The rest of the paper is organized as follows. We outline rules and regulations on congress members' stock trading in Section 2. We discuss related literature and our contributions in Section 3, followed by the development of hypothesis and our motivation in Section 4. We then describe in details datasets and a variety of variables in Section 5. Section 6 presents results of our baseline regressions and also addresses concerns and questions readers might have. Finally, Section 7 reiterates the results in a summary and wish for this study to be a helpful tool in deciding the way forward for congressional stock trading.

2 Background

This section describes the laws and regulations governing the stock trades of the US congress members and also offers a comparison to parallel regulations applied to corporate insiders. Additionally, I briefly touch on the changes/amendments made to the regulations and a few events that highlight the level of enforcement or the lack thereof regarding legislative stock trading.

The media and the public (Steve, 2011) have long voiced their concerns over the plausibility of U.S. politicians possessing non-public information advantage and using it to trade stocks and other financial securities.[6] However, not until 2012 was there a fairly comprehensive law governing congress members and detailing public disclosure procedures, reporting requirements, and penalties for failing to disclose stock trades. In theory, the STOCK Act, passed on April 4 of 2012, intends to prevent congress members from unfairly benefiting from stock trades made with insider knowledge or non-public information and require them to compulsory online disclosure of stock trades. The law was also adopted as

[6]Congressional Staffers Gain From Trading in Stocks

a response to the public's dismay over some evidence (Schweizer, 2011) that supported the claim that politicians definitely incorporate non-public information in their trades.

The public's demand for more accountability may not be without its reasons. To begin with, government officials including congress members are not subject to as stringent a regulation as corporate insiders when it comes to trading on material non-public information. For example, under Section 16a of the Securities and Exchange Act of 1934, corporate insiders must report their open market trades to the Securities Exchange Commission (called SEC henceforth) within two days after the end of the month the trade occurs.[7] Failure to do so could result in being charged by the SEC for illegal insider trading. On the other hand, up until the STOCK Act, congress members could get away with disclosing their trades as late as 5-17 months after the transactions (Karadas et al., 2022). The law reduced the gap between the transaction and reporting date to 30-45 days, which is still significantly larger than what is allowed for corporate insiders. Another example of lack of more scrutiny on politician trading behavior is related to trade reversal. Unlike corporate insiders who are prohibited from reversing trades within six months, there is no similar inhibition placed upon stock trades of congress members. Furthermore, lawmakers have near immunity from the SEC investigations. In a 2011 congressional hearing, Robert Kuzami, who headed the SEC's Enforcement division from 2009 to 2013, stated that the SEC's insider trading laws do not apply to congress, which funds the SEC (Huang and Xuan, 2017).[8]

The increased transparency brought about by the STOCK Act was short-lived, however. A review submitted by the National Academy of Public Administration to President Obama in March 2013 advanced the position that disclosure of lawmakers' financial trades in a freely downloadable public database raises serious security concerns.[9] A month later, both the Senate and the House passed a bill which removed the public disclosure requirements. In the same month, President Obama signed the bill into law.[10] As a result, information about congress members' financial trades continue to be fragmented and researchers have to hand-collect data from financial disclosure reports or rely on external third-party aggregators. Although the amended STOCK Act remains in effect, no lawmaker has been charged with violation of the act. For example, following the infamous 2020 congressional insider trading scandal, the justice department launched investigations into senators Kelly Loeffler, Jim Inhofe, Dianne Feinstein, and Richard Burr for potential violations of the STOCK Act from their stock tradings executed just before the coronavirus pandemic affected the financial market. The inves-

[7] Before 2002, the date range was 10 day

[8] It appears that SEC however can aid the investigations of the Justice Department into politician stock tradings as was seen in the 2020 congressional insider trading

[9] The STOCK Act: An Independent Review of the Impact of Providing Personally Identifiable Financial Information Online

[10] "Did Obama and congress use national security fears to gut the STOCK Act?"

tigation concluded with no charges pressed against lawmakers. Despite repeated media reports alleging this 'non-corporate' insider tradings by at least 78 lawmakers who traded on private information about COVID-19,[11] no one was eventually convicted and then-House Speaker Nancy Pelosi went so far as to say Congress members "should be able to participate in a free-market economy."[12] Recently, Senators Kirsten Gillibrand and Josh Hawley unveiled details of the "Ban Stock Trading for Government Officials Act" which would ban Congress members, their spouses, and dependents from stock trading. The proposed legislation also does not permit lawmakers to trade and own stocks through blind trusts.[13] As the public perception and lawmakers support for banning themselves from stock trading keep changing with time, it is definitely crucial for researchers to analyse the matter from varying angles and we hope that this study is not only timely, but also can add a small piece of insight, albeit incomplete, to this controversial and evolving issue.

3 Literature Review

A number of studies have investigated the information advantage of politician trades in various settings. The first study analyzing the trades of congress members in a detailed empirical methodology is done by Ziobrowski et al. (2004). Constructing synthetic calendar-time portfolios which mirror the purchases and sales of US Senators, they show that between 1993 and 1998, these portfolios beat the market by approximately 97 basis points a month. Similarly, Karadas (2019) constructs one-week holding period calendar-time portfolios from congress members' trades for 2004-2010 and demonstrates that members with important committee assignments outperform the market by as high as 20% in a year, with an even larger 35% outperformance for portfolios of powerful Republicans.

C. Eggers and Hainmueller (2013) however argue that the use of synthetic portfolios may not be suited to testing the possibility of trading on information as calendar-time portfolio returns can be significantly different from the returns members attained with their real portfolios. Instead, they reconstructed actual portfolios of members from information available on financial disclosure forms and carried out the transaction-based panel regression analysis using Fama-French Three-Factor model and Four-Factor Carhart model. Their results show that other than investments in local companies and firms related to campaign contributors, congress members' trades in the 2004-2008 period actually

[11] 78 members of Congress have violated a law designed to prevent insider trading and stop conflicts-of-interest
[12] Nancy Pelosi Defends Lawmakers Who Get Rich Off Stock Market While In Office
[13] Senators propose banning stock trades for US Congress, president

under-performed a passive index fund by 2-3% per year. They report that the under-performance remains persistent even in various sub-samples: party affiliation, the House and the Senate, and powerful members from party and/or committees. In a similar vein, Belmont et al. (2020) present evidence, based on long-term buy-and-hold abnormal returns, that politicians' trades do not particularly seem to be informed under various specifications for benchmark adjustments. Over a period of 2012-March 2020, they find that stocks purchased by senators under-perform after adjusting for the CRSP value weighted index, industry-size matched portfolios, and the Daniels Greenblatt Titman and Wermers size-value-momentu matched portfolio.

To address the concern that abnormal returns of congressional trades are merely the result of superior trading skills possessed by politicians or their agents and that the presence of abnormal returns do not necessarily mean congress members use private information to their advantage, Hall et al. (2017) employ a novel empirical setting where they single out newly elected congress members during 2004 and 2010 in sample construction. They find that prior to joining congress, trades of the new members did not show signs of informed trading. Only after joining the congress did the trades of newly elected members start to earn abnormal returns, lending indirect evidence that becoming a congress member probably comes with information advantage useful for beating the market.

Rather than inferring from abnormal returns whether insider information advantage underlies politician trades, Hanousek et al. (2022) turn to a price-based microstructure measure of information asymmetry, known as abnormal idiosyncratic volatility (AIV). The idea is that because AIV can be used to deduce the likelihood of insider tradings (Yang et al., 2020), higher than normal AIV of senator-purchased stocks around the transaction date could indicate the presence of information-driven trades. They report that senator buy trades are indeed significantly associated with high AIV values. The average 5-day period AIV of senator purchases is more than two times larger than that of quarterly earning announcements. Moreover, this association between AIV and senator purchases varies with types of legislative work and personal attributes of senators such as, age and tenure. Karadas et al.(2022) diverge from studies that focus more on excavating the component of firm-specific information advantage in members' trades. Instead, following Jiang and Zaman (2010), they develop a monthly aggregate index out of congressional tradings that is capable of filtering out the macroeconomic component of those trades. Because there is a statistically significant relation between the one-month lagged aggregate trading index and market returns, they conclude that politicians trades on not-yet-public or private macroeconomic information.

As for economic policy uncertainty, several studies document how policy uncertainty could affect firm policies, investment decisions, and market microstructure. Baker et al. (2016) shows that a 1% increase in policy uncertainty is associated with a 0.43% rise in a firm's option-implied volatility. They show that, especially for firms with high sensitivity to government spending/purchases, an increase in economic policy uncertainty could reduce the firm-level quarterly investment rate. Using merger and acquisition data from 1985 to 2014, Bonaime et al. (2018) similarly document that policy uncertainty is strongly and negatively associated with M&A activity. In another evidence of government-based uncertainty affecting financial outcome, Koijen et al. (2016) show that policy uncertainty affects profitability outlook, which, in turn, impact equity R&D of firms in the healthcare sector.

Because there is no one-size-fit-all approach to analyzing the information advantage embedded in politicians trades and EPU (economic policy uncertainty) too is not an all-encompassing index capable of predicting every economic outcome, we are careful to admit that our methodology of linking short-term abnormal returns of politician trades to EPU does not tell a whole story of how, if any, politicians gain information advantage and whether they really incorporate non-public information into their stock trading decisions. Despite the limitations, our study comes with four contributions to the existing literature. First, most prior studies only confirm that politicians enjoy higher abnormal returns. Since abnormal returns could be realized due to a different set of factors (for example, congress members and/or their financial advisors are simply market-savvy investors), we go a step further and look for whether there could be a measure that is predictive of abnormal returns. Second, a large body of research on politician trades tilts their focus to the use of exogenous shock, for example, the passage of the STOCK Act or the amendment of the STOCK Act, and examines the impact these shocks have on trade by politicians and their family members (Karadas, 2019). This study however shows that independent of a short-term or seasonal shock, there is a time-series measure that could be associated with returns of politicians' trades. Third, our study is also related to the growing literature that looks at the impact of different types of uncertainty on economic and financial outcomes such as M&A activity (Bonaime et al. , 2018), research and development (Atanassov et al., 2016), and investment cycle (Julio and Yook, 2012). Fourth and slightly similar to the third, this paper is also rather close in identity to the literature that documents relations between financial markets, economic outcomes and various indices including EPU. For example, Cline (2022) investigates how firm-specific political risk, as perceived by conference calls, affects corporate insider trading and finds that both trading volume and transaction value increase with the political uncertainty index. Using Beny (2008)'s 5-point insider trading law (ITL) index, Brockman et al., (2014) show that the level of restrictive insider trading law and dividend payouts are negatively correlated. Lastly, the predictive power of EPU about stock market returns was shown by Brogaard and Detzel (2015). Our study however might be closet to El Ghoul et al. (2022) who showed that EPU is positively related with profitability and volume of corporate insider purchases. It s is worth highlighting two main differences between their work and ours. El Ghoul et al. (2022) provide evidence of a link between EPU and corporate insiders' trades. Ours looks at trades of politicians since economic policy uncertainty is more intimately tied with activities of politicians and less with corporate insiders. Second, they measure profitability as long-term abnormal returns (market-adjusted abnormal returns over the 180 calendar days following the transaction). We take a different approach by measuring trades' performance as short-term abnormal returns and not use long-term windows in our tests (See a longer explanation for why in Section 6.7). Although not directly related to the literature, this work also adds to the ongoing discussion surrounding government officials' regulation of stock trading. As the public's trust in governmental institutions wanes,[14] the findings from this study could serve as another evidence or consideration for lawmakers intending to implement stricter regulations for congressional trades.

4 Motivation and Hypothesis Development

At a first glance, it seems intuitive that economic policy uncertainty may hold explanatory power for return patterns of politician trades. However, it is not as straight-forward to determine a specific channel that links the uncertainty and trading decisions (thus returns) since we cannot assess, with high accuracy, which information component of uncertainty index is useful for who in what industry, and so on. Nonetheless, in this section, we discuss why there might be a connection between the returns of congressional trades and economic policy uncertainty by grounding our reasons to findings from academic literature and relevant book(s).

The association between congress' legislative work and stock market performance has been documented since about 30 years ago. Coined as the 'Congressional Effect', Singer (1992) highlighted a seemingly strange phenomenon that stock market performance is better when the Congress is out of session than when it is in session. Lamb et al. (1997) add more credence to the claim in the book with their empirical evidence which shows that both the average daily returns and cumulative returns during recess are always higher than while the congress is in session. Their explanation rests upon the idea that the market reacts to anticipations of higher economic uncertainty caused by legislative activities during active Congress sessions. These are some of the earliest works showing that politicians' actions do have implications for the stock market. Because lawmakers, the main drivers of this uncertainty,

[14]Public Trust in Government:1958-2022

know how their actions will change the stock market, a firm, or an industry (for better or for worse), it is reasonable to deduce that (some) politicians possess valuable information advantage useful for beating the market. By extension, if they really leverage the advantage to avoid losses or increase gains amidst uncertainty, there would be a statistically significant relation between the abnormal returns of their trades and uncertainty. To be more specific, we postulate that abnormal returns of purchases by legislators should have a positive relation with EPU because legislators, equipped with informational advantage, can execute more informed buy trades and beat benchmark return(s) when uncertainty is higher. In contrast, sales trades should have a negative relation with EPU. One problem however is the choice of uncertainty measures. A recent work by Krieger and Pace (2020) reasons that if open congress sessions really raise the uncertainty, it would be reflected in the Chicago Board Option Exchange market Volatility Index (VIX), a widely-used proxy for economic uncertainty. They find that VIX during sessions are indeed higher than when out of session.

However, we argue that, at least when testing for the relation between uncertainty and congressional trades, EPU is a better fit than VIX. While EPU and VIX are correlated, their information content is not the same. VIX, constructed from option prices (Whaley, 1993) primarily captures uncertainty related to stock returns (Baker et al., 2016). In other words, VIX does not encapsulate the uncertainty directly generated by lawmakers' activities; rather, it captures the uncertainty of stock returns which are partially caused by legislative actions of congress. In contrast, EPU, by virtue of its design, is a measure of uncertainty primarily arising from policies or changes in policies that are in more direct control of lawmakers. To clarify further, we demonstrate a short example. One of the components of EPU is related to government spending (See Section 5.1 for details on the construction of the index). At any given time, when uncertainties about government spending rise, certain politicians may possess insider knowledge about which sectors or firms will benefit (lose) from a growth (decline) in government spending. They can then trade stocks based on such valuable information. In this way, lawmakers can make informed trades even when policy uncertainty affects other investors without information privileges, generating abnormal returns that vary with EPU.

The literature investigating the presence or lack of information-driven trades by politicians and those connected to them largely centers on examining the abnormal returns in transaction-based portfolio setting (Karadas, 2018) or difference-in-difference setting relative to an exogenous shock (Huang and Xuan, 2017; Bourveau et al., 2016). Here, we propose that it is also possible to draw inferences about the extent of informative trades among politicians from the connection between abnormal returns and relevant time-series uncertainty indices. One way by which an investor can earn abnormal returns is managing the uncertainty with relevant market-wide, firm-specific, or industry-specific information that can counteract the uncertainty-induced risk. If this type of market-influencing uncertainty is also directly and mostly generated by lawmakers' decisions and actions, the uncertainty becomes less of an issue for politicians although the uncertainty remains an unknown force for other investors. It is then logical to assert that politicians possess useful insider information that could help them mitigate the negative impact of the uncertainty. If they do make use of such information and trade accordingly, we would see a positive relation between abnormal returns and uncertainty for purchases and a negative one for sales (just like we hypothesized above).

To test this hypothesis, here again, we assert that EPU is a good candidate and reinforce our claims with two additional reasons. Our first rationale relies on the well-known 2020 congressional insider trading scandal. In the first half 2020, EPU shot up to its highest value since 1985, indicating an unusually heightened uncertainty. It was later reported that, despite this increased uncertainty, a number of lawmakers and executive officials made stock trades that appear to be remarkably well-timed.[15] [16] [17] Our interpretation is as follows. As market participants were increasingly uncertain about government policies in response to the spread of COVID-19, EPU (a measure of policy uncertainty) went up to its extreme values. Congress members, who are the core of policymaking in the nation, were however less unfazed by the brewing uncertainty and increased tradings at crucial times precisely because of information advantage.[18] This means that EPU could be an index that can possibly tell us about trade patterns and returns of lawmakers. Figure 1 and Figure 2 containing plots of natural log of yearly mean of EPU and natural log of total number of congressional trades in each year, present a rather interesting piece of evidence that there is indeed a relation between politician trades patterns and EPU. When nbi or 3ci (two types of EPUs, more details in Section 5.1) is higher in a given year, legislators' total number of trades also increased. If legislators are not privileged to useful information against uncertainty, they would have scaled down transactions rather than executing more trades.

Next, the validity of the conjecture that legislators can make informed trades against the uncertainty related to their work is at least contingent upon two things. First, the uncertainty index in question should be correlated with lawmakers activity, for instance, uncertainty index should be higher when congress is in session than out of session. Although we do not report average EPU values separately for active and recess congress periods, we employ a chain of inferences based on other studies.

[15]As Covid hit, Washington Officials Traded Stocks With Exquisite Timing

[16]Senate Intel chair unloaded stocks in mid-February before coronavirus rocked markets

[17]Notably, in our sample, 2020 also saw the highest number of politician trades.

[18]We also find that, in our sample, the number of yearly trades have a strong positive correlation with yearly average of EPU

Because EPU and VIX are positively correlated[19] and considering that VIX is higher for days when the congress is in session (Krieger and Pace, 2020), it is plausible that EPU too would display variations with congress activities. Second, the uncertainty index should be a leading indicator of the stock market risk. In other words, the market should react to the changes in uncertainty; otherwise the uncertainty in question does not impact the market and information advantage over the uncertainty would then be useless for earning abnormal returns. As seen in Baker et al. (2016), EPU index is positively associated with the frequency of large stock market movements, suggesting that policy uncertainty, most of which stemming from legislative work, can shape the risk in the market. Subsequently, information available at the source of this uncertainty has utility in navigating the market. Overall, going by these reasons above, it is apparent that EPU is a reliable uncertainty index for unpacking whether congress members trade on private information. Lastly, we are careful not to draw a distinction between firm-specific, industry-specific, or market-wide information advantage congress members have against policy uncertainty. This is because economic policies cover a wide range of decisions that have the potential to affect firms and industries individually or the entire market separately or simultaneously in numerous ways. However, in the following empirical tests, we use three different types of return adjustments to ensure that our results are robust to different types of abnormal return benchmarks.

Our last hypothesis concerns with the strength of relation between two different types of EPU and abnormal returns of congressional trading activities. It is worth noting that EPU index is available in two different types of measures. Although the two have a overlapping component, the designs of index construction are slightly divergent. The first measure, news-based index, is solely generated by textual analysis of keywords related to economic policy uncertainty in 10 leading U.S. newspapers.[20]An uncertainty index based on words, by its nature, conveys a more fuzzy aspect of uncertainty. Subject to bias in reporting and differences in opinions due to ideological slant, it could contain some degree of non-negligible noise in its measure.[21] In contrast, the second measure, three-component index, is a weighted average of new-based index values **and** uncertainty caused by tax, fiscal, and monetary policies. The design of the second measure ensures that not only does the three-component index suppresses the noise in news-based index values, it also covers uncertainty caused by a wider range of policies under the watch of legislators. For this reason, we consider the latter to be a cleaner measure of uncertainty for our tests and thus expect the relation between EPU and abnormal returns to be stronger for three-component index than for news-based index.

[19]with a correlation of 0.58 as reported by Baker et al. (2016)

[20]These are: USA Today, Miami Herald, Chicago Tribune, Washington Post, Los Angeles Times, Boston Globe, San Francisco Chronicle, Dallas Morning News, New York Times, and Wall Street Journal.

[21]Newspaper - which way do they lean?

5 Data, Sample, and Variables

There are multiple data providers for aggregation of stock tradings by congress members. The main sources of information for most aggregators come from the U.S. Office of Government Ethics, the Senate Office of Public Records, and the Office of the Clerk of the House. We use the data compiled and provided to us by QuiverQuantitative, an online FinTech service that scrapes and collects financial data across the internet and aggregates it into an easy-to-use web platform for retail investors. Among various data sets it offers are congress trading, government contracts, and corporate lobbying. The platform also have a service that tracks and regularly reports the latest stock trades of Representatives, Senators in both separate and combined dashboards.

Covering both Representatives and Senators for the 2014-2023 period, our data set comprises 30,252 common stock transactions along with other important information such as politician name, Party Affiliation, date of transaction, amount, and ticker. Notably, when politicians report financial transactions in the Financial Disclosure Forms, they are not required to report the number of shares bought or sold and the exact amount transacted. The amount in our dataset are thus mostly expressed in intervals, for example, $1,001 - $15,000 and $15,001 - $50,000. We link tickers to their corresponding permnos using the Center for Research in Security Prices (CRSP)/Compustat Merged Annual library from WRDS. We also obtain Global Company Key (GVKEY), and 4-digit SIC industry codes to be used for Fama-French 12-industry identification later. After these steps, we identified 221 politicians who traded 2,205 unique common stocks constituting a total of 28,406 transactions. Out of these transactions, 14,039 were purchases and 14,206 were sales, and the rest were marked as exercise or exchange. Breaking down by party affiliation, 101 Democrats accounted for 15,423 transactions, 118 Republicans for 12,933, and 2 independents making up 50 transactions. A total of 175 Representatives were responsible for a majority of transactions, having conducted 20,985 out of 28,406 trades. The remainder 7,421 were transacted by 47 Senators. Table 1 gives a more granular detail of transactions along House and Party. (Note that 175+47=222 instead of 221 identified politicians above because Jacky Rosen from the Democratic Party was a Representative from 2017 to 2019, and became a senator since 2019). Table 2 and Table 3 gives additional summary statistics of transactions in the sample, describing the yearly breakdown of trades by party affiliation or transaction type. Table 4 reports the breakdown of transactions (only purchase and sale) by industries. Using Fama-French 12 industry classifications, we find that the two top industries traded by legislators are Finance/Money, and Business Equipment. Consumer durables is the least popular industry among politicians. We also see some patterns of differences in industry preferences between Democrats and Republicans. For example, despite Republicans having fewer number of total transactions, Republicans' trades in Utilities and Energy significantly outnumbered Democrats' trades. Democrats meanwhile appear to prefer stocks in Healthcare and Business Equipment. Table 5, containing the yearly breakdown of transactions in each 12 industry, also reveals some interesting insights. In 2020, lawmakers intensified trading stocks from Health, Finance/Money, Other, and Shops industries. It could be that politicians with private information about COVID-19 probably purchased Health stocks and sold Shops stocks. These are some of the interesting facts we get a glimpse of from summary statistics.

We rely on several data sources for our empirical tests. We use the CRSP daily stock product to obtain the stock returns. We use shares outstanding, price, and returns from the CRSP monthly stock file to get market capitalization, the product of price and share outstanding. Momentum in this paper follows Carhart (1997), defined as the compounded return over months $t-12$ through $t-2$. Two financial ratios used in regression tests, book-to-market and return on assets are from WRDS Financial Ratios Suite. VIX and GDP figures are taken from the Federal Reserve bank of St. Louis Economics Research database (`https://fred.stlouisfed.org/`).

We opt for cumulative abnormal reutrn (CAR) measurement to assess the short-term performance of politician trades in relation to economic policy uncertainty. CARs are calculated in two steps: the first involves taking the difference between the daily return of a stock and the corresponding benchmark portfolio/index return for each trading day in the event window, and the second step sums up each daily return difference into a single cumulative value. Mathematically, it is expressed as:

$$CAR_s[0, w] = \sum_{d=0}^{w} (R_s^d - R_{\text{benchmark}}^d) \tag{1}$$

where $CAR_s[0, w]$ is the cumulative abnormal return of a stock $'s'$ over the period from the day of transaction to successive $'w'$ days. $R_{\text{benchmark}}^d$ is the benchmark return to control for risk factors.

We employ three different benchmarks: S&P 500 index, returns of decile portfolios formed according to year-end capitalization, and Fama-French 12-industry returns. All the returns of benchmarks are in daily frequency. S&P 500 index is treated as the proxy for general market return, which we retrieve from the CRSP Daily S&P 500 Index table. To get size-benchmarked returns, we utilize size portfolio returns from the CRSP Indexes (Annual) erdport1 table which contains daily returns of portfolios based on year-end-capitalization, formed by sorting all stocks from NYSE, AMEX, and NASDAQ into deciles. We include size-adjustment because our sample comprises companies of varying sizes (measured by capitalization).[22] Consequently some of the small firms in the sample may not be included the calculation of S&P 500 index returns. This means that the first market adjustment we did may not be applicable to some of the (small) firms in the sample. Besides, since firm size is known to be a crucial determinant of a firm's expected return, computing abnormal returns by adjusting for size has been a recognized method as well. For industry-benchmarked abnormal returns, we require rules for 12 industry classifications according to SIC codes and industry returns. These data are retrieved from Kenneth R. French's website (`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`) The reason for industry adjustment is mostly due to some reports alleging that government officials including lawmakers may have access to industry-specific private information.[23] If lawmakers combine industry-related information with information edge over uncertainty to pick or dump the right stocks in a specific industry, their trades' performance may top the industry returns they invested in. To ascertain whether this is the case, we add industry adjustment model to our measures of abnormal returns.

5.1 Policy Uncertainty

The policy uncertainty index, developed by Baker et al. (2016) is designed to measure the level of policy-related economic uncertainty by averaging uncertainty from three underlying components related to news coverage, tax code policies, and monetary and fiscal policy. The news-based index, which is given the largest weight, is meant to capture uncertainty about economic policy decision makers, policy actions, and the economic consequences of those policy actions (or the lack of actions). To do so, they build a list of keywords and use textual analysis to analyze the occurrences of those terms in the content of 10 leading U.S. newspaper publications. The tax-based uncertainty is derived from lists of temporary federal tax code provisions compiled by the Congressional Budget Office (CBO). Finally, the last component is made up of two sub-components reported in the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. The first sub-component measures uncertainty over the future state of the economy, as implied by dispersion in CPI forecasts. Similarly, the second sub-component estimates uncertainty inferred from the purchase of goods and services by the state, local, and federal governments.

We download the policy uncertainty data from `https://www.policyuncertainty.com/us_monthly.html` which have both uncertainty index aggregated from three components and only the

[22]The smallest market capitalization is $3 million and the largest $2.4 trillion

[23]Hundreds of Energy Department Officials Hold Stocks Related to Agency's Work Despite Warnings

news-based index (henceforth 3ci and nbi respectively). The latest data available ends at June, 2022 for both indices, therefore our regression tests do not make use of transactions in the second half of 2022 and 2023. Figure 3 plots both 3ci and nbi indices from 2014 to 2022. Both indices are closely related, with a correlation of 0.980. For the 1985-202 period, the correlation between the two is 0.920. Over the 2014-2022 period, the means of 3ci and nbi respectively are 135 and 167(rounded to whole numbers). The uncertainty spiked drastically in the first half of 2020, which we attribute to the COVID-19 crisis, with a much higher jump for nbi reaching as high as 500. The abnormal jump in early 2020 could distort the long-run/overall time-series average of policy uncertainty, and we find that 3ci and nbi average around 121 and 146 respectively without 2020 in the sample. In the following empirical tests, we find that unusually high indices (as well as volatile returns) in 2020 affect the reliability of regression results involving industry benchmarks. We provide a plot of the two indices for a longer time period January, 1985 to July, 2022 in Appendix A. Barring the years of extreme uncertainty due to economic crisis and market chaos, both nbi and 3ci show a slow upward trend. This suggests that uncertainty, even in relatively normal periods, is getting higher with time, which is further confirmed by the fact that the average of uncertainty for the entire period of available data is only approximately 114 for 3ci and 121 for nbi.

6 Empirical Methodology and Results

As expounded in the hypothesis section, if politicians are privileged to non-public/private/insider information which they utilize in their stock investments and divestment, their abnormal returns should vary with economic policy uncertainty. This is because lawmakers can make informed trade decisions afforded by their information advantage from the act of lawmaking and enforcement. Therefore, they may be shielded from unexpected or unpredictable swings or losses generated by policy uncertainties, and their abnormal returns should exhibit variation with policy uncertainty index. In this section, our empirical results imply that politicians possess and do use some degree of information advantage by documenting a statistically significant relation between abnormal returns and uncertainty indices.

6.1 Baseline Regression

Following Jagolinzer et al. (2020) with slight modifications, we construct our baseline regression equation as:

$$
\begin{aligned}
AR_{s,t}[0,w] = \kappa + \beta \cdot \text{logEPU}_{t-1} + \alpha_1 \cdot \text{umd}_{t-1} + \alpha_2 \cdot \text{ret}_{t-1} + \alpha_3 \cdot \text{logmktcap}_{t-1} \\
+ \alpha_4 \cdot \text{bm}_{t-1} + \alpha_5 \cdot \text{roa}_{t-1} + \delta_s + \epsilon
\end{aligned} \tag{2}
$$

where the variable $AR_{s,t}[0,w]$ represents the cumulative abnormal return of a stock transaction made in month t, calculated over a specified window period. We choose a 25-day period $AR_{s,t}[0,25]$ for our tests, with day 0 corresponding to the date of transaction. $logEPU_{t-1}$ is the natural logarithm of either 3ci or nbi of the month before the transaction month t. As an illustration, consider a trade transacted on 26Feb, 2019; in this case $logEPU_{t-1}$ is the natural logarithm of 3ci or nbi recorded for Jan, 2019. Similarly, umd_{t-1} is the momentum of past month, measured as the compounded return over months $t-12$ through $t-2$ (based on Carhart, 1997). ret_{t-1}, bm_{t-1}, roa_{t-1} are the monthly return, book-to-market, and return-on-asset of the past month respectively. Similarly, $logmktcap_{t-1}$ is the natural logarithm of market capitalization of the month before the transacted month. To get the natural-logged market capitalization in a given month, we first multiply the month's public share outstanding by 1000 (because the number of shares is recorded in thousands), and then by the price at the end of the month. As a last step, we apply the natural logarithm function to the resulting number. δ_s denotes firm-fixed effects. Because of the presence of firm-fixed effects in the regression, it is imperative to cluster standard errors by firms, which we did for all our tests. In addition, since stock returns are known to be serially correlated, we also cluster standard errors by time **(year-month)** to give us a more accurate and truthful relation between abnormal returns and uncertainty.

6.2 CARs

First, separately for purchases and sales, we report summary statistics of cumulative abnormal returns adjusted for three different benchmarks. The number of transactions in the reported tables are smaller than 28,406 mentioned in the data section because there are instances where stock returns are not found in the WRDS tables we used. For example, when using S&P 500 index, we were able to get CAR[0,25] for 26,488 transactions out of 28,406. Table 6 shows that mean of CAR[0,25] adjusted for S&P500 index, industry, and size portfolios are positive for both purchases and sales. Standard deviations are always significantly larger than the mean of CARs across all three specifications, indicating a wide variation in legislator's trade short-term CAR performance. It is also worth noting that maximum CARs are always larger in magnitude than minimum CARs for both purchases and sales.

Mean, minimum and maximum across all three benchmark adjustments are close to one another.[24]

6.3 Abnormal Returns and EPU (nbi and 3ci)

Table 7 to Table 9 present the results of running eq. (2), with CAR[0,25] as the dependent variable adjusted for S&P500, size, and Fama-French 12-industry respectively. In all 3 tables, columns (1) to (6) report the findings for purchase transactions while columns (7) to (12) correspond to sales. Within each Purchase and Sale section, the first three specifications are for when nbi is used as an uncertainty index, and the next three are for when 3ci is an uncertainty index. For three columns/specifications under each EPU index type (nbi or 3ci), we report results of three regressions: the first corresponding to the baseline model, the second additionally accounts for VIX while the third specification adds quarterly GDP growth as a control. Although EPU is generally regarded as distinct from variables related to macroeconomic conditions or market uncertainty (Beckmann and Czudaj, 2017; El Ghoul et al., 2021), we added the two variables above to address the concern that EPU may be partially (or fully) absorbing the effect of macroeconomic situations or marketwide uncertainty. Note that since VIX and EPU are correlated (See Section 4), we extract the portion of VIX that is orthogonal to nbi and 3ci respectively, and use the orthogonalized values in regression tests. The effect of EPU, if found after controlling for orthogonalized VIX or GDP growth, presents a rather concrete confirmation that legislative trading is related to the uncertainty originating from political processes.

We find, in Table 7, positive relation between lawmakers buy trades' short-term outperformance over the general S&P 500 market. The coefficient for $logEPU_{t-1}$ in column (4) is 0.0187 and is 1% statistically significant. This is larger and also more significant than the 5% significant coefficient 0.0143 in column (1) when nbi is the uncertainty index, an early evidence in support of our hypothesis about 3ci having a stronger relation with performance of legislators' trades. On the other hand, we do not observe a consistent pattern that indicates politicians sales are informed as the coefficients of $logEPU_{t-1}$ are insignificant in columns (7) to (10), and only 10% significant in columns (11) and (12). When CARs are adjusted for size, Table 8 shows that both purchases and sales made by politician generally do not display any significant relation with either nbi or 3ci (except for column 3, 4, and 6 wherein coefficients on $logEPU_{t-1}$ are only 10% significant). This potentially means that politicians information advantage over the economic policy uncertainty do not go beyond beating the general market. In column (4) of Table 8 which has 3ci as an interest variable, the coefficient for $logEPU_{t-1}$ is

[24]For example, CAR[0,25] maximum of purchases are 2.0460, 2.0687, and 2.085 for S&P 500, size, and industry adjustments respectively.

at 10% significance. Meanwhile, in column (1) which is the same as column (4) in specification except for uncertainty index, we do not find any statistical significance on $logEPU_{t-1}$. This again implies that 3ci is possibly a stronger predictor of politician trades' performance than is nbi. In strong similarity to Table 7, we do not detect any relation in all columns between size-adjusted CAR[0,25] and policy uncertainty when it comes to sales. Next, we test for a relation between industry-adjusted abnormal returns and EPUs, and the results are reported in Table 9. Comparing column (4) to (1) and column (6) to (2), there is a 5% statistically significant association between 3ci and CAR[0,25] (which is stronger than 10% connection found with nbi). The statistical significance, however, doesn't seem to be stable. As seen column (2) and column (5) which controls for VIX, we no longer detect a statistical relation. Consistent with prior results on sales, we again do not observe that an increase (decrease) in EPU is related to decrease (increase) in industry-adjusted CARs of sell transactions.

The results so far indicate that while abnormal returns and EPU could be related, the evidence produced so far is weak and unreliable except for when legislators stock trades' performance is benchmarked against S&P 500. However, this rather perplexing result could also be driven by a subset of stock trades belonging to specific industries, a group of lawmakers, or a specific year. It is worth nothing that our sample period includes 2020 in which the financial market exhibited extreme fluctuations in prices and anomalies in its market microstructure (Sun et al., 2022; Haddad et al., 2021). Given this suspicion, a natural question following this observation is whether the results we produced so far would change with the exclusion of transactions from 2020.[25] Bearing this in mind, we reran regressions for all four benchmark adjustments without including transactions in 2020. The results obtained from excluding 2020 data points are discussed in the next Section 6.4.

6.4 Abnormal Returns and EPU (nbi and 3ci) without 2020

In this section, we report the results of eq. (2) using all transactions but those from 2020. We do so because we previously highlighted the potential for transactions in 2020 to drastically alter the outcomes of regression analysis due to unusual market fluctuations from COVID-19, an extraordinary jump in both nbi and 3ci index, and the large number of transactions executed by lawmakers during 2020. Hence, it is worth investigating whether there would be any changes to the results detailed in

[25] This suspicion is also justified by the fact that the results seen in Table 7 to Table 9 didn't change much when we examined whether the results would remain the same after excluding certain industries or trades from certain politicians.

Section 6.3 when transactions from 2020 are excluded.[26]

The first four columns of Table 10 illustrate that the association between abnormal returns of congressional buy trades and EPU is strengthened when data from 2020 are removed. The coefficients on $logEPU_{t-1}$ in the first six columns of Table 10 are all 1% significant and larger in magnitude than the corresponding coefficients from Table 7. R^2 values are also much larger when 2020 transactions are excluded. Regarding sales, the positive coefficients in column (7) to (12) imply that when 2020 transactions are not accounted for, sell trades' abnormal returns get worse with EPU. The strength of relation for sale trades is however less significant and decidedly smaller in magnitude than what is found for buy trades. Moving on to size-adjusted CARs and its corresponding results in Table 11, the coefficients in the first six columns representing buy trades' CARs are all positive and highly significant at 1%, a major deviation from the results seen in Table 8. Not only that, the effect of policy uncertainty is also economically large. For example, the coefficient in column (4) indicates that a 1% increase in 3ci is associated with about 0.0226% increase in size-adjusted CAR[0,25] for buy trades.[27] After removing 2020 transactions, our results do not indicate any statistical connection between sale trades' size-benchmarked CARs and EPU. We find similarly strong results in column (1) to column (6) of Table 12 containing results of estimating eq. (2) with industry-adjusted CARs of all non-2020 transactions as the response variable. Although the coefficients are smaller than those in Table 10 and Table 11, all of them are significant at either 1%. We again do not see that sales transactions appear to be informed after adjusting legislators' stock trades with industry benchmarks. Overall, a short synthesis of these findings above informs us that when the effect of abnormal market conditions caused by COVID-19 is removed, legislators seem to be privileged to information advantage against economic policy uncertainty to the extent that their stock purchases appear to be informed while the sales are not. We explain why sale trades could not be informed in Section 6.7.

6.5 More analysis

6.5.1 Do legislators information advantage vary with age?

Some studies on insider trading (both non-corporate insiders like politicians and corporate insiders) present evidence that trading behavior varies with investors' age (Korniotis and Kumar, 2011;

[26] Because the impact of COVID-19 on market stability occurred mostly in the first half of 2020, one might argue that it might be more appropriate to remove only the transactions from first half of 2020. We find that a majority of transactions in 2020 came from the first half of 2020. Based on this observation, we contend that removing all transactions of 2020 does not pose a design methodology problem since the number of transactions made in second-half of 2020 is relatively much smaller

[27] The average size-adjusted CAR[0,25] for buy trades is 0.11% as seen in Table 6

Hanousek et al., 2022). Among the politicians, with other things equal, it is quite likely that the older members of congress have longer years of service than the younger ones. By extension, the older members supposedly have more power, connections and influence, which in turn may increase their access to informational advantage. Besides, older members with extensive political experience will also probably be better at discerning the quality and relevance of non-public or not-yet-public information for making informed stock trading decisions. Given this conjecture, we find it appropriate to consider whether the way information advantage is capitalized for financial gains in stock trades differ between older and younger politicians. To examine this assumption, we first look at the age distribution of lawmakers in our dataset. We find that the median age of politicians in our sample at the end of 2022 is 63 years. Then, we create a new variable named old_age, which takes on a value of one if a transaction is made by a politician aged 63 or older, and zero otherwise. Afterwards, we rerun eq. (2) with the addition of a new interaction variable $logEPU_{t-1}$ * old_age. In our analyses which exclude 2020 transactions, we did not observe a statistical significance on the interaction term. Because we didn't find any significance, we chose not to report the results in tables. We put forth two possibilities (but mutually exclusive) to explain the absence of statistical significance. First, it could be argued that age is not a good proxy for the number of terms in office. While this explanation may hold some merit under some circumstances (for example, it **might** be true for our sample), anecdotal evidence informs us that up until recently, the frequent changing of Congress seats is not the norm. On average, the turnover rate of Congress seats is approximately 12 years, implying a general correlation between age and tenure.[28] Therefore, we relax the assumption made in the first explanation. Our second explanation allows for the positive correlation between age and tenure. Then, we note that because the median age of sampled politicians is 63, with the 25^{th} percentile at 56, it is reasonable to deduce that a majority of the politicians in our dataset are already older and experienced politicians who are equally adept at navigating around uncertainty with privileged information.[29] Thus the interaction term should not exhibit any statistical significance even after segmenting legislators into old age and young age groups using median as a breakpoint.

[28]Some members of Congress have been there for decades, but seats typically change hands more frequently

[29]Transactions by those older than the median age comprises 55% of total transactions in the sample. Number of transactions by politicians above 25th percentile age represents 76% of all trades in the sample. This does not necessarily mean that our sample is biased as it is entirely possible that older legislators execute more stock trades than younger/newer legislators

6.5.2 Do legislators information advantage vary with industries?

In this section, we explore whether positive effects we documented so far as purchases are stronger in some groups of industries than others. This idea is inspired by the fact that the stock market performance of industries may not be equally sensitive to ups and downs of economic policy uncertainty. To clarify further with an example: given that one component of EPU is related to the federal and state governments spending which is decided and legislated by the Congress, it stands to reason that industries which are more exposed to government expenditure may be more affected by uncertainty.[30] Similarly, industries which are highly regulated by governments are likely to be more connected to ebbs and flows of policy uncertainty generated when lawmakers propose, amend, or implement new regulations. Subsequently, information advantage against uncertainty which legislators are presumed to possess may not be the same across industries. In other words, the value or magnitude of information advantage may be stronger for industries with higher exposure to EPU. Therefore, uneven impact of EPU on industries and nonuniform information advantage across industries imply that if politicians are leveraging on (partially or fully) uncertainty-proof information in conducting some of their trades, we would expect documented positive effects to be more pronounced in a subset of industries highly exposed to EPU components.

Out of 12 industries assigned to firms in our sample, we identified six industries with higher exposure to economic policy uncertainty: Energy, Manufacturing, Health, Money, Business Equipment, and Others. These six industries are chosen for the following reasons. Spending on military is usually the largest component of Federal Discretionary spending, proceeds of which goes into manufacturing of various types of weapons, gadgets, engineering systems, and engineering services.[31] We included energy industry for two reasons. First, fossil fuel industry is heavily subsidized by the government through provisions of numerous tax codes.[32] [33] Second, recent years have also witnessed a surge in energy production and associated downstream services in the US.[34] This also sparked some regulatory changes despite the energy industry already being a highly regulated industry.[35] Overall, spending on military and changing energy production environment in turn affects Manufacturing and Others (which include engineering services, mines, and constructions) industries. Given that Medicare&Health, and Educa-

[30] There are two main types of government spending: Mandatory and Discretionary. Lawmakers have to approve discretionary spending plan every year. Although mandatory spending does not require annual approval by legislators because its spending are mandate by laws, uncertainty surrounding mandatory spending can still arise from proposals to amend existing laws or enact a new law. For instance, Social Security Act was last amended in 2019.

[31] Federal Spending: Where Does the Money Go

[32] Fact Sheet — Fossil Fuel Subsidies: A Closer Look at Tax Breaks and Societal Costs (2019)

[33] Reforming global fossil fuel subsidies: How the United States can restart international cooperation

[34] How America's 'most reckless' billionaire created the fracking boom

[35] Biden Makes Sweeping Changes to Oil and Gas Policy

tion are next two largest components of Federal mandatory spending after Social Security, we conclude that Health and Business Equipment are also industries more intertwined with government spending and thus policy uncertainty.[36] Lastly, we added Money as a representative industry that could be most sensitive to changes in tax codes and monetary policies.

Having identified those industries and after excluding the transactions involving stocks whose industry classification is not one of the six industries above, we rerun the same regression model outlined by eq. (2). The results of these regressions on **only purchase trades** are reported in Table 13 which include 2020 transactions and Table 14 without 2020 trades. Both EPU indices (nbi and 3ci) are examined in the analyses. The first two columns correspond to abnormal returns adjusted for S&P 500, the next two for size, and the last two for industry. We begin the discussion of our results with S&P 500 benchmarks. Comparing the results from column (1) and (4) ofTable 7 to column (1) and (2) of Table 13, we find that magnitude of coefficients on both nbi and 3ci are larger when only the six industries with high exposure to economic policy are considered. When comparing the $logEPU_{t-1}$ coefficients in column (1) and (4) of Table 10 to column (1) and (2) fromTable 14, the same pattern is observed, that is, the relation between EPU and abnormal returns of politicians' buys are always stronger when only the six industries characterized by high exposure to policy uncertainty are in the sample. When we switch to using size adjusted abnormal returns, we get another evidence that industries marked by high sensitivity to policy uncertainty are where lawmakers appear to have better information advantage. This is because while coefficients for $logEPU_{t-1}$ in column (1) and (4) of Table 8 are insignificant or only 10% significant respectively, we document more positive and 5% significant coefficients for $logEPU_{t-1}$ in Table 13's column (3) and (4). With the exclusion of 2020 transactions, we continue to find that $logEPU_{t-1}$ coefficients in columns corresponding to the baseline model are all smaller in magnitude than their peer coefficients reported in column (3) and (4) of Table 14. Some of the results in Table 14 suggest that politicians' advantage in information advantage is indeed quite large for industries more influenced by policy uncertainty. For example, the coefficient on column (4) specifies that a 1% increase in 3ci is followed by a rather impressive 0.0295% increase in size-adjusted CAR[0,25]. Next, results obtained with industry-adjusted CAR[0,25] mirror the results presented above. Table 9's $logEPU_{t-1}$ coefficients are smaller than its counterparts in column (5) and (6) of Table 13, whether the EPU in question is either nbi or 3ci. When we limit the sample to non-2020 transactions falling under the six EPU-sensitive industries classification, we again find larger coefficients (stronger relationship with EPU) for trades in those six industries, as can be seen from 1% significant coefficients

[36] Business Equipment industry covers Electronic Equipment, Computer and Software. Note that the demand for these types of products and services are also affected by military spending.

of 0.0157 and 0.0212 from Table 12 in contrast to 0.0186 and 0.0252 from Table 14 at the same level of significance. We also note that all the results from Table 13 and Table 14 continue to support our hypothesis that 3ci is a more effective variable than nbi in capturing the economic policy uncertainty stemming from activities of congress members since both magnitude of coefficients and adjusted R^2 values are always higher for specifications using 3ci. In summary, since we find consistently larger relation between EPU and abnormal returns across all three benchmarks, the results in this section further solidify our hypothesis that politicians indeed enjoy information advantage against economic uncertainty originating from their acts of policymaking. Not only that, they do appear to leverage on that informational edge since abnormal returns of buy transactions in stocks of industries more exposed to economic policy uncertainty show a stronger relation with uncertainty

6.6 Why do results seem contrary to the expectation with the inclusion of 2020 transactions?

6.6.1 Longer-term CARs and non-linear relation

So far, we have quite consistently observed a positive relation between EPU and short-term abnormal returns of buy trades for S&P 500, size, and Fama-French 12-industry adjustments once we include data points from the chaotic year of 2020 (and when we examine the trades in industries whose performance is more prone to policy uncertainty caused by legislative activities). Given that 2020 is also the year with some of the highest EPU indices values, it is rather puzzling that the positive effect is almost wiped out for size and significantly reduced for Fama-French 12-industry adjustments when 2020 data points are included (See Table 8 and Table 9). This appears to be contradictory to the natural expectation that the positive effect should even be stronger with the inclusion of 2020 since EPUs are abnormally high in that period, especially in the first half of the year. We present our conjecture to explain why this discrepancy might exist. Our regression model essentially studies how short-term abnormal returns vary linearly with the economic policy uncertainty. However, in 2020, because COVID-related uncertainty was causing unprecedented volatility in the financial market and there was higher-than-usual noise regarding where the market might be headed next. Consequently, the model could suffer from two drawbacks: the unreliability of short-term CAR measurements in 2020 and the possibility of non-linear relationship between EPU and abnormal returns.

To address the first issue, it seems logical to first simply measure (slightly) longer-term abnormal returns of 2020 trades and investigate if they are, on average, positive for buys and negative for sales. To do so, we utilized WRDS Daily Event Study tool and calculated politicians trades' CAR under CAPM model, Fama-French 3-factor model, and Carhart 4-factor model.[37] The abnormal returns were measured at three distinct periods: [0,60], [0,90], and [0,120]. We report our results in Table 15. We find that except for CAPM model, long-term abnormal returns of 2020 buy transactions are all negative, indicating that politicians' stock purchases during 2020 are on average not informed. In contrast, sales' negative abnormal returns measured over longer periods [0,90] and [0,120] suggest politicians may have had useful information about when to unload the equities from their portfolios. ~~We do not however test for the sign and magnitude of relation between EPU and longer-term abnormal returns (See Section 6.7 for an explanation).~~ Overall, this exploratory analysis also seems to suggest that politicians' information advantage amid market fluctuations caused by COVID-19 may have shifted from buy trades (as seen in Section 6.4) to sell trades in 2020. Still, because this investigation is simple and rough, we concede that further research awaits to uncover and understand the flow of politician stock trading that took place in 2020. Regarding the second issue, we add $logEPU_{t-1}^2$ term to eq. (2) and report the regression results for purchases in Appendix A Table 17. We find that the relation between the added square term and abnormal returns of stock buys are indeed all negative and statistically significant in all six columns. One interpretation of these results is that while politicians may be informed against uncertainty for buys, there exists a threshold beyond which they too lost information advantage because the uncertainty has become too large to grasp and understand. In such cases, the relation between short-term abnormal returns and EPUs is no longer linear, with a negative coefficient on the quadratic term. In untabulated results, we also observe that the statistically significant negative relation with the square term disappears when 2020 transactions are excluded. These results further corroborate our intuition that informational advantage of even privileged legislators as a group may decline when the uncertainty is too large. This claim, however, opens up another valid question of whether all types of crisis or only a specific kind amplifying the uncertainty give rise to the fall in informational advantage ~~and thus negative relation between short-term abnormal returns and EPU.~~ In the next section, we propose that the nature of COVID-19 and the government's response to it could explain why legislators experienced a drop in informational advantage as economic policy uncertainty dramatically rose to never-before-seen levels. Put it differently, we ask what is it about COVID-19 that disabled legislators to take more advantage of uncertainty?

[37]The estimation parameters set for estimation window (days), minimum number of valid returns (observations) and Gap (days) are 250, 100, and 30 respectively.

6.6.2 Power, Skill, and Responsibility

First, we start by noting that Congress members may have had limited ability to comprehend the COVID-19, especially at the onset of the pandemic. This is because of the difference in disciplines a majority of Congress members are trained in or familiar with and the areas related to COVID-19. It has been documented by the media that Congress is overwhelmingly made up of lawyers (Bonica, 2017).[38] On the other hand, one needs to possess skills and knowledge about medicine, health, and science to be able to digest and process information about COVID-19 — a skill that lawyers-turned-congresspeople are probably not equipped with. Besides, the deteriorating quality of expertise relating to science, medicine, and technology among Congress members is also a well-known fact. Because of Congress members' low and declining proficiency in science and technology, the executive branch rather than the legislative branch, has been at the forefront of formulating policies and overseeing matters on science, technology, and medicine for the past four decades.[39] Not surprisingly, at the start of the pandemic, executive agencies and officials were more prominent in responding to the spread of virus, resulting in decreased power (and thus information advantage) of Congress.[40] At the expense of Congress' power, the important role played by the executive branch such as Department of Health and Human Services (HHS), Centers for Disease Control and Prevention (CDC), and Food and Drug Administration (FDA) during the Cornonavirus pandemic could also explain seemingly information-motivated stock trades of these agencies' officials.[41] Overall, non-STEM background and the reduced power of the Congress in dealing with the pandemic could have prevented them from fully utilizing their privileges in stock trading during the pandemic.[42] In another word, informational advantage of congress members against policy uncertainty may have shifted to the executive branch even as EPU — an index more closely tied to legislative activities (rather than executive branch) in normal times — rises drastically. We leave it to future research to investigate the extent of differences in informational advantage enjoyed by the legislative and executive branch during the pandemic.

[38] Are There Too Many Lawyers in Congress? - The New York Times (nytimes.com)

[39] Congress's Role in the Coronavirus Catastrophe (issues.org)

[40] For example, Coronavirus Task Force was largely made up of executive officials

[41] Some anecdotal evidence can be seen here, "Collectively, officials at another health agency, Health and Human Services, reported 60% more sales of stocks and funds in January than the average over the previous 12 months, driven by a handful of particularly active traders."

[42] One probable counterargument to our explanation is that legislators could still possess valuable information benefit when Congress gets into action in later stages of the pandemic by passing various bills: the Coronavirus Preparedness and Response Supplemental Appropriations (CPRSA) Act, the Coronavirus Aid, Relief, and Economic Security (CARES) Act, etc. We should note however that these bills were passed in an unusually short amount of time, leaving it less room for legislators to process the information that could be useful to them. For example, the Trump Administration asked the Congress for emergency COVID funding on Feb,24, 2020 and CPRSA was passed on Mar 5, 2020.

6.6.3 EPU that could have been in 2020

Stemming from market volatility and increased chaos in policy making at the onset of COVID-19 in the U.S., EPU values were uncharacteristically high for near entirety of 2020. As COVID crisis is largely unanticipated and unprecedented in terms of impact on the financial market, distribution of information advantage among investors including politicians is likely to be extreme to a high degree. Consequently, trading decision and patterns during this period could have been markedly different than what could have been under normal times. Indeed, we know that the number of (reported) stock trades by politicians noticeably rose in 2020. However, as seen in Section 6.6, these trades on average don't seem to particularly fare well under long-term CAR measurements. Earlier, we proposed two possible (and not necessarily mutually exclusive) reasons to explain counter-intuitive regression results obtained when 2020 transactions are accounted for.[43]

In this section, we adopt a different method by constructing an alternate scenario wherein COVID-19 didn't occur, and as a result, EPUs in 2020 would have been lower than COVID-affected values we have in hindsight. The nature of this approach requires us to estimate EPUs that could have been without the disruption of COVID-19. To do so, we first fit a time-series model to the natural logarithm of 3ci (henceforth log3ci) over the period from 1985 to 2019. With auto.arima command from 'forecast' library in R programming, log3ci is modelled as an ARIMA(2,1,1) process.[44] In mathematical notation, log3ci is:

$$Y_t = (1+\phi_1)Y_{t-1} + (\phi_2 - \phi_1)Y_{t-2} - \phi_2 Y_{t-3} + \theta_1 \epsilon_{t-1} + \epsilon_t \tag{3}$$

where t stands for time subscript, Y_t is the log3ci at month t, ϵ_t is the innovation/residual while ϕ_1, ϕ_2, and θ_1 are estimated parameters.[45] Forecast values of log3ci (and also lognbi) relative to real ones are reported in Table 16. We then substitute those 2020 forecast figures for real log3ci of 2020. With hypothetical log3ci numbers for COVID-absent 2020 in hand, we can re-estimate eq. (2) without the need for excluding transactions from 2020, except with one caveat. By using forecast 2020's log3ci,

[43] One of them is mechanical, arguing that the relationship between EPU and abnormal returns are non-linear/quadratic, with negative loading on the square term of EPU. Another is concerned with power, skill, and responsbility of Congress during the pandemic.

[44] For time-series modeling, R programming, not Python, was used. A fitted model for natural logarithm of nbi is ARIMA(2,1,1) as well. The model fitted for the raw 3ci too is ARIMA(2,1,1). There is no glaringly large difference between fitting a model first to untransformed 3ci (1985-2019) then taking natural logarithm of the estimated 2020 3ci AND fitting a model to log3ci (1985-2019) to get estimates of log3ci in 2020.

[45] The estimates are 0.4808, -0.0325, and -0.8207 respectively. See diagnostic test of the estimated model in Appendix B.

we impose a constraint that 2020 had been a normal year. However, at this point, this constraint has been applied only to the variable of interest (log3ci on left hand side of the regression equation). To achieve consistency on both sides, it is not ideal to include all 2020 transactions since the large number of trades in that year are partially attributable to COVID-19. We thus use the average transactions count of 2019 and 2021 to proxy for the number of trades that could have been made by politicians in an otherwise normal 2020. Calling this approximate number 'x', we thereafter randomly draw 'x' number of transactions from all 2020 transactions in the sample.[46] We repeat this random sampling process for 300 times, obtaining largely distinct 300 sets of transactions for the right hand side. In the last step, we execute eq. (2) 300 times on each of the transactions sets. Reported in Figure 4, we find that when size-adjusted CAR[0,25] is set as a response variable, the coefficient of interest is 1% significant in all of the 300 iterations. Figure 5 further shows that all coefficients are positive, with the minimum at about 0.0002 and maximum at 0.0042. Changing from size-adjusted to industry-adjusted CAR[0,25], we continue to find, in Figure 6 and Figure 7, that coefficients on log3ci are all positive and statistically significant in all 300 rounds. For brevity, we don't report results when S&P500 is the benchmark. Overall, results from this section confirms that COVID-19 crisis in 2020 is an extremely abnormal event that distorted both politicians' trade profitability and regression tests. Had 2020 been a normal year, we show that the positive relation between legislative stock trades and economic policy uncertainty would have been stable.

6.7 Endogeneity and other concerns

In this section, we address (currently) seven issues and concerns readers may have with regard to our sample, methodology, and results.

First, we recognize that an alternative option to $logEPU_{t-1}$ is the EPU that is concurrent with the month of transactions. However, the deliberate use of $logEPU_{t-1}$ (including past month values of other control variables in the model) helps us eliminate endogenous simultaneity. If we go by concurrent_EPU, the test results might be subject to errors caused by simultaneity. In contrast, using $logEPU_{t-1}$ in the model can suppress the potential simultaneity error and also provide a clear delineation of causality.

Second, we explain our choice of short-term CAR over long-term measurements in our tests.

[46] This estimated numbers are 4586 for size-benchmarked abnormal returns and 4883 for industry-benchmarked abnormal returns. In our tests, we use 4500 and 5000 transactions respectively, with 34 as the seed number for reproducibility.

We did not use periods longer than 25 days out of the concern that the results may be additionally confounded by the effect of concurrent EPU on CARs of some days falling on the next month. A short example would help to provide more clarification. For the sake of simplicity, we will treat all days as trading days. Then when we compute CAR[0,25] for say, a buy trade on Mar16 of 2022, some days in the calculation process would spill over onto April.[47] Additionally, because EPU is serially correlated, the positive effect we find between CAR[0,25] and EPU recorded for Feb, 2022 might be tainted by relation between EPU of Mar, 2022 and some portion of CARs corresponding to days in April.[48] We are also wary against drawing statistical inferences from regressions where longer-term CARs are used as response variables due to the fact that a battery of literature documents measurement error and model specification problems associated with long-horizon abnormal returns (Fama, 1998; Lyon et al., 1999). Essentially, there is not a consensus on whether mispricing or measurement problem (since long-term CARs tend not to meet normality assumption (Bodie et al., (2014)) drive long-horizon abnormal returns. The potential for measurement error due to risk/benchmark adjustment is also higher in long-interval CARs as error from the estimated abnormal return increases with the length of time interval and the question of which risk factor or benchmark is more appropriate for adjustment is a bigger concern in calculating long-term CARs (See Eckbo, 2007). Thus, according to Brown and Warner (1980), risk-adjusted returns of short window period are more powerful in measuring abnormal returns. For these reasons, we employ short-term CARs rather than long-term CARs in this study.

Third, throughout Table 7 to Table 14, R^2 values are minuscule, casting doubt on the suitability of the model. However, it is widely acknowledged in asset pricing literature that models regressing returns (or abnormal returns) on firm fundamentals, financial ratios and stock characteristics almost always have low R^2 values. This is because returns are known to be highly unpredictable and random. Efficient market hypothesis also informs us that if markets are efficient, prices quickly reflect any new information, thus lowering the R^2. If anything, the fact that abnormal returns of legislators stock transactions are not explained well by firm fundamentals and financial ratios, but are significantly associated with EPUs, reinforce our hypothesis that legislators' stock investment patterns are partially driven not so much by firm characteristics as by economic policy uncertainty.

Next, in our model, we consciously did not add time fixed effects for the reason that there is a collinearity between time fixed effects and EPU which is also a time series index. Moreover, we also address a concern over the omission of a (linear) time trend in our models. In our calculation of CARs, we did not observe any significant (linear) time trends. Given the lack of a time trend in the response,

[47] Apr1st,2020 - Apr9th,2020

[48] For example, one-month lag autocorrelation of the natural log of 3ci series for the period 2014-2022 is 0.7833.

adding a variable to account for it would not have been necessary and also would not have improved the explanatory power of the model.[49]

Notwithstanding the fact that the left-hand side variables in our model doesn't have a time trend, some readers might still have concerns over the potential for bias in coefficients of EPU indices. We fully recognize this concern since we found out, via the Augumented Dickey-Fuller (ADF) test, some peculiarities of EPU time-series. Specifically, while both nbi and 3ci for the period 1985-2022 are stationary, the natural logarithm of nbi is not stationary (but the natural logarithm of 3ci continues to be stationary). Likewise, if we restrict the time series to our sample period 2014-2022, both the raw policy uncertainty and the transformed logged time series are not stationary. When the interest variable is not stationary, t-statistics tends to be **not** asymptotically normal and thus the case for spurious regression arises. (See the seminal paper Granger and Newbold, 1974). Subsequently, we would need to exercise caution in interpreting the statistical significance of coefficients. While it would be tempting to transform the unaltered EPU indices into first difference series or percentage changes, we do not favor the approach for a specific reason — results obtained from regression using these transformed variables are not aligned with our hypothesis. Whereas the use of logged EPU can support our conjecture that higher uncertainty is connected with higher abnormal returns, neither first differencing nor percentage change variables do not permit us to effectively test our hypothesis. To illustrate, suppose for a moment that higher percentage change in EPU is associated with greater abnormal returns. This finding doesn't distinguish between two possible paths to a large EPU change: a small EPU in month t-1 increasing to a medium, but still small, EPU in month t, versus, a large EPU in month t-1 rising by a large magnitude to an even larger EPU value in month t. Given this limitation, we choose an alternative approach wherein the non-stationary logged EPU series is separated through the additive decomposition into three components: trends in time, seasonal, and random. The process is designed such that the random component is generally stationary. We then re-estimate eq. (2) with CAR[0,25] of non-2020 transactions as responses, and the stationary random component of logged 3ci as an interest explanatory variable. We excluded 'nbi' from our tests as it exhibits less stability compared to '3ci' and demonstrates a weaker relationship with abnormal returns. Using the stationary irregular portion of logged 3ci has an added advantage of removing the confounding effects of uncertainty growing over time (which we described in Section 5.1). Furthermore, it ensures that the uncertainty in question is indeed random and unpredictable for a majority of financial market participants. If the statistical significance observed earlier remains, the evidence of politicians having information advantage against uncertainty

[49] No clear time trend in CARs mean that the absence of time trend explanatory variable in the model does not cause spurious regression from omitted variable (linear time trend)

is then strengthened. We report the decomposition plot and results of regressions in Appendix A. Table 18 shows that the statistical significance on the 3ci term persists.

We also recognize that yearly distribution of transactions in our sample may be biased towards certain years since there are fewer transaction records in the early part of the sample period. It seems implausible that lawmakers, for some (unknown) reasons, traded less frequently in 2014 than in 2022. Unfortunately, as detailed in Section 2, putting together legislators' trade records is a daunting task. To make matter worse, data collection methods and processes among aggregators may not be the same as another, leading to samples slightly different in size. The small dataset size in this paper does have limitations in that we are unable to run tests on subsamples along the line of member types, committee assignments or party affiliation.[50] However, we maintain that our sample size still is sufficiently large and sample period long enough to test for the hypothesized relation.

Lastly, for some specifications in result tables, we find statistically significant positive relation between abnormal returns of sales and policy uncertainty (for example, column 7 and 10 of Table 10, implying that politicians do not take advantage of informational advantage against uncertainty to execute timely sale trades. However, it is not prudent to rule out the possibility that lawmakers **entirely** refrain from incorporating information advantage in sale trades, especially when we have rather consistent evidence showing opposite results for buy transactions. Unable to dismiss the former point, positive coefficients may seem perplexing at first. However, the positive coefficients may be less surprising in light of some studies that show insider sale trades are generally less informed than purchases. This difference is attributed to the fact that sales are more likely to be driven by liquidity or diversification (Jiang et al. 2021; Jagolinzer et al. 2011; Lakonishok and Lee 2001). Based on these studies, we argue that, politicians, who are regarded as non-corporate insiders, may display parallel characteristics as corporate insiders in their sale patterns. Since there is nothing that can shield lawmakers from encountering liquidity constraints or facing the need to re-balance portfolios just like any other individual investors do, we posit that the positive coefficients could well be due to diversification or liquidity issues.

[50]To the extent that insider trading of congress members has been around for long and not a partisan phenomenon (Barbabella et al., 2019), we can reasonably expect the positive effect documented here to be prevalent in both parties, Representatives, and Senate (Ziobrowski et al., 2004).

7 Conclusion

Quite a number of academic works and media reports have highlighted a number of ways politicians can reap (undeserving?) financial benefits by exploiting their positions, power, and/or connection (Querubin and Snyder, 2011; Lenz and Lim, 2009). One among those enrichment paths is their ability, using non-public/valuable/market-changing information, to earn abnormal returns from stock trades. In spite of some studies showing that politicians collectively do not appear to beat the market when trading stocks (C. Eggers and Hainmueller, 2013), investors continue to believe politicians have informational advantage over outside investors[51] and the public's resentment at congressional stock trading is almost uniform.[52] As the public continues to ask a legitimate question of whether congress members have become **public servants in name only** and morphed into 'self-servants' preoccupied with fattening their wallets by unethically capitalizing on non-public information, our study could not have been timelier and the importance of its findings never been greater.

To dive into issue, we used the 2014-2022 stock transactions of both Representatives and Senators, and argued that a link between their stock trades' short-term abnormal returns and economic policy uncertainty index can help us infer the possible existence of information advantage among politicians. Depending on whether the sign of the connection is positive or negative for buy and sale trades separately, we can identify whether lawmakers may possess informational advantage. We observe that, except for periods characterized by unusual market volatility and uncertainty, short-term abnormal returns of politicians' buy transactions are very strongly and positively correlated with economic policy uncertainty. Their sale transactions on the other hand do not generally vary with changes in economic policy uncertainty. Overall, these findings imply that legislators act on informational advantage to pick the right stocks for buys precisely during times when increased market uncertainty, effected by heightened economic policy uncertainty, could instead discourage buy trades or intensify the risk of losses. Lastly, we do acknowledge that we have not yet pinned down a detailed mechanism on how this lawmakers-generated economic policy uncertainty gives rise to information advantage for politicians individually or as a group. Notwithstanding this deficiency, it is still our hope that our preliminary results — which are robust to different window periods and benchmark adjustments — will bring more attention to this issue and help, in one way or more, all stakeholders in formulating the best solution to the problem of how best to regulate congressional trades.

[51] as evidenced by the plethora of trading products and websites offering services that mimic politicians' trades. For example, there are ETFs named after Nancy Pelosi (Ticker: NANAC) and Ted Cruz (Ticker: KRUZ)

[52] 86% of public supports a ban on stock trading among members of Congress

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Figure 1: Number of politician trades and news-based EPU index

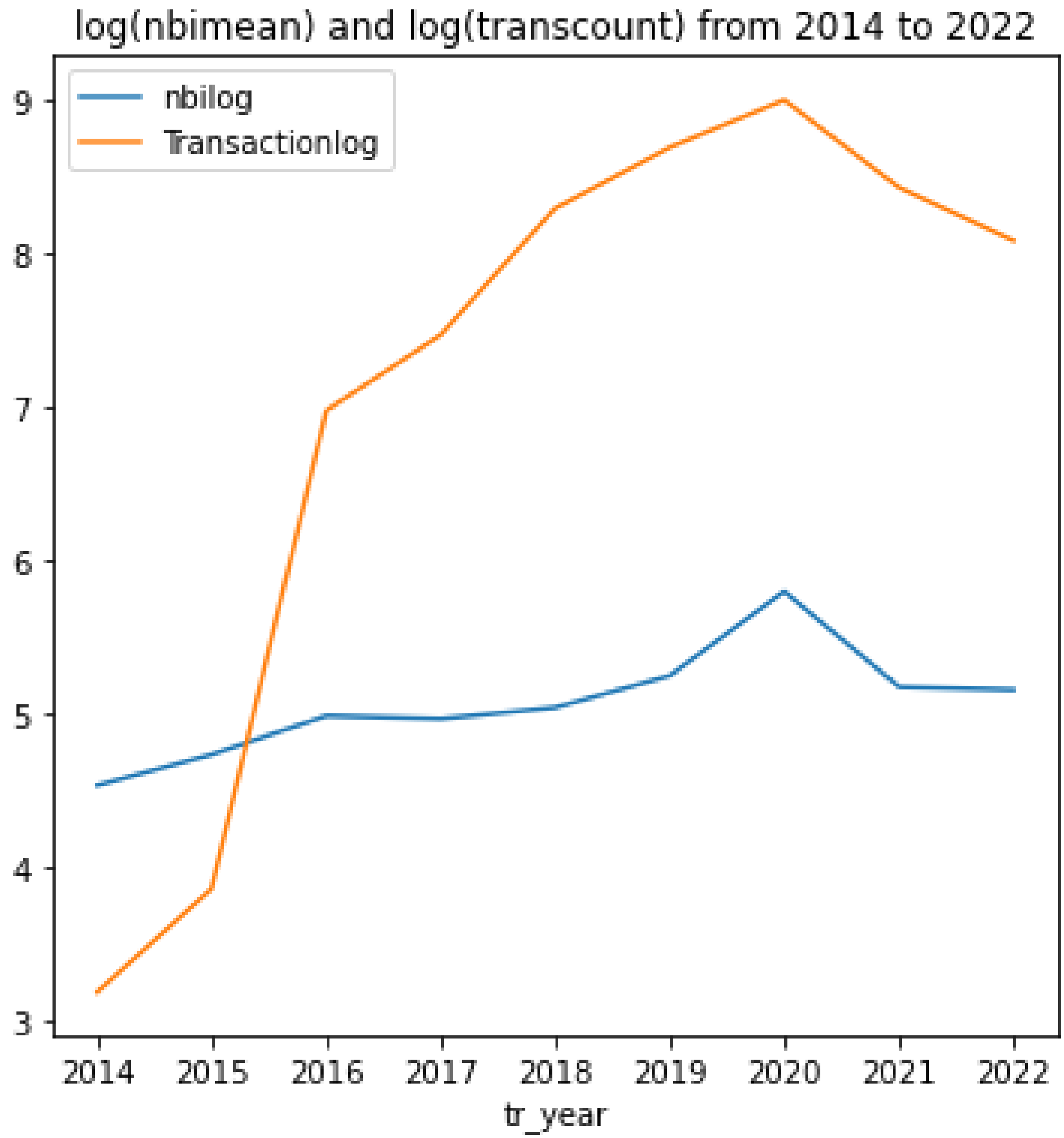


Figure 2: Number of politician trades and three-component based index

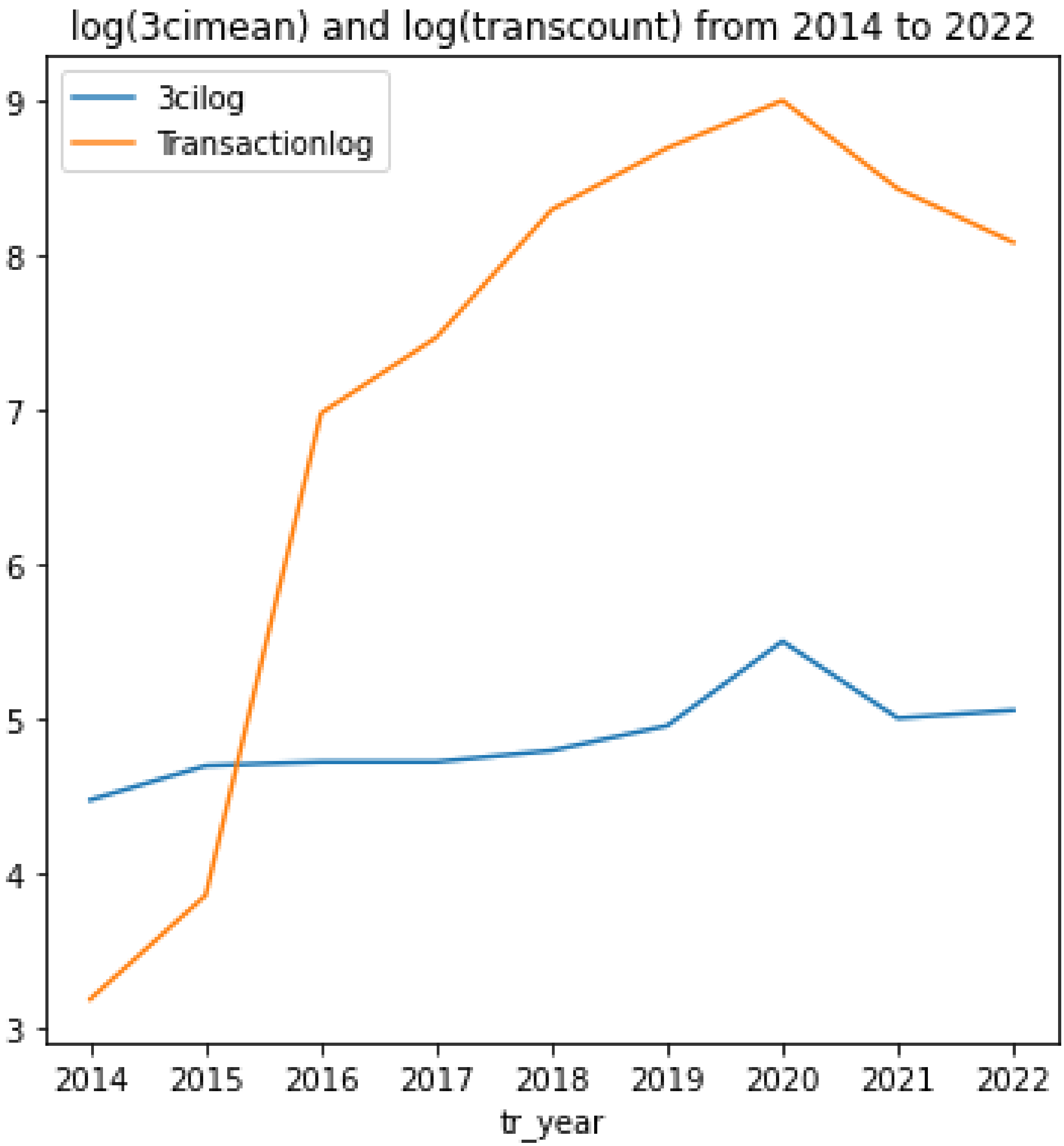


Figure 3: Policy Uncertainty from 2014 to 2022

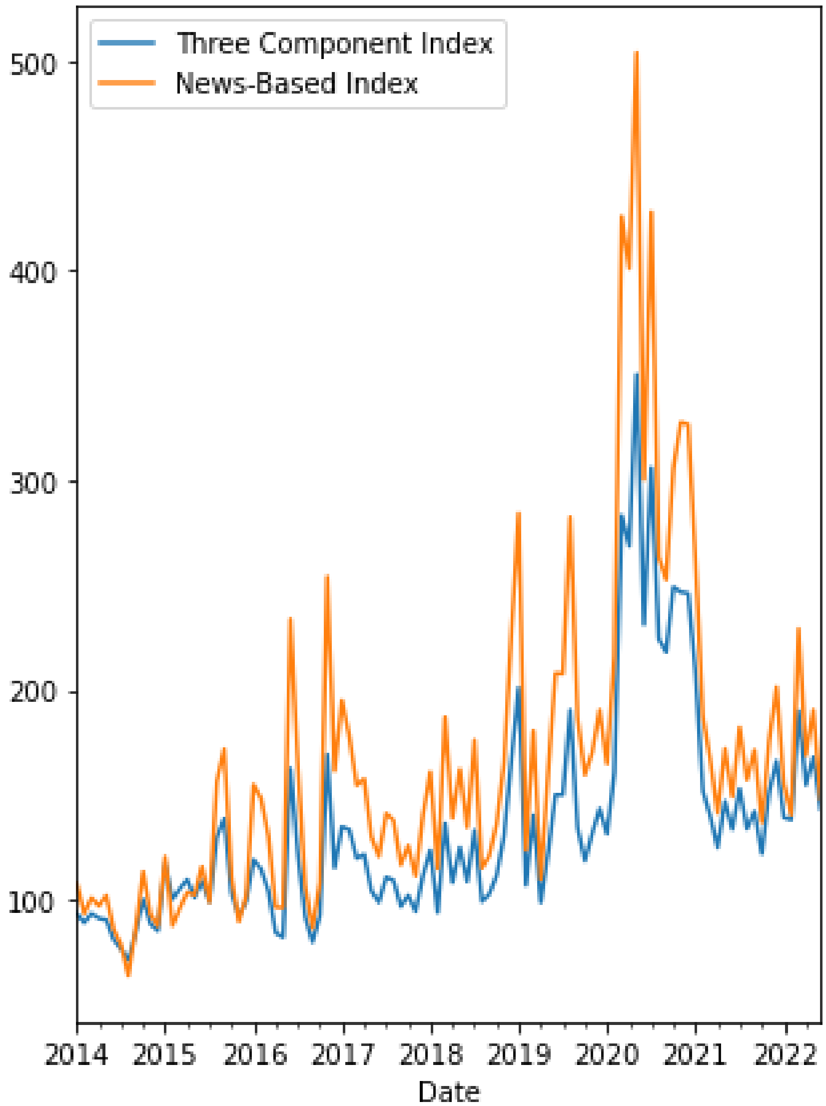


Figure 4: The statistical significance of coefficients on log3ci (with 2020 forecast) when size-adjusted CAR[0,25] is the dependent variable

```
In [49]: sigct10 = len([p for p in pvallit if p < 0.1])
    ...: sigct05 = len([p for p in pvallit if p < 0.05])
    ...: sigct01 = len([p for p in pvallit if p < 0.01])
    ...: print(f"Times coeffs are at least 10% significant:{sigct10}")
    ...: print(f"Times coeffs are at least 5% significant:{sigct05}")
    ...: print(f"Times coeffs are at least 1% significant:{sigct01}")
    ...: print(F"The minimum is:{min(pvallit)}")
    ...: print(F"The maximum is:{max(pvallit)}")
Times coeffs are at least 10% significant:300
Times coeffs are at least 5% significant:300
Times coeffs are at least 1% significant:300
The minimum is:0.00019943073698436287
The maximum is:0.004162785302455285
```

Figure 5: The histogram of coefficients on log3ci (with 2020 forecast) when size-adjusted CAR[0,25] is the dependent variable

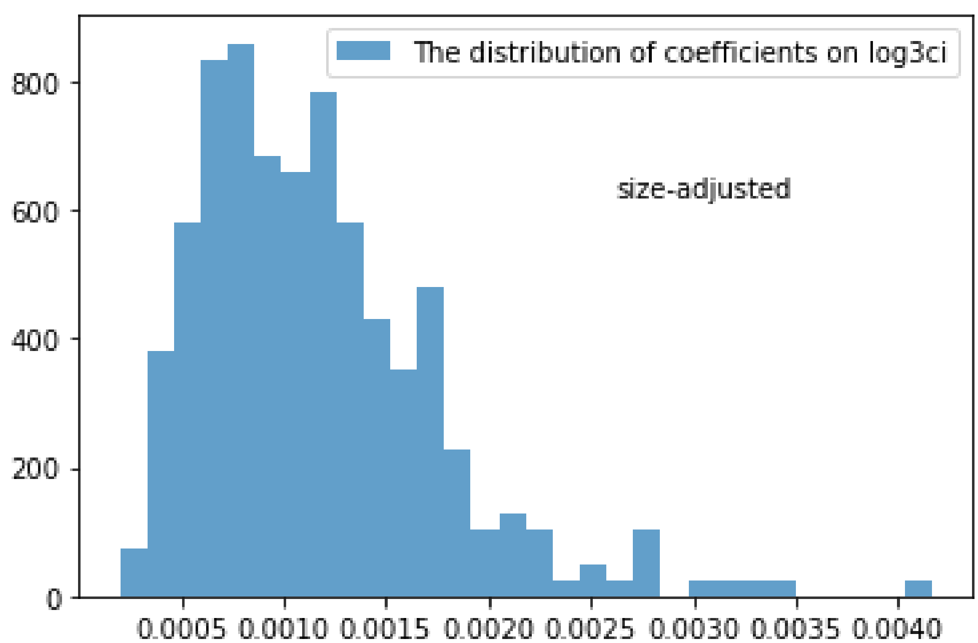


Figure 6: The statistical significance of coefficients on log3ci (with 2020 forecast) when industry-adjusted CAR[0,25] is the dependent variable

```
In [61]: sigct10 = len([p for p in pvallit if p < 0.1])
    ...: sigct05 = len([p for p in pvallit if p < 0.05])
    ...: sigct01 = len([p for p in pvallit if p < 0.01])
    ...: print(f"Times coeffs are at least 10% significant:{sigct10}")
    ...: print(f"Times coeffs are at least 5% significant:{sigct05}")
    ...: print(f"Times coeffs are at least 1% significant:{sigct01}")
    ...: print(F"The minimum is:{min(pvallit)}")
    ...: print(F"The maximum is:{max(pvallit)}")
Times coeffs are at least 10% significant:300
Times coeffs are at least 5% significant:294
Times coeffs are at least 1% significant:2
The minimum is:0.008896238821997082
The maximum is:0.06093281890988189
```

Figure 7: The histogram of coefficients on log3ci (with 2020 forecast) when industry-adjusted CAR[0,25] is the dependent variable

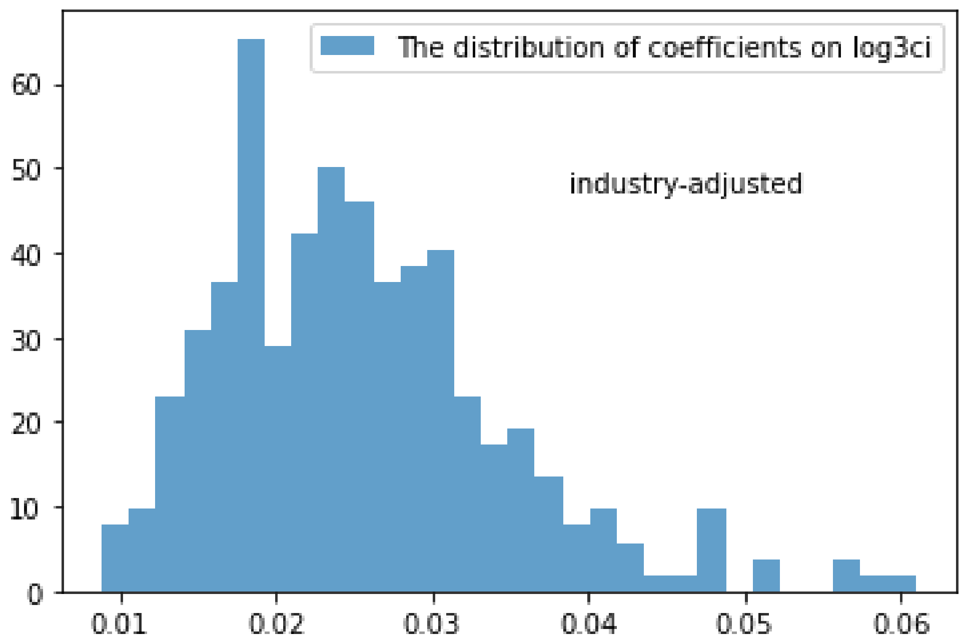


Table 1: Summary Statistics I

This table reports the breakdown of transactions by House and party affiliation.

House	Party	Number of Representatives	Transactions
Representative	Democrat	82	13526
	Republican	92	7443
	Independent	1	16
Senate	Democrat	20	1897
	Republican	26	5490
	Independent	1	34
Sum		222	28406

Table 2: Summary Statistics II

This table reports the breakdown of transactions by each year and party affiliation.

Year	Democrat	Republican	Independent
2014	0	26	0
2015	0	48	0
2016	242	652	4
2017	538	1029	9
2018	1112	2406	12
2019	3658	1744	11
2020	4584	3096	9
2021	2387	2077	2
2022	1672	1468	2
2023	1230	387	1
Sum	15423	12933	50

Table 3: Summary Statistics III

This table reports the breakdown of transactions by each year and transaction type.

Year	Purchase	Sale	Exchange	Exercise
2014	14	12	0	0
2015	19	29	0	0
2016	519	378	1	0
2017	891	684	1	0
2018	1904	1598	26	2
2019	2406	2979	28	0
2020	3781	3853	52	3
2021	2244	2201	17	4
2022	1605	1511	17	9
2023	656	961	1	0
Sum	14039	14206	143	18

Table 4: Summary Statistics IV

This table reports the breakdown of transactions by industry.

Industry	**Purchase+Sale**	**Purchase+Sale by Dems**	**Purchase+Sale by Reps**	**Purchase+Sale by inds**	**Purchase**	**Sale**
Consumer Durables	680	398	280	2	350	330
Telephone and Television Transmission	976	529	436	11	472	504
Chemicals and Allied Products	1134	575	558	1	566	568
Utilities	1235	480	754	1	662	573
Oil, Gas, Coal Extraction and Products	1299	369	922	8	671	628
Consumer Nondurables	1318	719	597	2	637	681
Manufacturing	1922	1048	873	1	874	1048
Wholesale, Retail, and Some Services	2527	1249	1272	6	1279	1248
Healthcare, Medical Equipment, and Drugs	2678	1591	1084	3	1279	1399
Other	3403	1798	1604	1	1771	1632
Finance	5145	2931	2210	4	2603	2542
Business Equipment	5928	3644	2274	10	2875	3053
Sum	28245	15331	12864	50	14039	14206

Table 5: Summary Statistics V

This table reports the breakdown of transactions by year and industry.

Year	**BusEq**	**Chems**	**Durbl**	**Enrgy**	**Hlth**	**Manuf**	**Money**	**NoDur**	**Other**	**Shops**	**Telcm**	**Utils**
2014	0	0	0	7	2	6	2	0	7	2	0	0
2015	4	1	2	4	3	3	14	4	10	3	0	0
2016	178	63	24	48	118	36	130	31	101	86	33	50
2017	253	87	66	81	224	83	225	97	162	170	67	61
2018	663	137	118	221	275	259	626	181	409	314	102	225
2019	1222	236	102	248	488	377	928	348	599	428	211	226
2020	1537	321	163	291	728	496	1503	308	959	779	257	347
2021	1119	134	112	170	346	329	755	160	642	393	139	167
2022	636	121	59	189	319	230	637	102	357	249	140	103
2023	338	49	37	50	189	121	362	90	161	105	47	69

Table 6: Summary Statistics of CARs

(a) S&P 500 adjusted value-weighted cumulative abnormal returns

CAR	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
		Purchase			
CAR[0,25]	13322	0.001002	0.1041	-1.0725	2.0460
		Sale			
CAR[0,25]	13166	0.003640	0.1250	-1.374	2.5763

(b) Size-adjusted cumulative abnormal returns

CAR	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
		Purchase			
CAR[0,25]	12390	0.0011	0.0941	-1.034	2.0687
		Sale			
CAR[0,25]	12237	0.003538	0.1178	-1.3456	2.5365

(c) Fama-French 12 industry adjusted value-weighted cumulative abnormal returns

CAR	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
		Purchase			
CAR[0,25]	13322	0.0009778	0.0999	-1.0376	2.085
		Sale			
CAR[0,25]	13166	0.003421	0.1191	-1.205	2.5331

Table 7: S&P 500 adjusted CAR[0,25] and economic policy uncertainty

This table reports regression results of politicians' trades S&P 500 adjusted cumulative abnormal returns [0,25] on economic policy uncertainty. Regressions are run for purchase and sale separately. EPU is measured in two different indices: news-based index (nbi) and three-component index(3ci). The variable $logEPU_{t-1}$ is the natural logarithm of EPU (either nbi or 3ci) of the month $t-1$ if the transaction is in month t. Similarly, umd_{t-1}, ret_{t-1}, $logmktcap_{t-1}$, bm_{t-1}, and roa_{t-1} are from the month $t-1$ if the transaction is in month t. umd stands for momentum and is the compounded return over months $t-12$ through $t-2$. $GDPgrow_t$ is the quarterly GDP growth in the quarter to which the transacted month t belongs to. ret stands for the monthly return of a stock at the end of month t. logmktcap denotes the natural logarithm of multiplication of public share outstanding and 1000 and price. bm represents book-to-market of a firm at the end of month t. roa is return-on-asset at the end of month t. VIX_orth_epu is the component of VIX orthogonal to either nbi or 3ci. Firm- and time-clustered standard errors are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	Purchase						Sale					
	nbi			3ci			nbi			3ci		
constant	0.1642**	0.1758**	0.1683**	0.1606**	0.1690**	0.1657**	0.2615**	0.2590**	0.2788**	0.2568**	0.2482**	0.2800**
	(0.0784)	(0.0796)	(0.0795)	(0.0763)	(0.0764)	(0.0782)	(0.1179)	(0.1179)	(0.1133)	(0.1180)	(0.1135)	(0.1106)
$logEPU_{t-1}$	0.0143**	0.0117**	0.0160***	0.0187***	0.0160**	0.0203***	0.0169	0.0174	0.0244	0.0218	0.0246*	0.0291*
	(0.0056)	(0.0056)	(0.0058)	(0.0068)	(0.0070)	(0.0070)	(0.0131)	(0.0131)	(0.0117)	(0.0157)	(0.0152)	(0.0140)
umd_{t-1}	0.0009	0.0006	0.0009	0.0009	0.0008	0.0009	0.0065	0.0066	0.0068	0.0065	0.0066	0.0067
	(0.0084)	(0.0084)	(0.0084)	(0.0084)	(0.0084)	(0.0084)	(0.0134)	(0.0134)	(0.0132)	(0.0133)	(0.0133)	(0.0132)
ret_{t-1}	0.0159	0.0232	0.0137	0.0164	0.0207	0.0144	-0.0502***	-0.0513**	-0.0560**	-0.0491***	-0.0521**	-0.0546**
	(0.4929)	(0.0240)	(0.0248)	(0.0228)	(0.0236)	(0.0245)	(0.0184)	(0.0220)	(0.0223)	(0.0181)	(0.0219)	(0.0218)
$logmktcap_{t-1}$	-0.0219***	-0.0215***	-0.0232***	-0.0233***	-0.0027***	-0.0246***	-0.0365***	-0.0366***	-0.0418***	-0.0380***	-0.0386***	-0.0435***
	(0.0069)	(0.0067)	(0.0074)	(0.0070)	(0.0069)	(0.0077)	(0.0075)	(0.0076)	(0.0091)	(0.0075)	(0.0079)	(0.0095)
bm_{t-1}	-0.0023	-0.0011	-0.0042	-0.0045	-0.0031	-0.0062	0.0561*	0.0558*	0.0459	0.0540*	0.0526*	0.0440
	(0.0229)	(0.0224)	(0.0224)	(0.0226)	(0.0221)	(0.0221)	(0.0322)	(0.0319)	(0.0293)	(0.0316)	(0.0308)	(0.0287)
roa_{t-1}	-0.0532	-0.0572	-0.0502	-0.0502	-0.0541	-0.0477	0.1032*	0.1033*	0.1080*	0.1045*	0.1055*	0.1094*
	(0.0465)	(0.0460)	(0.0470)	(0.0467)	(0.0459)	(0.0473)	(0.0613)	(0.0613)	(0.0588)	(0.0611)	(0.0609)	(0.0587)
$VIX\_orth\_epu_{t-1}$		0.0021			0.0016			-0.0003			-0.0013	
		(0.0013)			(0.0013)			(0.0021)			(0.0023)	
$GDPgrow_t$			0.0557			0.0499			0.2107			0.1973
			(0.0701)			(0.0714)			(0.1375)			(0.1272)
Obs.	9025	9025	9025	9025	9025	9025	9396	9396	9396	9396	9396	9396
R^2	0.0135	0.0147	0.0138	0.0143	0.0149	0.0146	0.0339	0.0339	0.0376	0.0345	0.0348	0.0379
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Size adjusted CAR[0,25] and economic policy uncertainty

This table reports regression results of politicians' trades size adjusted cumulative abnormal returns [0,25] on economic policy uncertainty. Regressions are run for purchase and sale separately. EPU is measured in two different indices: news-based index (nbi) and three-component index(3ci). The variable $logEPU_{t-1}$ is the natural logarithm of EPU (either nbi or 3ci) of the month $t-1$ if the transaction is in month t. Similarly, umd_{t-1}, ret_{t-1}, $logmktcap_{t-1}$, bm_{t-1}, and roa_{t-1} are from the month $t-1$ if the transaction is in month t. umd stands for momentum and is the compounded return over months $t-12$ through $t-2$. $GDPgrow_t$ is the quarterly GDP growth in the quarter to which the transacted month t belongs to. ret stands for the monthly return of a stock at the end of month t. logmktcap denotes the natural logarithm of multiplication of public share outstanding and 1000 and price. bm represents book-to-market of a firm at the end of month t. roa is return-on-asset at the end of month t. VIX_orth_3ci is the component of VIX orthogonal to 3ci. Firm- and time-clustered standard errors are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	Purchase						Sale					
	nbi			3ci			nbi			3ci		
constant	0.1317**	0.1383**	0.1335**	0.1301**	0.1372**	0.1323**	0.2550***	0.2425***	0.2741***	0.2526***	0.2357***	0.2785***
	(0.0661)	(0.0675)	(0.0668)	(0.0647)	(0.0647)	(0.0660)	(0.0902)	(0.0875)	(0.0924)	(0.0871)	(0.0852)	(0.0909)
$logEPU_{t-1}$	0.0068	0.0053	0.0075*	0.0089*	0.0065	0.0096*	0.0063	0.0090	0.0145	0.0082	0.0137	0.0164
	(0.0043)	(0.0045)	(0.0044)	(0.0052)	(0.0053)	(0.0051)	(0.0107)	(0.0090)	(0.0123)	(0.0124)	(0.0104)	(0.0135)
umd_{t-1}	-0.0001	-0.0003	-0.0001	-0.0001	-0.0002	-0.0001	0.0082	0.0086	0.0085	0.0082	0.0084	0.0084
	(0.0064)	(0.0064)	(0.0064)	(0.0064)	(0.0064)	(0.0064)	(0.0116)	(0.0116)	(0.0115)	(0.0116)	(0.0115)	(0.0115)
ret_{t-1}	0.0241	0.0282	0.0231	0.0243	0.0279	0.0234	-0.0267	-0.0322*	-0.0331*	-0.0263*	-0.0321*	-0.0323*
	(0.0214)	(0.0226)	(0.0222)	(0.0214)	(0.0220)	(0.0222)	(0.0161)	(0.0189)	(0.0187)	(0.0160)	(0.0186)	(0.0184)
$logmktcap_{t-1}$	-0.0146**	-0.0143**	-0.0151**	-0.0152***	-0.0147***	-0.0158***	-0.0299***	-0.0302***	-0.0357***	-0.0304***	-0.0316***	-0.0366***
	(0.0057)	(0.0056)	(0.0060)	(0.0058)	(0.0057)	(0.0061)	(0.0071)	(0.0072)	(0.0088)	(0.0074)	(0.0076)	(0.0091)
bm_{t-1}	-0.0124	-0.0118	-0.0133	-0.0135	-0.0123	-0.0142	0.0491**	0.0479*	0.0380*	0.0483**	0.0456*	0.0372
	(0.0187)	(0.0184)	(0.0185)	(0.0186)	(0.0183)	(0.0184)	(0.0247)	(0.0246)	(0.0230)	(0.0245)	(0.0240)	(0.0227)
roa_{t-1}	-0.0665	-0.0688	-0.0652	-0.0651	-0.0685	-0.0640	0.0597	0.0599	0.0649*	0.0602	0.0619	0.0656*
	(0.0481)	(0.0475)	(0.0485)	(0.0483)	(0.0474)	(0.0486)	(0.0388)	(0.0388)	(0.0367)	(0.0388)	(0.0385)	(0.0367)
$VIX\_orth\_epu_{t-1}$		0.0012			0.0014			-0.0018			-0.0025	
		(0.0009)			(0.0010)			(0.0018)			(0.0019)	
$GDPgrow_t$			0.0244			0.0218			0.2317*			0.2208*
			(0.0480)			(0.0486)			(0.1235)			(0.1147)
Obs.	9043	9043	9043	9043	9043	9043	9419	9419	9419	9419	9419	9419
R^2	0.0077	0.0081	0.0078	0.0079	0.0084	0.0080	0.0202	0.0209	0.0255	0.0204	0.0215	
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Fama-French 12-industry adjusted CAR[0,25] and economic policy uncertainty

This table reports regression results of politicians' trades Fama-French 12-industry adjusted cumulative abnormal returns [0,25] on economic policy uncertainty. Regressions are run for purchase and sale separately. EPU is measured in two different indices: news-based index (nbi) and three-component index(3ci). The variable $logEPU_{t-1}$ is the natural logarithm of EPU (either nbi or 3ci) of the month $t-1$ if the transaction is in month t. Similarly, umd_{t-1}, ret_{t-1}, $logmktcap_{t-1}$, bm_{t-1}, and roa_{t-1} are from the month $t-1$ if the transaction is in month t. umd stands for momentum and is the compounded return over months $t-12$ through $t-2$. $GDPgrow_t$ is the quarterly GDP growth in the quarter to which the transacted month t belongs to. ret stands for the monthly return of a stock at the end of month t. logmktcap denotes the natural logarithm of multiplication of public share outstanding and 1000 and price. bm represents book-to-market of a firm at the end of month t. roa is return-on-asset at the end of month t. VIX_orth_3ci is the component of VIX orthogonal to 3ci. Firm- and time-clustered standard errors are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	Purchase						Sale					
	nbi			3ci			nbi			3ci		
constant	0.1393**	0.1467**	0.1412***	0.1369**	0.1437**	0.1392**	0.2794***	0.2667***	0.2974***	0.2749***	0.2589***	0.2994***
	(0.0681)	(0.0695)	(0.0688)	(0.0660)	(0.0662)	(0.0672)	(0.1000)	(0.0962)	(0.1026)	(0.0962)	(0.0933)	(0.1008)
$logEPU_{t-1}$	0.0075*	0.0058	0.0083*	0.0099**	0.0077	0.0107**	0.0087	0.0114	0.0165	0.0116	0.0158	0.0193
	(0.0042)	(0.0041)	(0.0044)	(0.0050)	(0.0050)	(0.0052)	(0.0124)	(0.104)	(0.0131)	(0.0143)	(0.0122)	(0.0146)
umd_{t-1}	-0.0032	-0.0033	-0.0032	-0.0032	-0.0032	-0.0032	0.0030	0.0033	0.0033	0.0030	0.0034	0.0032
	(0.0058)	(0.0058)	(0.0058)	(0.0058)	(0.0058)	(0.0058)	(0.0105)	(0.0105)	(0.0105)	(0.0105)	(0.0105)	(0.0105)
ret_{t-1}	0.0089	0.0136	0.0079	0.0092	0.0127	0.0083	-0.0459***	-0.0515**	-0.0519**	-0.0453***	-0.0515**	-0.0510**
	(0.0203)	(0.0215)	(0.0213)	(0.0201)	(0.0210)	(0.0212)	(0.0170)	(0.0219)	(0.0207)	(0.0168)	(0.0218)	(0.0203)
$logmktcap_{t-1}$	-0.0160***	-0.0158***	-0.0166***	-0.0168***	-0.0163***	-0.0174***	-0.0334***	-0.0337***	-0.0389***	-0.0342***	-0.0348***	-0.0400***
	(0.0062)	(0.0060)	(0.0064)	(0.0063)	(0.0062)	(0.0066)	(0.0074)	(0.0076)	(0.0091)	(0.0076)	(0.0078)	(0.0095)
bm_{t-1}	-0.0065	-0.0057	-0.0073	-0.0077	-0.0065	-0.0085	0.0427*	0.0416*	0.0322	0.0416*	0.0398*	0.0310
	(0.0179)	(0.0175)	(0.0174)	(0.0179)	(0.0176)	(0.0175)	(0.0243)	(0.0239)	(0.0232)	(0.0240)	(0.0234)	(0.0228)
roa_{t-1}	-0.0434	-0.0459	-0.0420	-0.0417	-0.0448	-0.0405	0.0995*	0.0998*	0.1044**	0.1002*	0.1008*	0.1053**
	(0.0377)	(0.0371)	(0.0384)	(0.0379)	(0.0370)	(0.0386)	(0.0538)	(0.0536)	(0.1141)	(0.0538)	(0.0535)	(0.0510)
$VIX\_orth\_epu_{t-1}$		0.0013			0.0013			-0.0018			-0.0021	
		(0.0011)			(0.0011)			(0.0020)			(0.0020)	
$GDPgrow_t$			0.0253			0.0229			0.2185**			0.2085
			(0.0509)			(0.0515)			(0.1141)			(0.1062)
Obs.	9025	9025	9025	9025	9025	9025	9396	9396	9396	9396	9396	9396
R^2	0.0089	0.0095	0.0090	0.0092	0.0097	0.0093	0.0285	0.0292	0.0331	0.0288	0.0297	0.0332
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: S&P 500 adjusted CAR[0,25] and economic policy uncertainty - excluding 2020 transactions

This table reports regression results of politicians' trades S&P 500 adjusted cumulative abnormal returns [0,25] on economic policy uncertainty without transactions made in 2020. Regressions are run for purchase and sale separately. EPU is measured in two different indices: news-based index (nbi) and three-component index(3ci). The variable $logEPU_{t-1}$ is the natural logarithm of EPU (either nbi or 3ci) of the month $t-1$ if the transaction is in month t. Similarly, umd_{t-1}, ret_{t-1}, $logmktcap_{t-1}$, bm_{t-1}, and roa_{t-1} are from the month $t-1$ if the transaction is in month t. umd stands for momentum and is the compounded return over months $t-12$ through $t-2$. $GDPgrow_t$ is the quarterly GDP growth in the quarter to which the transacted month t belongs to. ret stands for the monthly return of a stock at the end of month t. logmktcap denotes the natural logarithm of multiplication of public share outstanding and 1000 and price. bm represents book-to-market of a firm at the end of month t. roa is return-on-asset at the end of month t. VIX_orth_epu is the component of VIX orthogonal to either nbi or 3ci. Firm- and time-clustered standard errors are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	Purchase						Sale					
	nbi			3ci			nbi			3ci		
constant	0.0193	0.0219	0.0720	0.0131	0.0161	0.0611	0.1271	0.1299	0.1571*	0.1231*	0.1263*	0.1509
	(0.0641)	(0.0665)	(0.0757)	(0.0620)	(0.0644)	(0.0744)	(0.0773)	(0.0791)	(0.0951)	(0.0740)	(0.0748)	(0.0927)
$logEPU_{t-1}$	0.0216***	0.0226***	0.0195***	0.0289***	0.0290***	0.0253***	0.0100**	0.0105*	0.0086*	0.0138**	0.0138*	0.0116*
	(0.0066)	(0.0067)	(0.0064)	(0.0084)	(0.0084)	(0.0082)	(0.0045)	(0.0045)	(0.0046)	(0.0059)	(0.0059)	(0.0060)
umd_{t-1}	-0.0043	-0.0043	-0.0048	-0.0042	-0.0042	-0.0047	0.0023	0.0023	0.0015	0.0024	0.0025	0.0017
	(0.0051)	(0.0051)	(0.0048)	(0.0051)	(0.0051)	(0.0049)	(0.0078)	(0.0079)	(0.0078)	(0.0078)	(0.0079)	(0.0079)
ret_{t-1}	-0.0415*	-0.0370	-0.0426*	-0.0407*	-0.0381	-0.0416*	-0.0416	-0.0394	-0.0407	-0.0410	-0.0400	-0.0403
	(0.0228)	(0.0240)	(0.0228)	(0.0227)	(0.0239)	(0.0228)	(0.0259)	(0.0276)	(0.0254)	(0.0258)	(0.0264)	(0.0254)
$logmktcap_{t-1}$	-0.0145**	-0.0149**	-0.0192***	-0.0168***	-0.0170**	-0.0202***	-0.0189**	-0.0193**	-0.0214**	-0.0200**	-0.0203**	-0.0220**
	(0.0062)	(0.0064)	(0.0074)	(0.0066)	(0.0068)	(0.0076)	(0.0077)	(0.0079)	(0.0092)	(0.0080)	(0.0081)	(0.0092)
bm_{t-1}	0.0473**	0.0466**	0.0438**	0.0454**	0.0450**	0.0429**	0.0475**	0.0473**	0.0454**	0.0468**	0.0467**	0.0451**
	(0.0219)	(0.0218)	(0.0214)	(0.0217)	(0.0216)	(0.0213)	(0.0207)	(0.0207)	(0.0194)	(0.0203)	(0.0203)	(0.0193)
roa_{t-1}	0.0450	0.0420	0.0568	0.0473	0.0454	0.0563	0.0298	0.0299	0.0336	0.0309	0.0305	0.0338
	(0.0553)	(0.0544)	(0.0555)	(0.0555)	(0.0547)	(0.0556)	(0.0486)	(0.0486)	(0.0478)	(0.0484)	(0.0484)	(0.0478)
$VIX\_orth\_epu_{t-1}$		0.0013			0.0007			0.0007			0.0006	
		(0.0014)			(0.0013)			(0.0014)			(0.0016)	
$GDPgrow_t$			0.5077*			0.4198			0.2889			0.2453
			(0.2853)			(0.2845)			(0.3075)			(0.3110)
Obs.	6422	6422	6422	6422	6422	6422	6487	6487	6487	6487	6487	6487
R^2	0.0239	0.0243	0.0257	0.0246	0.0248	0.0258	0.0195	0.0196	0.0200	0.0198	0.0198	0.0202
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Size adjusted CAR[0,25] and economic policy uncertainty - excluding 2020 transactions

This table reports regression results of politicians' trades size adjusted cumulative abnormal returns [0,25] on economic policy uncertainty without transactions made in 2020. Regressions are run for purchase and sale separately. EPU is measured in two different indices: news-based index (nbi) and three-component index(3ci). The variable $logEPU_{t-1}$ is the natural logarithm of EPU (either nbi or 3ci) of the month $t-1$ if the transaction is in month t. Similarly, umd_{t-1}, ret_{t-1}, $logmktcap_{t-1}$, bm_{t-1}, and roa_{t-1} are from the month $t-1$ if the transaction is in month t. umd stands for momentum and is the compounded return over months $t-12$ through $t-2$. $GDPgrow_t$ is the quarterly GDP growth in the quarter to which the transacted month t belongs to. ret stands for the monthly return of a stock at the end of month t. logmktcap denotes the natural logarithm of multiplication of public share outstanding and 1000 and price. bm represents book-to-market of a firm at the end of month t. roa is return-on-asset at the end of month t. VIX_orth_3ci is the component of VIX orthogonal to 3ci. Firm- and time-clustered standard errors are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	Purchase						Sale					
	nbi			3ci			nbi			3ci		
constant	0.0117	0.0160	0.0625	0.0038	0.0100	0.0518	0.1123	0.1128	0.1588*	0.1056	0.1038	0.1531*
	(0.0600)	(0.0611)	(0.0695)	(0.0585)	(0.0593)	(0.0607)	(0.0685)	(0.0705)	(0.0849)	(0.0655)	(0.0665)	(0.0818)
$logEPU_{t-1}$	0.0162***	0.0171***	0.0141***	0.0226***	0.0227***	0.0190***	0.0070	0.0071	0.0047	0.0107	0.0107	0.0069
	(0.0051)	(0.0052)	(0.0051)	(0.0068)	(0.0067)	(0.0067)	(0.0055)	(0.0055)	(0.0047)	(0.0077)	(0.0077)	(0.0064)
umd_{t-1}	-0.0032	-0.0031	-0.0037	-0.0031	-0.0031	-0.0036	0.0034	0.0034	0.0022	0.0035	0.0034	0.0023
	(0.0039)	(0.0039)	(0.0037)	(0.0039)	(0.0039)	(0.0037)	(0.0066)	(0.0066)	(0.0065)	(0.0066)	(0.0067)	(0.0066)
ret_{t-1}	-0.0294	-0.0261	-0.0304	-0.0287	-0.0261	-0.0297	-0.0257	-0.0252	-0.0243	-0.0252	-0.0258	-0.0241
	(0.0213)	(0.0219)	(0.0214)	(0.0212)	(0.0218)	(0.0213)	(0.0255)	(0.0271)	(0.0249)	(0.0255)	(0.0262)	(0.0249)
$logmktcap_{t-1}$	-0.0103*	-0.0108*	-0.0148**	-0.0122*	-0.0125**	-0.0156***	-0.0157**	-0.0158**	-0.0196**	-0.0166**	-0.0165**	-0.0199**
	(0.0059)	(0.0059)	(0.0068)	(0.0062)	(0.0063)	(0.0070)	(0.0071)	(0.0073)	(0.0087)	(0.0075)	(0.0076)	(0.0088)
bm_{t-1}	0.0314	0.0309	0.0280	0.0298	0.0295	0.0273	0.0444**	0.0443**	0.0412**	0.0438**	0.0439**	0.0410**
	(0.0201)	(0.0201)	(0.0197)	(0.0199)	(0.0199)	(0.0196)	(0.0189)	(0.0189)	(0.0174)	(0.0184)	(0.0184)	(0.0173)
roa_{t-1}	0.0286	0.0237	0.0400	0.0307	0.0265	0.0398	0.0169	0.0169	0.0228	0.0180	0.0182	0.0230
	(0.0499)	(0.0484)	(0.0500)	(0.0499)	(0.0486)	(0.0500)	(0.0494)	(0.0494)	(0.0484)	(0.0491)	(0.0491)	(0.0484)
$VIX\_orth\_epu_{t-1}$		0.0020			0.0016			0.0001			-0.0003	
		(0.0013)			(0.0013)			(0.0013)			(0.0015)	
$GDPgrow_t$			0.4887			0.4191*			0.4491			0.4198
			(0.2439)			(0.2416)			(0.3306)			(0.3237)
Obs.	6438	6438	6438	6438	6438	6438	6504	6504	6504	6504	6504	6504
R^2	0.0146	0.0156	0.0167	0.0155	0.0162	0.0170	0.0154	0.0154	0.0170	0.0157	0.0158	0.0171
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 12: Fama-French 12-industry adjusted CAR[0,25] and economic policy uncertainty - excluding 2020 transactions

This table reports regression results of politicians' trades Fama-French 12-industry adjusted cumulative abnormal returns [0,25] on economic policy uncertainty without transactions made in 2020. Regressions are run for purchase and sale separately. EPU is measured in two different indices: news-based index (nbi) and three-component index(3ci). The variable $logEPU_{t-1}$ is the natural logarithm of EPU (either nbi or 3ci) of the month $t-1$ if the transaction is in month t. Similarly, umd_{t-1}, ret_{t-1}, $logmktcap_{t-1}$, bm_{t-1}, and roa_{t-1} are from the month $t-1$ if the transaction is in month t. umd stands for momentum and is the compounded return over months $t-12$ through $t-2$. $GDPgrow_t$ is the quarterly GDP growth in the quarter to which the transacted month t belongs to. ret stands for the monthly return of a stock at the end of month t. logmktcap denotes the natural logarithm of multiplication of public share outstanding and 1000 and price. bm represents book-to-market of a firm at the end of month t. roa is return-on-asset at the end of month t. VIX_orth_3ci is the component of VIX orthogonal to 3ci. Firm- and time-clustered standard errors are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	Purchase						Sale					
	nbi			3ci			nbi			3ci		
constant	0.0088	0.0110	0.0717	0.0034	0.0101	0.0666	0.1671**	0.1681**	0.1982**	0.1641**	0.1672**	0.1969**
	(0.0550)	(0.0568)	(0.0616)	(0.0537)	(0.0556)	(0.0607)	(0.0705)	(0.0717)	(0.0841)	(0.0692)	(0.0703)	(0.0837)
$logEPU_{t-1}$	0.0157***	0.0165***	0.0131***	0.0212***	0.0212***	0.0164***	0.0038	0.0040	0.0023	0.0057	0.0057	0.0031
	(0.0051)	(0.0053)	(0.0050)	(0.0064)	(0.0064)	(0.0065)	(0.0046)	(0.0047)	(0.0046)	(0.0062)	(0.0061)	(0.0063)
umd_{t-1}	-0.0058	-0.0058	-0.0065*	-0.0058	-0.0057	-0.0064*	0.0050	0.0050	0.0042	0.0051	0.0052	0.0043
	(0.0039)	(0.0039)	(0.0038)	(0.0039)	(0.0040)	(0.0038)	(0.0065)	(0.0065)	(0.0065)	(0.0065)	(0.0065)	(0.0066)
ret_{t-1}	-0.0256	-0.0217	-0.0269	-0.0249	-0.0221	-0.0262	-0.0264	-0.0256	-0.0255	-0.0262	-0.0252	-0.0254
	(0.0185)	(0.0192)	(0.0185)	(0.0184)	(0.0189)	(0.0185)	(0.0231)	(0.0251)	(0.0227)	(0.0232)	(0.0238)	(0.0228)
$logmktcap_{t-1}$	-0.0097*	-0.0101*	-0.0153***	-0.0114**	-0.0118**	-0.0160***	-0.0191***	-0.0192***	-0.0217***	-0.0196***	-0.0198***	-0.0218***
	(0.0052)	(0.0055)	(0.0059)	(0.0056)	(0.0056)	(0.0061)	(0.0069)	(0.0070)	(0.0079)	(0.0071)	(0.0071)	(0.0079)
bm_{t-1}	0.0338*	0.0332*	0.0296*	0.0324*	0.0319*	0.0290*	0.0256**	0.0255**	0.0235**	0.0253**	0.0253**	0.0234*
	(0.0177)	(0.0177)	(0.0173)	(0.0176)	(0.0177)	(0.0173)	(0.0122)	(0.0122)	(0.0123)	(0.0122)	(0.0122)	(0.0123)
roa_{t-1}	0.0192	0.0167	0.0333	0.0210	0.0165	0.0329	0.0443	0.0443	0.0482	0.0448	0.0445	0.0483
	(0.0461)	(0.0452)	(0.0457)	(0.0460)	(0.0446)	(0.0458)	(0.0434)	(0.0434)	(0.0429)	(0.0433)	(0.0432)	(0.0429)
$VIX\_orth\_epu_{t-1}$		0.0011			0.0017			0.0003			0.0006	
		(0.0011)			(0.0011)			(0.0012)			(0.0014)	
$GDPgrow_t$			0.6055***			0.5513***			0.2997			0.2887
			(0.1924)			(0.1943)			(0.2678)			(0.2728)
Obs.	6422	6422	6422	6422	6422	6422	6487	6487	6487	6487	6487	6487
R^2	0.0171	0.0714	0.0202	0.0176	0.0184	0.0201	0.0126	0.0126	0.0133	0.0127	0.0127	0.0133
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 13: CAR[0,25] and economic policy uncertainty (only six industries)

This table reports regression results of politicians' trades cumulative abnormal returns [0,25] on economic policy uncertainty using transactions only from six industries with high exposure to economic policy uncertainty, with S&P 500, size, and Fama-French 12 industry as benchmarks. The six industries are: Energy, Manufacturing, Health, Money, Business Equipment, and Other. Regressions are run for only purchases. EPU is measured in two different indices: news-based index (nbi) and three-component index(3ci). The variable $logEPU_{t-1}$ is the natural logarithm of EPU (either nbi or 3ci) of the month $t-1$ if the transaction is in month t. Similarly, umd_{t-1}, ret_{t-1}, $logmktcap_{t-1}$, bm_{t-1}, and roa_{t-1} are from the month $t-1$ if the transaction is in month t. umd stands for momentum and is the compounded return over months $t-12$ through $t-2$. ret stands for the monthly return of a stock at the end of month t. logmktcap denotes the natural logarithm of multiplication of public share outstanding and 1000 and price. bm represents book-to-market of a firm at the end of month t. roa is return-on-asset at the end of month t. Firm- and time-clustered standard errors are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	S&P 500		Size		Industry	
	nbi	3ci	nbi	3ci	nbi	3ci
constant	0.1220	0.1221	0.0909	0.0924	0.1132	0.1102
	(0.1089)	(0.1064)	(0.0882)	(0.0869)	(0.0950)	(0.0924)
$logEPU_{t-1}$	0.0195***	0.0250***	0.0101**	0.0126**	0.0095*	0.0130**
	(0.0065)	(0.0079)	(0.0048)	(0.0058)	(0.0054)	(0.0066)
umd_{t-1}	-0.0004	-0.0003	-0.0026	-0.0026	-0.0028	-0.0026
	(0.0129)	(0.0129)	(0.0105)	(0.0105)	(0.0116)	(0.0116)
ret_{t-1}	0.0081	0.0087	0.0166	0.0168	0.0046	0.0050
	(0.0249)	(0.0247)	(0.0252)	(0.0252)	(0.0236)	(0.0235)
$logmktcap_{t-1}$	-0.0200*	-0.0221**	-0.0120	-0.0131	-0.0145	-0.0157
	(0.0105)	(0.0108)	(0.0085)	(0.0087)	(0.0094)	(0.0097)
bm_{t-1}	0.0046	0.0013	-0.0099	-0.0114	0.0072	0.0053
	(0.0231)	(0.0229)	(0.0199)	(0.0199)	(0.0167)	(0.0167)
roa_{t-1}	-0.0964*	-0.0941*	-0.0927*	-0.0918	-0.0755	-0.0737
	(0.0558)	(0.0559)	(0.0563)	(0.0563)	(0.0476)	(0.0478)
Obs.	6292	6292	6307	6307	6292	6292
R^2	0.0190	0.0202	0.0098	0.0101	0.0116	0.0122
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Time-Cluster	Yes	Yes	Yes	Yes	Yes	Yes

Table 14: CAR[0,25] and economic policy uncertainty (only six industries and excluding 2020)

This table reports regression results of politicians' trades cumulative abnormal returns [0,25] on economic policy uncertainty using non-2020 transactions from six industries with high exposure to economic policy uncertainty, with S&P 500, size, and Fama-French 12 industry as benchmarks. The six industries are: Energy, Manufacturing, Health, Money, Business Equipment, and Other. Regressions are run only for purchases. EPU is measured in two different indices: news-based index (nbi) and three-component index(3ci). The variable $logEPU_{t-1}$ is the natural logarithm of EPU (either nbi or 3ci) of the month $t-1$ if the transaction is in month t. Similarly, umd_{t-1}, ret_{t-1}, $logmktcap_{t-1}$, bm_{t-1}, and roa_{t-1} are from the month $t-1$ if the transaction is in month t. umd stands for momentum and is the compounded return over months $t-12$ through $t-2$. ret stands for the monthly return of a stock at the end of month t. logmktcap denotes the natural logarithm of multiplication of public share outstanding and 1000 and price. bm represents book-to-market of a firm at the end of month t. roa is return-on-asset at the end of month t. Firm- and time-clustered standard errors are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	S&P 500		Size		Industry	
	nbi	3ci	nbi	3ci	nbi	3ci
constant	-0.0145	-0.0123	-0.0007	-0.0011	-0.0054	-0.0092
	(0.0909)	(0.0896)	(0.0880)	(0.0876)	(0.0729)	(0.0734)
$logEPU_{t-1}$	0.0302***	0.0381***	0.0229***	0.0295***	0.0186***	0.0252***
	(0.0094)	(0.0117)	(0.0075)	(0.0099)	(0.0068)	(0.0087)
umd_{t-1}	0.0034	0.0033	0.0053	0.0052	-0.0023	-0.0023
	(0.0124)	(0.0124)	(0.0104)	(0.0104)	(0.0101)	(0.0101)
ret_{t-1}	-0.0604**	-0.0593**	-0.0517*	-0.0508*	-0.0437*	-0.0429*
	(0.0293)	(0.0292)	(0.0278)	(0.0277)	(0.0246)	(0.0244)
$logmktcap_{t-1}$	-0.0154	-0.0185*	-0.0125	-0.0150	-0.0094	-0.0117
	(0.0098)	(0.0106)	(0.0092)	(0.0099)	(0.0079)	(0.0085)
bm_{t-1}	0.0522**	0.0492*	0.0335	0.0311	0.0303	0.0282
	(0.0264)	(0.0262)	(0.0254)	(0.0252)	(0.0200)	(0.0199)
roa_{t-1}	0.0266	0.0271	0.0277	0.0283	0.0034	0.0043
	(0.0645)	(0.0646)	(0.0578)	(0.0577)	(0.0538)	(0.0535)
Obs.	4453	4453	4467	4467	4453	4453
R^2	0.0270	0.0272	0.0182	0.0187	0.0155	0.0163
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Time-Cluster	Yes	Yes	Yes	Yes	Yes	Yes

Table 15: Long-term CARs of transactions in 2020

(a) Average long-term CARs of buy trades in 2020

	CAR[0,60]	**CAR[0,90]**	**CAR[0,120]**
CAPM	0.0131	0.0179	0.0246
Fama-French 3-factor	-0.0130	-0.0207	-0.0238
Carhart 4-factor	-0.0158	-0.0212	-0.0260

(b) Average long-term CARs of sell trades in 2020

	CAR[0,60]	**CAR[0,90]**	**CAR[0,120]**
CAPM	0.0214	0.0248	0.0175
Fama-French 3-factor	0.0078	0.0012	-0.0123
Carhart 4-factor	0.0060	-0.0010	-0.0142

Table 16: Real lognbi, log3ci and forecast lognbi and log3ci based on estimated time series model

Month, Year	**Recorded lognbi**	**Forecast lognbi**	**Recorded log3ci**	**Forecast log3ci**
Jan, 2020	5.10446	5.21573	4.87818	4.946027
Feb, 2020	5.37616	5.19674	5.07839	4.933607
Mar, 2020	6.05392	5.18814	5.64597	4.928288
Apr, 2020	5.99382	5.18433	5.59328	4.926134
May, 2020	6.2225	5.18264	5.85925	4.925272
Jun, 2020	5.70458	5.1819	5.44354	4.924927
Jul, 2020	6.05893	5.18157	5.72347	4.924789
Aug, 2020	5.57394	5.18142	5.41355	4.924734
Sep, 2020	5.53176	5.18135	5.38476	4.924712
Oct, 2020	5.72282	5.18133	5.51815	4.924703
Nov, 2020	5.79182	5.18131	5.5082	4.924700
Dec, 2020	5.78879	5.18131	5.50584	4.924698

8 Appendix A

Figure 8: Policy Uncertainty

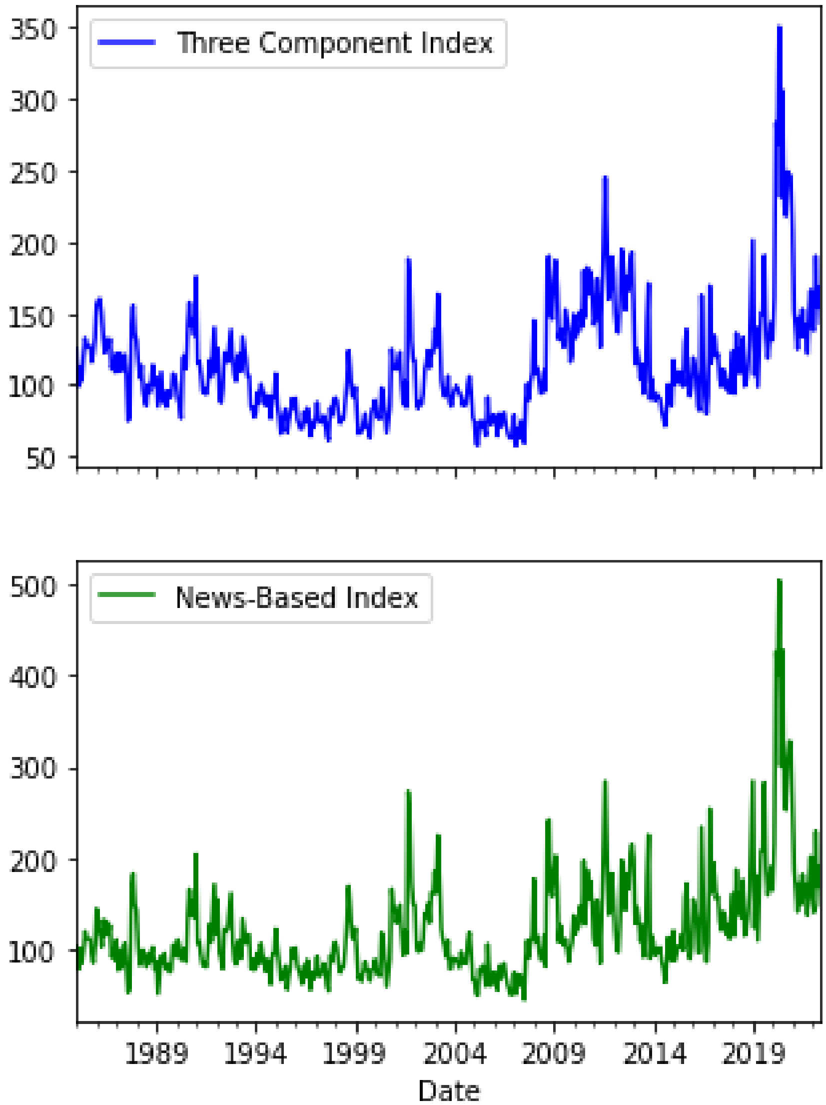
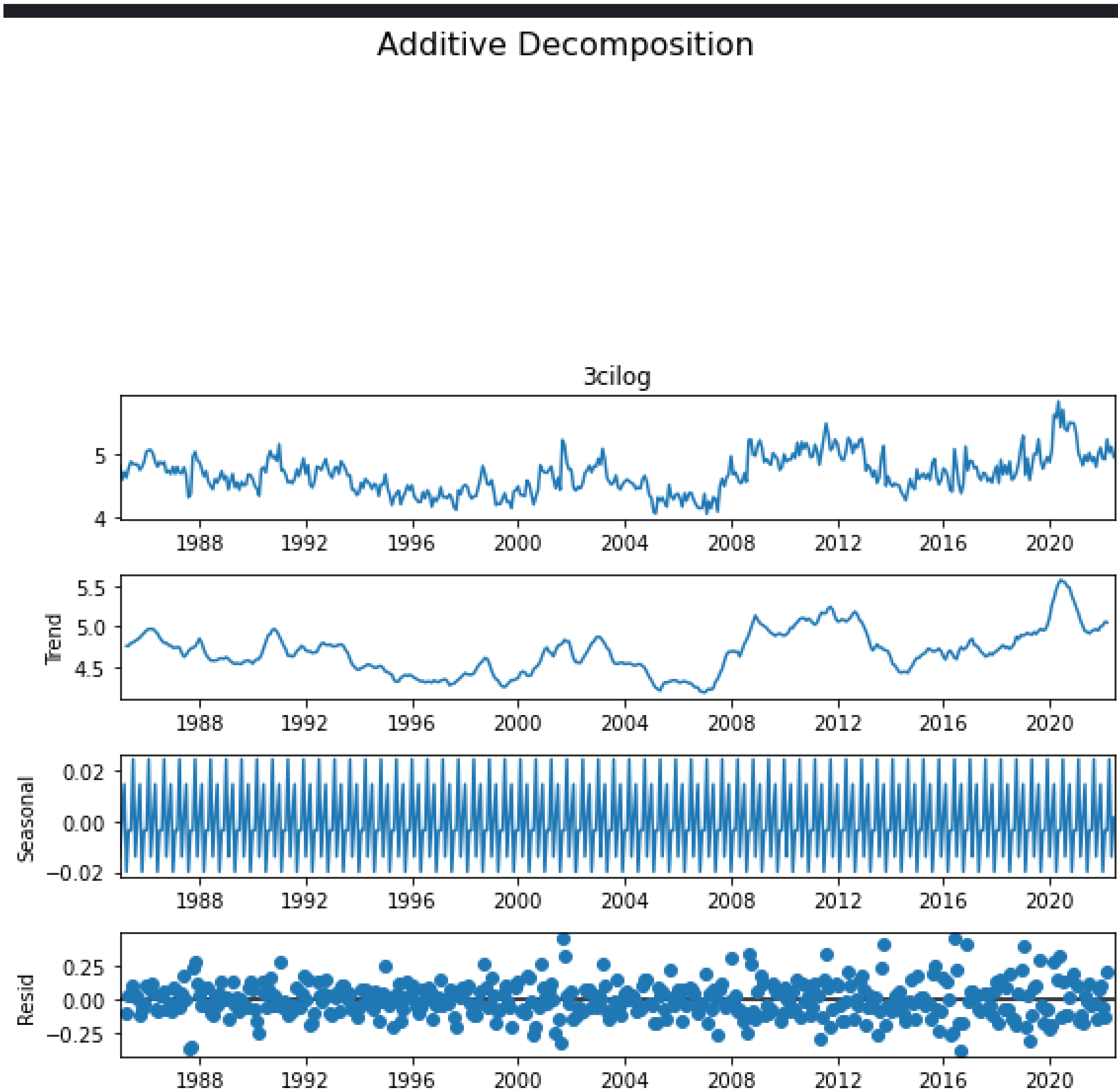


Figure 9: Decomposition of logged 3ci and test for stationarity of the residual component




```
The result for Dick Fuller test on residual of 3cilog:
                        Metric         Values
0              Test Statistics -1.059264e+01
1                      p-value  6.468527e-19
2             No. of lags used  1.400000e+01
3   Number of observations used  4.290000e+02
4           critical value (1%) -3.445685e+00
5           critical value (5%) -2.868301e+00
6          critical value (10%) -2.570371e+00
```

Table 17: CAR[0,25] and economic policy uncertainty (with square terms)

This table reports regression results of politicians' trades cumulative abnormal returns [0,25] on economic policy uncertainty while incorporating the square term of EPU, with S&P 500, size, and Fama-French 12 industry as benchmarks. Regressions are run for only purchases (including 2020). EPU is measured in two different indices: news-based index (nbi) and three-component index(3ci). The variable $logEPU_{t-1}$ is the natural logarithm of EPU (either nbi or 3ci) of the month $t-1$ if the transaction is in month t. The variable $logEPU_{t-1}^2$ is square of the natural logarithm of EPU (either nbi or 3ci) of the month $t-1$ if the transaction is in month t. Similarly, umd_{t-1}, ret_{t-1}, $logmktcap_{t-1}$, bm_{t-1}, and roa_{t-1} are from the month $t-1$ if the transaction is in month t. umd stands for momentum and is the compounded return over months $t-12$ through $t-2$. ret stands for the monthly return of a stock at the end of month t. logmktcap denotes the natural logarithm of multiplication of public share outstanding and 1000 and price. bm represents book-to-market of a firm at the end of month t. roa is return-on-asset at the end of month t. Firm- and time-clustered standard errors are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	S&P 500		Size		Industry	
	nbi	3ci	nbi	3ci	nbi	3ci
constant	-0.4116	-0.5393	-0.3512*	-0.5833**	-0.3830*	-0.5401*
	(0.2593)	(0.3804)	(0.2050)	(0.2869)	(0.1957)	(0.2784)
$logEPU_{t-1}$	0.2348**	0.2996*	0.1917**	0.2952**	0.2075***	0.2816**
	(0.1026)	(0.1578)	(0.0788)	(0.1174)	(0.0774)	(0.1159)
$logEPU_{t-1}^2$	-0.0204**	-0.0273*	-0.0171**	-0.0278**	-0.0185**	-0.0264**
	(0.0095)	(0.0154)	(0.0073)	(0.0114)	(0.0072)	(0.0113)
umd_{t-1}	0.0009	0.0009	-0.0001	-0.0001	-0.0032	-0.0032
	(0.0084)	(0.0084)	(0.0064)	(0.0064)	(0.0058)	(0.0058)
ret_{t-1}	0.0164	0.0181	0.0245	0.0261	0.0094	0.0109
	(0.0239)	(0.0230)	(0.0219)	(0.0215)	(0.0210)	(0.0204)
$logmktcap_{t-1}$	-0.0236***	-0.0253***	-0.0160***	-0.0173***	-0.0176***	-0.0187***
	(0.0071)	(0.0074)	(0.0058)	(0.0060)	(0.0063)	(0.0066)
bm_{t-1}	-0.0010	-0.0031	-0.0113	-0.0120	-0.0052	-0.0063
	(0.0220)	(0.0219)	(0.0180)	(0.0179)	(0.0172)	(0.0174)
roa_{t-1}	-0.0500	-0.0477	-0.0638	-0.0626	-0.0404	-0.0393
	(0.0466)	(0.0469)	(0.0483)	(0.0485)	(0.0379)	(0.0379)
Obs.	9025	9025	9043	9043	9025	9025
R^2	0.0150	0.0155	0.0090	0.0095	0.0104	0.0106
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Time-Cluster	Yes	Yes	Yes	Yes	Yes	Yes

Table 18: Re-estimating eq.(2) with stationary random part of 3ci (excluding 2020 transactions)

This table reports regression results of politicians' trades cumulative abnormal returns [0,25] on economic policy uncertainty while excluding transactions made in 2020. Benchmarks considered are S&P 500, size, and Fama-French 12 industry. Regressions are run for only purchases. EPU used is the three-component index (3ci). The variable $logEPUstat_{t-1}$ is the stationary component of the natural logarithm of EPU (3ci) recorded for the month $t-1$ if the transaction is in month t. Similarly, umd_{t-1}, ret_{t-1}, $logmktcap_{t-1}$, bm_{t-1}, and roa_{t-1} are from the month $t-1$ if the transaction is in month t. umd stands for momentum and is the compounded return over months $t-12$ through $t-2$. ret stands for the monthly return of a stock at the end of month t. logmktcap denotes the natural logarithm of multiplication of public share outstanding and 1000 and price. bm represents book-to-market of a firm at the end of month t. roa is return-on-asset at the end of month t. Firm- and time-clustered standard errors are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% respectively.

	(1) S&P500	**(2)** size	**(3)** industry
constant	0.0912	0.0653	0.0584
	(0.0690)	(0.0661)	(0.0608)
$logEPUstat_{t-1}$	0.0287**	0.0209**	0.0157**
	(0.0112)	(0.0098)	(0.0071)
umd_{t-1}	-0.0051	-0.0039	-0.0065
	(0.0050)	(0.0038)	(0.0040)
ret_{t-1}	-0.0362	-0.0243	-0.0269
	(0.0235)	(0.0221)	(0.0195)
$logmktcap_{t-1}$	-0.0110*	-0.0078	-0.0069
	(0.0066)	(0.0062)	(0.0056)
bm_{t-1}	0.0524**	0.0354*	0.0410**
	(0.0233)	(0.0213)	(0.0192)
roa_{t-1}	0.0481	0.0420	0.0101
	(0.0610)	(0.0528)	(0.0495)
Obs.	6422	6438	6422
Adj. R^2	0.0220	0.0135	0.0173
Firm-FE	Yes	Yes	Yes
Firm-Cluster	Yes	Yes	Yes
Time-Cluster	Yes	Yes	Yes

9 Appendix B

Figure 10: Diagnostics test on log3ci model estimation

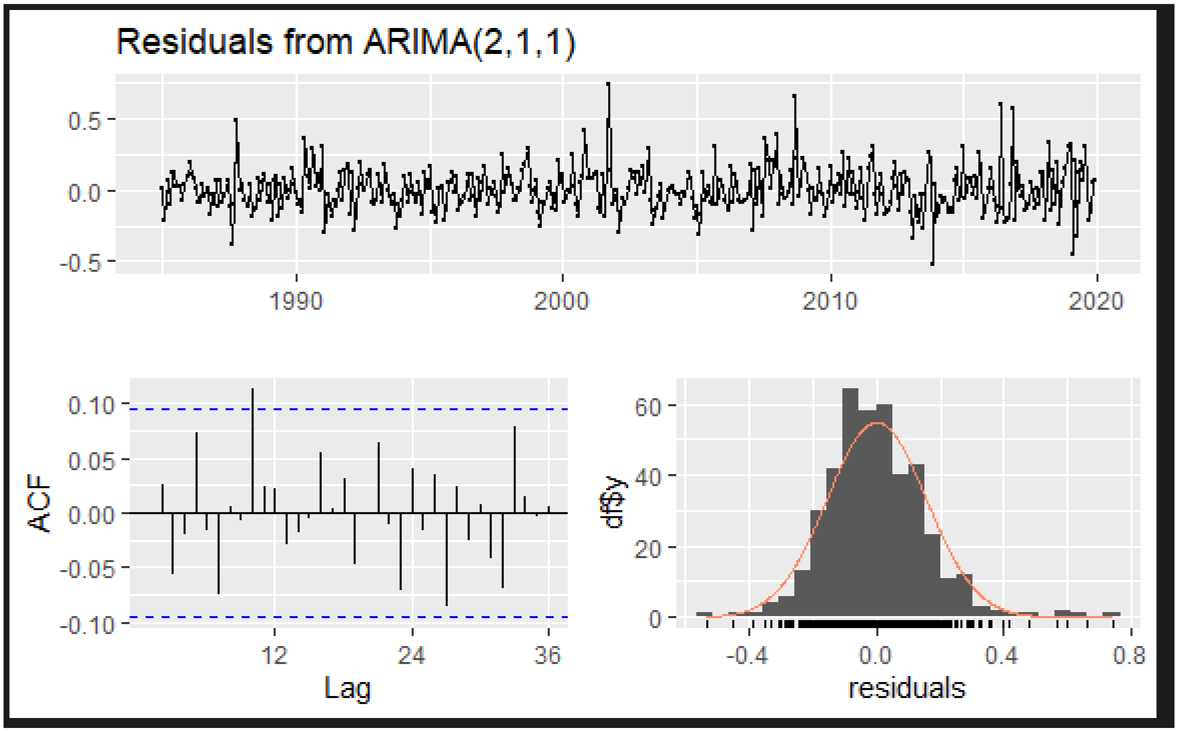


Figure 11: Plot of log3ci up to 2019 and forecast for 2020

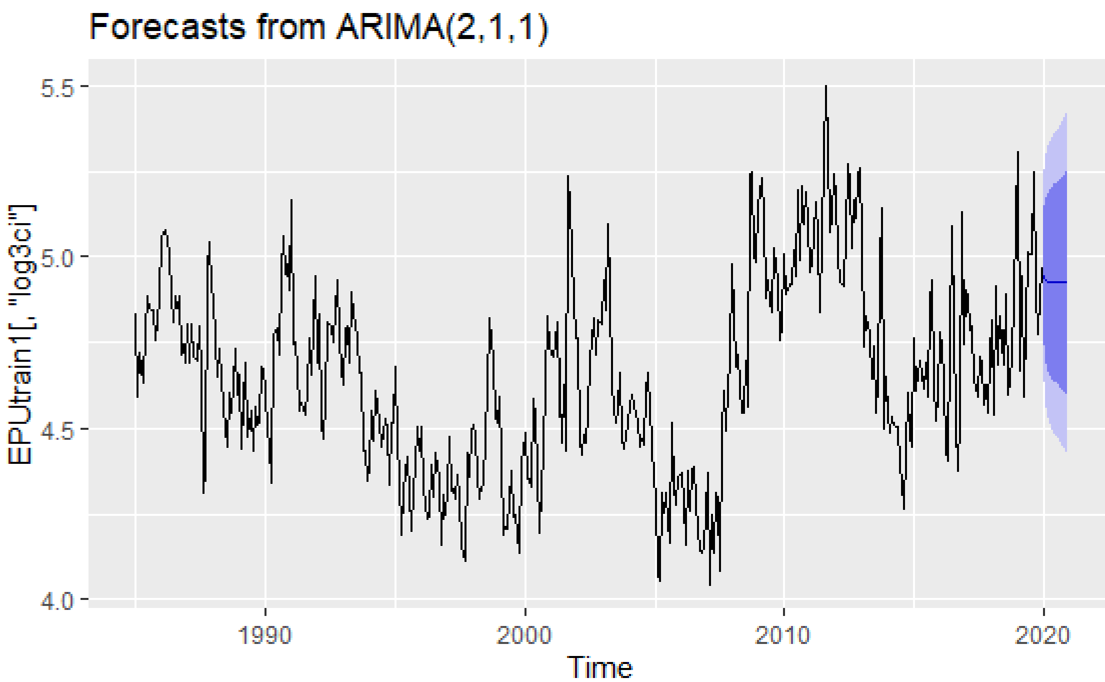


Figure 12: Plot of log3ci real and 2020 forecast