Shaping Economies Through Tax News: Analyzing the Influence on Economic Aggregates, Firm Behavior, and Financial Markets

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Abstract

This paper focuses on the economic consequences of "anticipated" shocks to taxes, specifically news or foresight about future shifts in tax policy. I apply an advanced topic model known as seeded Latent Dirichlet Allocation (LDA). This model o□ers advantages over unsupervised LDA and lexicon-based methods, providing a more nuanced and decades over time, starting from the Truman administration. Comparative analysis indicates that the metrics derived from Romer (2010), as only cited tax news measure by Leeper et al. (2012). The tes both macroeconomic and firm-level perspectives, pre-al evidence that tax foresight significantly influences eco-s, corporate behavior, and financial markets. First, news of ates output in the short term, and the e□ect of such news □erent economic states. Second, firms with greater market reactive to news of tax hikes, accelerating investment at a their counterparts. Third, firms that are heavily reliant purchases show increased stock price volatility when at-licy among investors is high. Finally, both stock and bond immediate responses when there is news of tax hikes, as as steps toward fiscal responsibility and

primarily by factors related to credit supply conditions. Overall, my findings at the asset market level suggest that news of tax hikes can

Norwegian news data to examine macroeconomic forecasting models. In 2018, Hansen et al. published what is, to my understanding, the first paper to feature LDA applications in a top-tier economics journal. They applied the LDA model to statements from the Federal Open Market Committee (FOMC) to study how individual contributors focus their attention during meetings. Dybowski and Adämmer (2018) used the correlated topic model, a variation of the conventional LDA, to analyze the macroeconomic effects of tax policy sentiment. They found that optimistic tax policy statements stimulate consumption, investment, and output, even after controlling for tax foresight using Leeper et al.'s (2012) implicit tax rate as the foresight proxy.

The paper proceeds as follows. Section 2 describes how I measure tax news. Section 3 presents the identification strategy for tax news shocks. Sections 4, 5, and 6 examine how tax news affects economic aggregates, firm-level dynamics, and asset markets, respectively. Section 7 concludes.

2 Measuring Tax News Through Advanced Topic Modeling

The field of economics has experienced a paradigm shift in the analysis of news and policy discourses through the application of machine learning algorithms. Topic modeling has emerged as a leading methodology to scrutinize the latent structures within a large corpus of documents. The method offers invaluable insights into financial news, policy debates, and prevailing economic sentiments. Scholars have leveraged topic modeling algorithms to gain a nuanced understanding of economic discourses, track market sentiment evolution, and even forecast market behavior based on evolving news narratives. The importance of topic modeling lies in its capacity to render a high-dimensional

data structure into comprehensible topics that can inform economic decision-making and forecasting.

2.1 Overview of Topic Modeling

Topic modeling, as a technique, sits at the intersection of machine learning and natural language processing, aiming to discover the latent topical patterns in a collection of documents. This section serves as an overview of the methodology used in this study.

2.1.1 Classic Latent Dirichlet Allocation (LDA) Model

The Latent Dirichlet Allocation (LDA) model, originally introduced by Blei et al. (2003), posits that any document collection can be e□ectively represented by a finite set of underlying topics. A defining feature of LDA is that it identifies topics that permeate through all documents in the corpus, albeit in varying proportions. This makes LDA a universally applicable tool, crossing disciplinary boundaries from computational linguistics to economics. The LDA model's advantages, such as its reproducibility and automated nature, make it particularly attractive for researchers handling massive collections of text data. It streamlines the research process by reducing the time and e□ort involved, thereby mitigating the biases that may arise from human interpretation or lexicon-based methods.

In the domain of natural language processing, understanding the thematic structure of large textual corpora is a non-trivial task. One common approach to tackle this problem is to represent the text corpus in its "bag-of-words" form, depicted as the article-term matrix, *w*

Figure 1: Article-Term Matrix and Topic Distributions After LDA

the size of the vocabulary.

While the topics, $_k$, encapsulate the prevalent themes throughout the corpus, LDA views each individual article as a composite of multiple topics. The article-speci c parameter vector

terms of distribution notation, the i-th term in the article is described as:

$$x_{(t;i)} \quad \text{Mult}(\ z_{(t;i)}\ ; 1); \quad z_{(t;i\ )} \quad \text{Mult}(\ _t\ ; 1): \tag{2}$$

The Gibbs sampling algorithm aims to find the values of $_k$ and $_t$ that most closely mimic the articles present in the actual text corpus.

The approximated proportion of topic k within article t can be represented by the frequency of its terms being allocated to topic k:

$$\hat{}_{t;k} = \frac{\sum_{i=1}^{N_t} I(\hat{z}_{t;i} = k)}{\sum_{q=1}^{K} \sum_{i=1}^{N_t} I(\hat{z}_{t;i} = q)} \tag{3}$$

where $\hat{z}_{t;i}$ is the estimated topic assignment for each term i in article t.

Similarly, the estimated topics themselves are derived from the frequency at which each term v in the vocabulary is assigned to topic k, summed across all articles:

$$\hat{}_{k;v} = \frac{\sum_{t=1}^{T} \sum_{i=1}^{N_t} I(\hat{z}_{t;i} = k) I(x_{t;i} = v)}{\sum_{m=1}^{V} \sum_{t=1}^{T} \sum_{i=1}^{N_t} I(\hat{z}_{t;i} = k) I(x_{t;i} = m)} \tag{4}$$

Lastly, the aggregate proportion of each topic k at a specific point in time (such as a month or a quarter) can be calculated by summing over all articles published at that time. Therefore, the estimated proportion of topic k during quarter is given by:

$$\hat{}_{;k} = \frac{\sum_{t2} \sum_{i=1}^{N_t} I(\hat{z}_{t;i} = k)}{\sum_{t2} \sum_{q=1}^{K} \sum_{i=1}^{N_t} I(\hat{z}_{t;i} = q)} \tag{5}$$

2.1.2 Seeded LDA Model

However, the unsupervised version of the LDA algorithm, operating within a generative probabilistic framework,

2.1.3 Lexicon-Based Method for Measuring Tax News

In the elds of nance and economics, lexicon-based techniques for te
ysis rely on an established set of terms that have been systematically cl
based on their sentiment|either positive, negative, or neutral|or in re
to a specialized subject area such as economic policy uncertainty. These
ignated terms are given speci c numerical weights or scores, which can ra
from simple frequency counts to more complex metrics. The purpose of t
is to capture the overarching sentiment or thematic focus within a given te
corpus.

One of the primary strengths of using lexicon-based approaches is the ease with which results can be interpreted. Since these methods hinge on a predetermined set of terms, the resulting analyses are usually straightforward and easily comprehensible. This level of interpretability is especially advantageous for stakeholders who may lack expertise in the area of natural language processing (NLP). Moreover, lexicon-based methods boast computational e ciency and scalability, qualities that make them well-suited for scrutinizing extensive datasets or for use-cases that necessitate real-time analytical insights.

However, these methods are not without their This

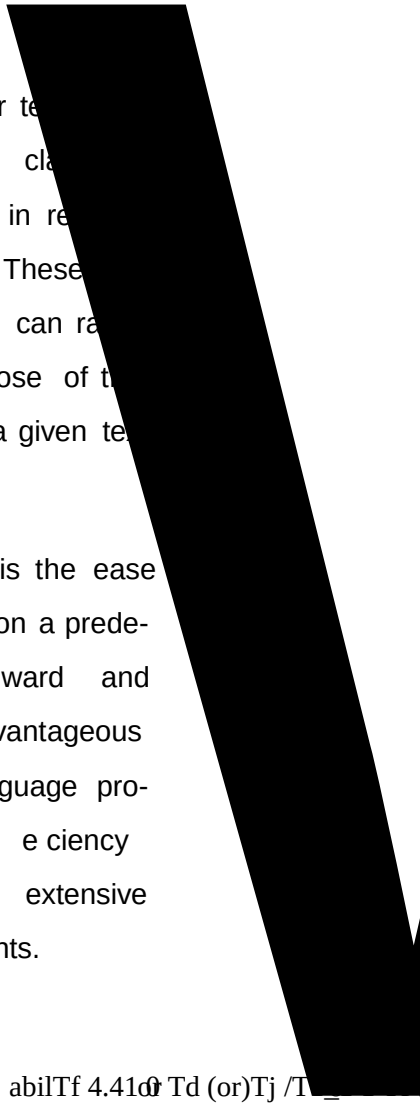

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Figure 2: The American Presidency Project (APP) Website Homepage

Note: https://www.presidency.ucsb.edu/presidents

presidential speeches and statements (Romer and Romer, 2010). Major news outlets such as the WSJ generally quote the president's words in their articles, and presidents could also direct news attention towards top issues that are on the administration's agenda, helping the forward-looking public form expectations (Eshbaugh-Soha, 2013). For instance, the APP archives a statement made by former President Donald Trump on April 21, 2017, during which he commented on signing an executive order and memorandums related to the regulation of the nancial services industry. In this statement, he noted, "And we'll be having a big announcement on Wednesday having to do with tax reform. The process has begun long ago, but it really formally begins on Wednesday. So go to it." The WSJ and Reuters promptly cited this remark in their coverage on the same day. Therefore, the APP seems to be an appropriate source for obtaining tax legislation news.

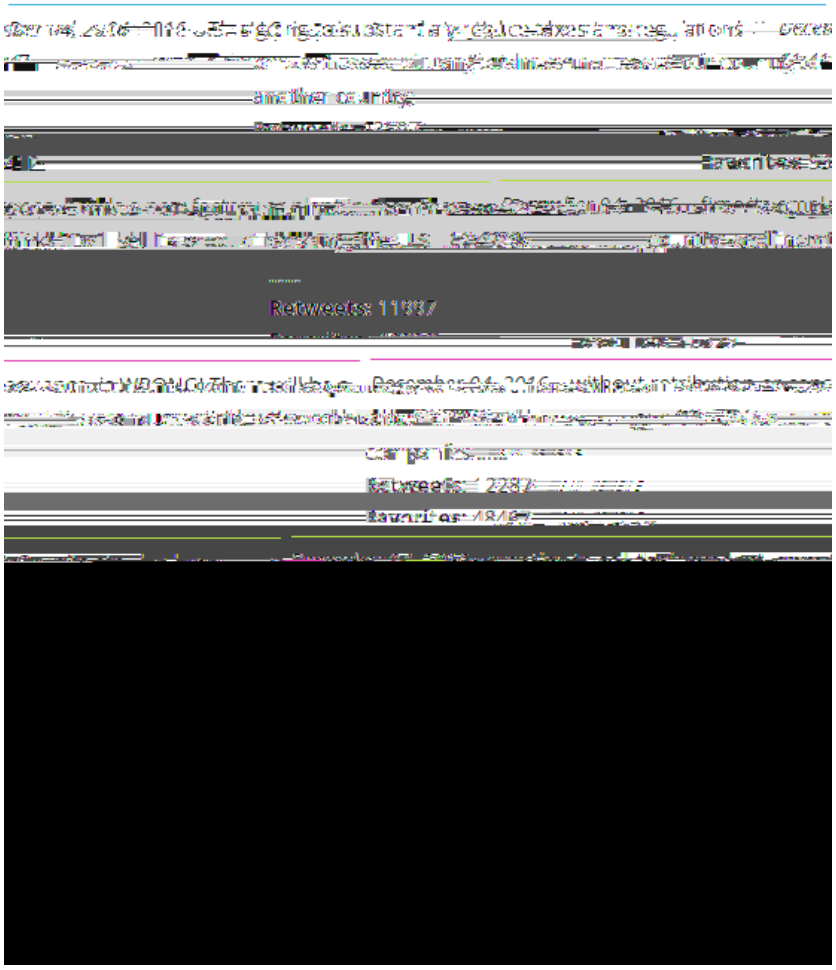
To shed light on the insights the seeded LDA model is expected to glean about future tax policy changes, I o er a chronological sequence of documents from former President Donald Trump, ranging from the initial discussion of tax reform to its eventual legislative enactment:

1. Interview with Bill O'Reilly of Fox News (Date:

6. Remarks on Signing Legislation on Tax Reform (Date: December 22, 2017)

ˆ As you know,

Figure 3: Former President Trump's Tweets About Potential Tax Changes Before His Inauguration



Both sources provide a wealth of direct quotations from presidents, standard phrases commonly found in tax policy narratives, legislative motivations, and aggregate revenue change estimates for each tax act. Leveraging this rich data, reforms are categorized into either tax hikes or tax cuts. Subsequently, NLP techniques are employed to distill the most frequently occurring bigrams|two-word sequences|from each category of texts.

The decision to focus on bigrams over unigrams or trigrams is a calculated one. Unigrams lack the contextual depth required for this analysis, while trigrams are less frequently encountered in the source narratives, making them less representative. Over-reliance on either could introduce undesirable artifacts such as over tting and semantic misspeci cation due to excessive subjective judgment.

Given these considerations, the top three bigrams for each topic are selected to serve as seed words in the LDA model's inference process.

Figure 5: Word Cloud of the Seeded-LDA-Identi ed Tax Topics

(a) Tax cut topic

(b) Tax hike topic

ular textual analysis algorithms with the bag-of-words assumption is that the model is likely to classify the sentences such as \there will be no new tax increases" as a signal about future tax hikes. It should also be lyh will

with spending reductions and revenue enhancements.

Figure 6 also implies that tax policy has been more intensively and consistently discussed since the 1980s, as evidenced by higher news spikes and slower reversion to the zero line. This trend may be explained by the structural shifts in tax policy objectives, the high policy priority of using tax instruments, and the notion that tax cuts are more often and openly discussed by presidents than tax hikes. Before the 1980s, the main tax policy objective was to ght high in ation (see Figure 7) or to nance wars (e.g., for the Korean and Vietnam Wars nancing) by triggering a series of tax increases. Since the 1980s (the 2000s especially), however, the government has been relying on tax policy to ght recessions or promote long-run growth. This priority relies on using either demand-side tax cuts such as the large-scale tax rebate, increases in standard deductions, and individual general tax credits aimed to boost private spending or supply-side measures such as massive corporate income tax reductions as well as reductions in top individual rates.

It should be noted that although de cit issues are also debated and de cit-driven tax hike acts are enacted accordingly, economic growth and tax cut policy still dominate after the 1980s regardless of how de cits deteriorate. Figure 8 shows the de cit trend over time, which may shed some light on the tax policy priority shifts.

2.5 Placing the LDA-Identi ed Tax News Information Flow Within the Existing Measures

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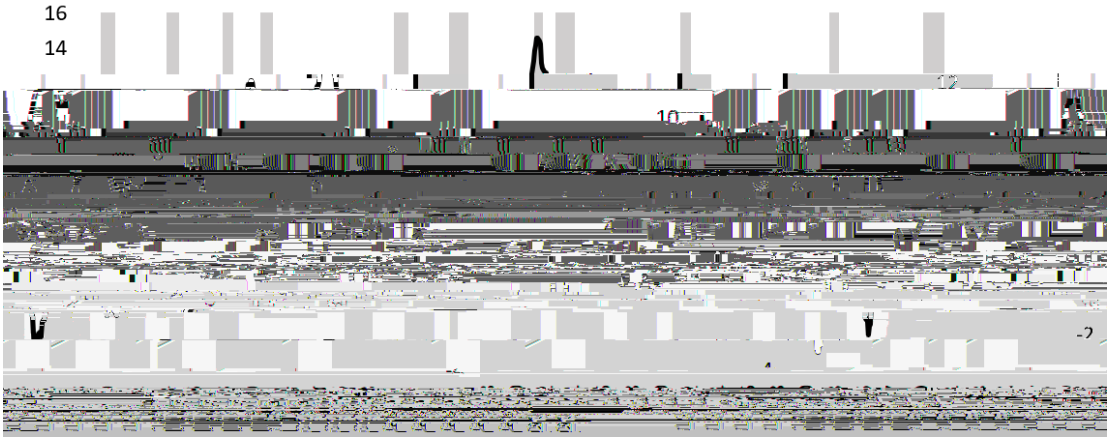
Figure 7: In ation Rate

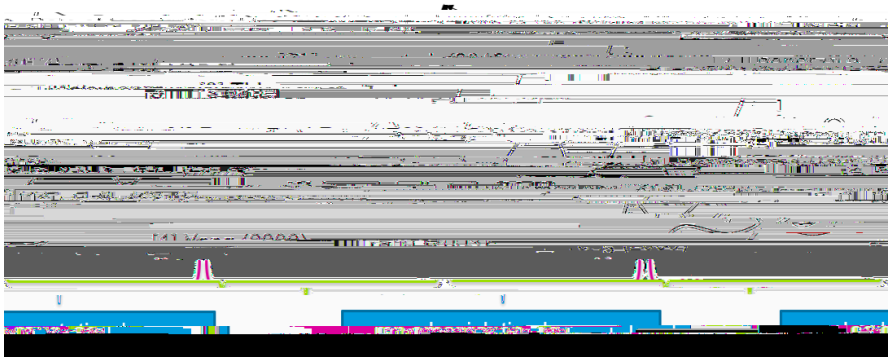


Note: Shaded areas denote recessions.

Figure 8: Federal Surplus Share of GDP

Note: Shaded areas denote recessions.

Figure 9: General Form of News Information Flow



torical overview of the evolution and progression of federal income tax policy in the United States from 1947 to 2009, covering reform motivations, legislative timelines, crucial tax-related provisions, and anticipated

going process of information dissemination and the subsequent adjustments in expectations that occur well be6oi0 1 e (ell)]TJ /T1_1 1 Tf ( )Tj /T1_0 3.19 6.372 0 Td [(t)-20 (he)]TJ /

Figure 10: NTNI vs. Implicit Tax Rate

Note: ITR data is obtained directly from Leeper et al. (2012) and its coverage is narrower than NTNI.

default risk. Kueng (2018) also points out that there are other factors than expected tax rates a ect municipal yield spreads. My measure overcomes these limitations by directly extracting tax news from a collection of news documents with the help of LDA algorithm. Figure 10 shows NTNI and implicit tax rate (ITR). Both are normalized to a 0-1 scale for a straightforward comparison.

To assess the predictive power of my tax news measure in relation to future tax changes, I conduct predictive regressions following the approach of Leeper et al. (2012) and Romer and Romer (2010) as outlined by Fantozzi and Muscarnera (2021). I estimate the following regression equation:

$$_t = \quad + \quad \text{NTNI}_{t\,j} \; + \sum_{i=1}^{4} \; _i \; \text{Controls}_{\,t\,i} \; + u_t \qquad (6)$$

where $j = 1; 2; : : : ; 4$, could be the implicit tax rate from Leeper et al. (2012) or narrative tax changes (expected change in tax liabilities at time of implementation) from Romer and Romer (2010), and the controls include lags of the dependent variable, output growth, tax revenue growth, government spending growth, change in debt-to-GDP ratio, in ation, change in interest rate, and

change in unemployment rate. The predictive power of NTNI on the implicit tax rate or narrative measures is determined by the F-statistic on the exclusion of NTNI.

Table 2: Predictive Power of NTNI

	j			
Source	1	2	3	4
Leeper et al. (2012)	14:92	8:02	5:96	2:35
Romer and Romer (2010)	5:28	13:26	38:07	27:57

Table 2 shows that NTNI is a strong predictor for both the implicit tax rate and narrative tax changes based on the typical rule of thumb that an F-statistic of more than 10 (Stock and Yogo, 2002). The NTNI can forecast a tax change one quarter earlier than the implicit tax rate and at least two quarters ahead of the narrative tax shocks identi ed by Romer and Romer (2010).

2.6 Comparative Analysis of Tax News Measures Using a Pre-de ned Lexicon

Are humans or computers better at identifying tax hike and tax cut news in a large corpus of documents? Many of the prior papers use subjectively determined word lists to produce news-based indexes and the results are robust within their research settings or questions (Loughran and McDonald (2011); Baker et al. (2016); Šyziak and Sheng (2022)). For this approach to be e ective, the process must be

our focuses are di erent. It should be noted that I am not making a conclusion here that LDA is superior to conventional textual analysis methods. One approach should not t all, and the choice needs to be case-speci c.

I decompose each article into paragraphs and then keep those that contain \tax". If an article is not tax-related, then no paragraph will be retained. With tax-related articles, I then follow routine pre-processing steps such as stop word removal and lemmatization. To determine whether a news article is mainly about tax hike or tax cut, I count, for each article, the number of paragraphs that contain at least one term in tax hike term set and the number of paragraphs that contains at least one term in tax cut term set. An article is then coded as tax hike (tax cut) if the number of tax-hike paragraphs is greater (less) than that of tax-cut paragraphs. Lastly, I obtain the average number of coded articles within each month weighted by the absolute di erence between the number of tax hike and tax cut paragraphs and denote the two resultant series as tax hike news index and tax cut news index. Alternatively, I can simply count the monthly number of coded articles.

Table 3 summarizes the key terms extracted from the same documents (i.e., presidential speeches compiled by Yang (2009) and Romer and Romer (2009)) I used for seed word selection in the previous section. Unlike those terms explicitly indicating future in ation path (e.g., rise, fall, or unchanged) in Šyziak and Sheng (2022), term selection for implying a tax hike or cut policy change should be mainly based on term co-occurrence. For example, the term \loophole" is likely to occur in a speech about tax hikes. Clearly LDA method shares the same logic as the lexicon-based one, but the former can minimize the risk of subjectivity and determine the importance of each term to the tax topic rather than treating them equally.

reasons. Ultimately, the results of the lexicon-based approach provide con - dence that LDA is an e ective tool for identifying tax-related news topics with minimal subjectivity.

3 Tax News Shock Identi cation

In accordance with the methodology proposed by An et al. (2022), tax news shocks can be easily identi ed by conducting a regression analysis of tax news with lags of scal variables, other macroeconomic variables, and the tax news itself. The regression residuals are then referred to as tax news shocks. Specifically, I perform a regression of the NTNI on an extensive set of lagged variables, such as output growth, tax revenue growth, government spending growth, alterations in the debt-to-GDP ratio, in ation, changes in interest rates, uctuations in unemployment rates, economic policy uncertainty (Baker et al., 2016), and the NTNI itself. I then acquire the regression residuals (i.e., unforeseen information about future tax changes) as tax news shocks. For clarity in subsequent empirical analyses, I standardize the obtained news shock series to have a mean of zero and a standard deviation of one. Figure 12 illustrates the (standardized) new shocks over time, with spikes corresponding to tax reform episodes. In my sample, prominent instances of extensive tax cut episodes include the Economic Recovery Tax Act of 1981, the Economic TaxAct

Figure 11: Lexicon-Based Results (Bottom Panel) vs. LDA Results

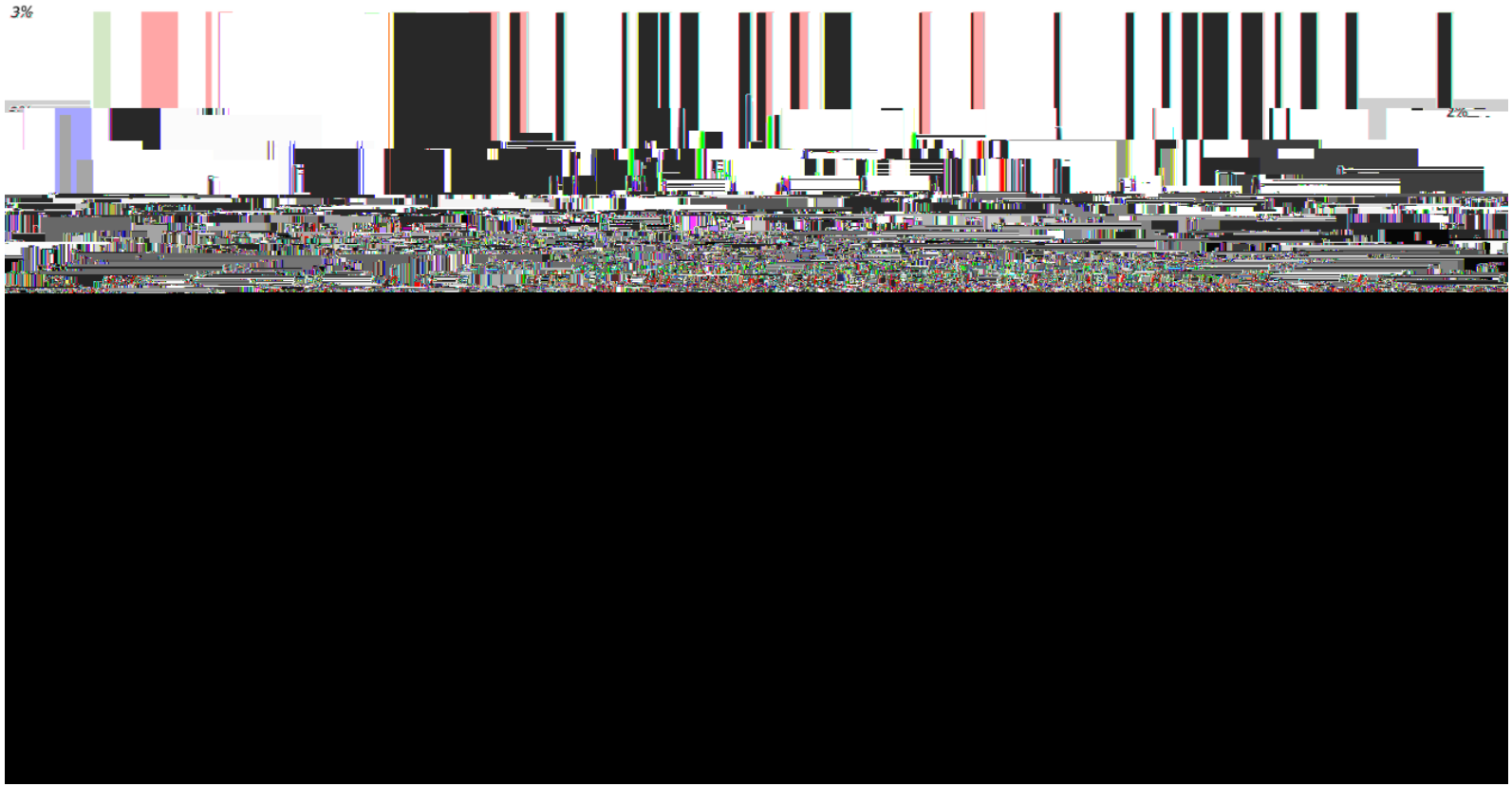


Figure 12: Tax News Shock Over Time

mately 0.9) with the tax news shock identi ed through regression residuals. This correlation provides reassurance regarding the validity of the tax news shock as identi ed in accordance with the methodology proposed by An et al. (2022). Details can be found in the Appendix.

4 Macroeconomic E ects of Tax News Shock

4.1 Model Speci cation

Recent scal literature increasingly used Jord a's (2005) local projections (LP). Compared to SVARs, LP allows a more parsimonious speci cation since not all variables are required to be included in all equations, and it does not impose dynamic restrictions embedded in SVARs. In addition, LP also easily accommodates state dependence or nonlinearities (Auerbach and Gorodnichenko, 2013; Ramey and Zubairy, 2018; Born et al., 2020).

I begin by estimating a linear LP model given by:

$$y_{t+h} = {}_t + {}_h(L)\text{control}_{t\ 1} + {}_h\text{shock}_t + {}_{t+h} \tag{7}$$

for $h = 0; 1; : : : ; 20$, where y_{t+h} is the response of an outcome variable of interest

(e.g., the cumulative change in the log of real GDP) at horizon $t+h$ to a tax (hike) news shock at time t, and control $_{t\ 1}$ includes a rich set of predetermined control variables including lags of output growth, tax revenue growth, government spending growth, in ation, change in debt-to-GDP ratio, change in interest rate, and change in unemployment rate. In addition, following Ramey and Zubairy (2018), I also include lags of tax news shocks to control for any serial correlation in the news variable. $_{h}(L)$ is a lag polynomial of order 4. The impulse response for H periods is obtained from a sequence of estimates $_{h}$.

I also investigate whether the output e ect of tax news shock is dependent on the state of the economy by using a state-dependent LP as follows:

$$\begin{aligned} y_{t+h} &= I_{t\ 1}\,[\ _{A;t} + \ _{A;h}(L)\text{control}_{\ t\ 1} + \ _{A;h}\,\text{shock}_{\,t}] + \\ &(1 \quad I_{t\ 1}\,)[\ _{B;t} + \ _{B;h}(L)\text{control}_{\ t\ 1} + \ _{B;h}\,\text{shock}_{\,t}] + \ _{t+h} \end{aligned} \tag{8}$$

where I_t is a dummy variable that indicates the state fA,Bg of the economy in the previous period. $_{A;h}$ and $_{B;h}$ measure the state-dependent responses of variable y_{t+h} at time $t+h$ to a tax news shock at time t. Following Ramey and Zubairy (2018), I use the Newey-West correction for standard errors (Newey and West, 1987).

To imply whether the state-dependent responses are statistically di erent to tax news shocks, I test at each year of the forecast horizon the following hypothesis:

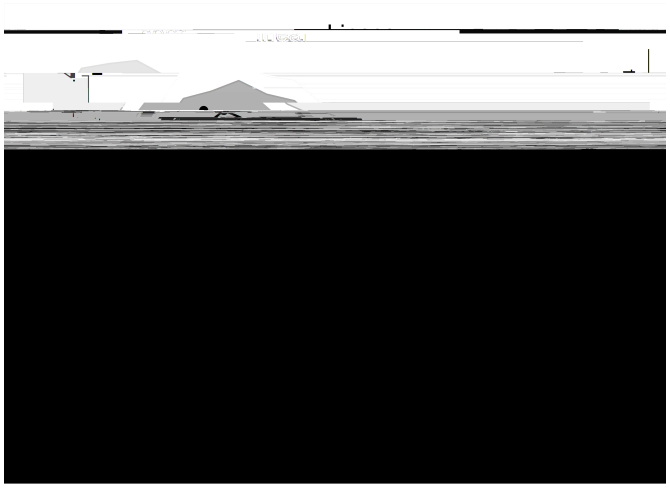
$$H_0 : \ _{A;h} \quad _{B;h} = 0$$

This hypothesis can be tested with a simple two-sided t-test. A similar approach is applied by Klein (2017) to test whether the e ects of scal consolidations in high and low private-debt states are di erent.

Speci cally, the paper takes into account four meticulously chosen economic

(i.e., tax hike news

Figure 13: Output Response to a Tax News Shock



Note: Impulse response to a positive one-standard-deviation shock to tax news; Shaded areas are the 90 and 68 (darker) percent con dence intervals constructed by the Newey-West method.

Economic activities rest on households and rms making billions of consumption and investment decisions. Such decisions are not only directly in uenced by economic realities (e.g., household's disposable income), but also indirectly driven by economic perceptions (e.g., perceptions that could respond to remarks and evaluations by the

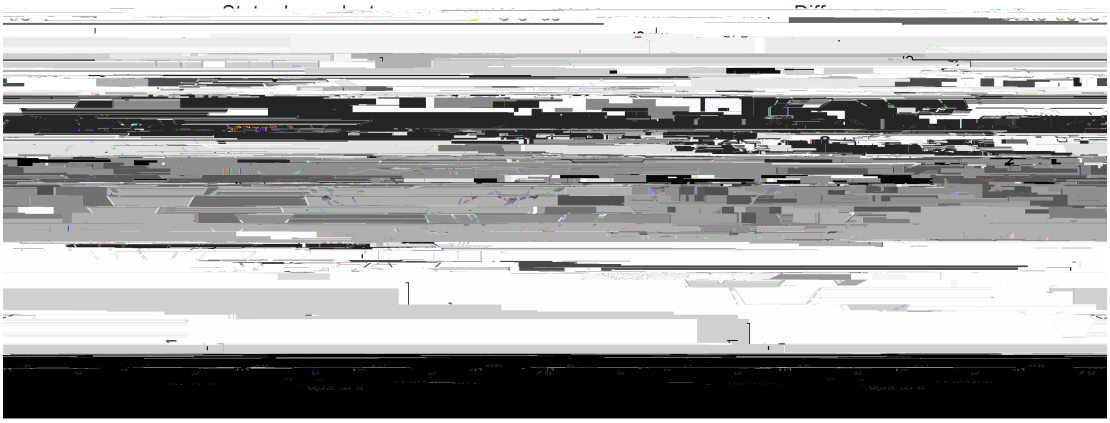
Figure 14: Consumption and Investment Responses to a Tax News Shocks

(a) Consumption response (b) Investment response

Note: Impulse response to a positive one-standard-deviation shock to tax news; Shaded areas are the 90 and 68 (darker) percent con dence intervals constructed by the Newey-West method.

consumption1(0a1k38278351 1Tf(Shock)7840 1m31.8561 1d5(Nation)T0 991se1 Tf ( )Tj /T /T1_1 1ao2ehng

Figure 15: Output Response to a Tax Hike News Shock: Slack States (Red: Unemployment Rate 6.5)



Note: The blue dashed line with circles is the response in low-unemployment states and the red dashed line is the response in high-unemployment states; 90 percent con dence intervals (e.g., red error bars and shaded areas) constructed by the Newey-West method are shown; The right panel shows the estimated di erence between state-dependent responses.

omy. The right panel of the gure shows the respective di erences $_{A;h}$ $_{B;h}$ for output at each quarter of the forecast horizon. A negative value indicates that the response in bad times is lower than in good times. The error bars indicate statistical signi cance at the 90 percent level, and therefore it complements the results in the left panel.

The ndings are consistent with the research conducted by Hayo and Mierzwa (2022). They gather information on proposed tax alterations during the initial phase of the lawmaking process (for example, when a measure was initially announced in a white paper or as part of a parliamentary discussion), which may not always correspond to the ultimate timing of tax

4.3.2 Tax News Shock During Different States of Tax News Attention

It would also be worth studying whether the output effects of a tax news shock could differ, conditional on the level of media attention. A recent paper by An et al. (2022) investigates the role of inattention in shaping the impact of monetary policy on macroeconomic variables and finds that inattention, measured as proportion of forecasters who do not revise their forecasts of a target economic variable such as GDP growth, significantly amplifies the effects of monetary policy shocks, implying that the economic variables are more responsive to changes in monetary policy when agents are inattentive. Additionally, the results suggest that inattentive agents generate more persistent responses to monetary policy shocks, which can have important implications for the conduct of monetary policy.

Regarding the use of news as a measure of attention, Bybee et al. (2023) apply the unsupervised LDA model to the full text of WSJ articles for 1984-2017, summarize business news into interpretable topical themes (one of them is the tax theme), and define them as categorical news/media attentions. Although my source of news is different from theirs, major news outlets such as the WSJ generally quote the president's words in their articles, and presidents may also direct media attention towards top issues that are on the administration's agenda (Eshbaugh-Soha, 2013). The correlation between my ATNI and their WSJ general tax attention index is strong (about 0.7) and spikes are coincident in both. Therefore, I can study, with my tax news data, whether tax news shocks have differential output effects under different levels of attention.

Figure 16 clearly shows that, when media attention on tax is low (i.e., less than the sample median), a tax hike news shock can have a more significant output boosting effect during the anticipation period and a larger contraction when tax changes become effective in comparison to high-attention states. This falls

Figure 16: Output Response to a Tax News Shock: States of Tax News Attention (Red: High

Figure 17: Output Response to a Tax News Shock: States of Tax News Attention (Red: High Attention States De ned by Following An et al. (2022))

Note: The blue dashed line with circles is the response in low-attention states and the red dashed line is the response in high-attention states; 90 percent con dence intervals (e.g., red error bars and shaded areas) constructed by the Newey-West method are shown; The right panel shows the estimated di erence between state-dependent responses.

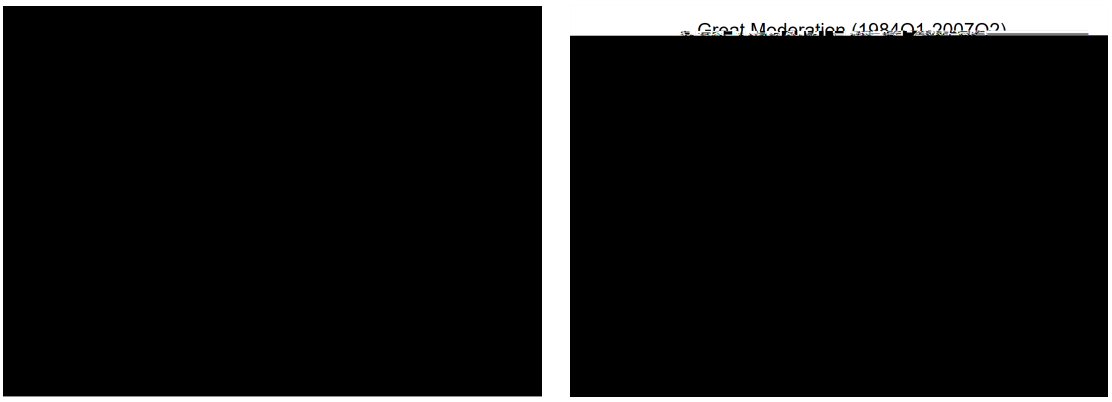
empirical model by replacing MPS and I with my tax news shocks and news attention, respectively. I also borrow the same set of control variables from my previous local projection model.

Figure 17 shows that an unexpected tax hike news shock during low-attention states brings up real GDP. This impact reaches its maximum after ve quarters and subsequently transitions into a negative e ect. In contrast, tax news shock does not have a sizeable real impact with high attention. As further shown in the right panel, the di erential responses or real GDP between high and low attention states are statistically signi cant and economically meaningful. These results are consistent with those of An et al. (2022), even though their attention measure and shock variable totally di er from mine.

To the best of my understanding, these ndings present novel contributions to the existing body of knowledge on tax policy and di

4.3.4 Tax News Shock During Di erent

Figure 19: Output Response to a Tax News Shock: Fiscal and Monetary Policy Mix



(a) (b)

Note: Shaded areas are the 90 and 68 (darker) percent con dence intervals constructed by the Newey-West method.

In contrast, one of the key features of the Great Moderation was lower and more stable in ation rates compared to the preceding Great In ation period. With less concern about the erosion of purchasing power, households and rms were less motivated to alter their actions in anticipation of tax hikes. In addition, during the Great In ation, the government used scal actions to adjust the economy and the Federal Reserve was supposed to support the policy by preventing an increase in market interest rates (Meltzer, 2005; Bianchi and Ilut, 2017). However, during the Great Moderation, improved monetary policy and the central role of the Federal Reserve in managing the economy led to better management of in ation expectations and greater economic stability (Blanchard et al., 2010), therefore reducing the need for people to adapt their behavior in response to anticipated tax changes.

4.3.5 Con dence Intervals Using Bootstrap Method

Instead of using the

porate

5.2 Firm-Level Price Markups

A rm's markup is de ned as the ratio of the price (P) to the marginal cost (MC). Estimating rm markups is empirically challenging for many reasons, one of whichhe

Figure 21: Evolution of Estimated Markups

Therefore, the e ects of tax news shocks are likely to be heterogeneous among the forward-looking rms with di erent levels of market power.

5.3 Empirical Framework

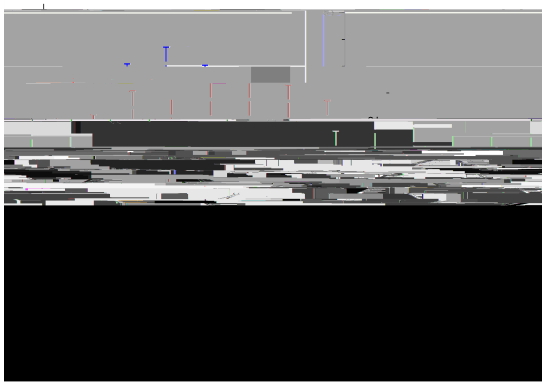
To estimate the dynamic e ects of tax news shocks on rm's real sales and in-

5.4 Unconditional Results

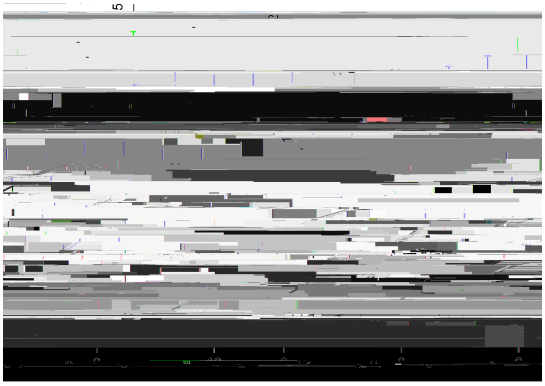
Figure 22 below present the impulse response of real sales, real total assets, real PPE, and real CapEx to a positive one-standard-deviation

Figure 22: Response of Real Sales and Total Assets to Tax News Shocks: Average E□ect

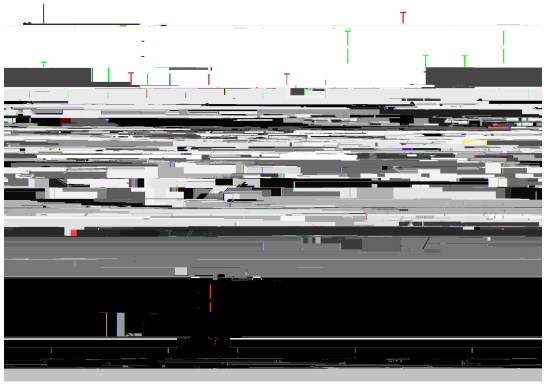
(a) Real sales (%)



(b) Real total assets (%)



(c) Real PPE (%)



(d) Real CapEx (%)

Note: The solid lines indicate the impulse response functions to a one-standard-deviation tax hike news shock; The vertical dashed lines denote 90 percent confidence bands constructed using the standard errors clustered by firm and time and adjusted for potential serial correlation using the Driscoll-Kraay method; The x-axis denotes quarterly time; The y-axis denotes percentage change.

duction inputs, firms can hedge against potential inflation and protect their purchasing power.

Simultaneously, firms may attempt to increase sales in the short term in anticipation of a tax hike. By generating higher revenues (for example, through promotions that may stimulate consumer demand) at the existing lower tax rates, companies can maximize after-tax profits, positioning themselves advantageously for when the tax increase is implemented (Yagan, 2015). In addition, businesses might try to move income from future periods to the present, recognizing more income at the lower tax rates currently in force before the tax hike. This can be accomplished through various strategies, such as changing accounting methods or accelerating revenue recognition (Auerbach and Hassett, 2002).

5.5 High- vs. Low-Markup Firms

In this section, the influence of a tax hike news shock on firms with di□ering market power is explored. Drawing from De Loecker, Eeckhout, & Unger's (2020) research on the implications of market power, it is clear that high-markup firms usually hold a significant advantage over their less powerful counterparts due to their inherent capabilities and resources. As suggested by the results (see Figure 23), these firms typically respond

Figure 23: Response to a Tax Hike News

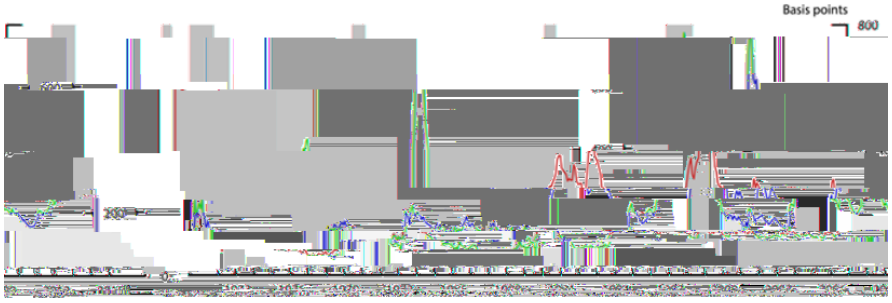
6 Tax News and Asset Markets

6.1 Tax News Shock and Asset Prices

Compared to monetary policy, fiscal policy's potential impact on asset markets has received less attention. Discussions have mainly focused on the e□ects of fiscal policy on macroeconomic variables such as GDP, consumption, and investment, little

Figure 25: Response of S&P 500 Composite Index to a Tax Hike News of uoc ( )Tk 58 83.49816

Figure 26: GZ Credit Spread Extended by Giovanni et al. (2016)



Note: The shaded vertical bars represent the NBER-dated recession. Giovanni et al. (2016)'s calculations based on: Center for Research in Security Prices (CRSP); CRSP/Compustat Merged Database, Wharton Research Data Services (WRDS), and Bank of America Merrill Lynch Bond Indices.

documented by Ji and Qian (2015), a tax hike that improves the government's balance sheet increases the possibility of a government bailout in case of a banking crisis, and such a reduction in the systemic risk can then reduce the risk premium charged by banks, and hence low-/T1_1 1 Tf/T1_1 1 Tks,

gov3a35yec14 0 Td[(incrhik)30 (e)]TJ/T1_1 1 Tf( )Tj/

Figure 27: Response of GZ Credit Spread to A Tax Hike News Shock

Note: Impulse response to a positive one-standard-deviation shock to tax news; Shaded areas are the 90 and 68 (darker) percent confidence intervals constructed by the Newey-West method.

cantly more informative–in both economic and statistical terms–about future economic activity than a component of expected defaults. I examine the behav

ior of the excess bond pre

lending standards in resp

Figure 28: Responses to A Tax HTmiu.4j/T1_0 7a. 0 h5/T1_0 1 Td 28:

risk component of the GZ spread is, in contrast to the excess bind premium, not reacting significantly in response to the tax news shock. This observation suggests that the variation in the GZ credit spread conditional on the tax news shock is driven by fac y related to credit supply co dy-namic response of ban strong and significantly nk equity response is cons the notion that it refl o itability or higher asset v n the balance sheet of response of the SLOOS va gests an immediate ation of lending standards lings related to th es excess bond premium, bank d lending stand co the evidence reported in Gil Zakrajsek (2 ere itability of the U.S. financial sector is as with in the excess bond premium. ether, the s su pothesis that balance sheet and merally o pply c an important transmission chann news o the re

The results also echo the findings i viou . High-m due to their substantial financial re ar or inform ss are better equipped to respond to tax s positively le, news shocks may improve credit supp which again or high-markup firms. While this 2. 0 g 0 Td0 Td[(f( )Tj .37

6.2 Tax News Attention and Stock Price Volatility

An increasing body of empirical evidence suggests that investor attention plays a crucial role in influencing asset prices (Da et al., 2011). Studies have shown that fluctuations in investor attention over time have significant implications for market dynamics. High levels of attention have been associated with buying pressures and sudden price reactions (Barber and Odean, 2008; Barber et al., 2009), while low levels of attention have been linked to underreactions to important announcements (Dellavigna and Pollet, 2009). This highlights the importance of investor attention in driving price movements and the incorporation of new information into asset valuations. Andrei and Hasler (2014) examine the relationship between attention to news and return volatility. They find that heightened attention to news (proxied by Google search data on financial and economic news) can contribute to increased volatility in stock prices. Building on this premise, the present study focuses specifically on the impact of tax news attention on stock volatility.

It is important to consider the underlying factors that may contribute to the relationship between tax news attention and stock volatility. One such factor could be the differential revenue exposure of firms to government contracts, which can vary across industries and companies. The potential for tax reforms, such as tax hikes, can significantly impact investor attention and subsequently contribute to stock volatility for firms highly exposed to government spending.

For instance, increased attention to tax-related news is likely to occur as investors closely monitor any proposed major changes in tax policy. In this context, firms with substantial revenue dependence on government contracts become particularly susceptible to the effects of tax-related news attention. A tax hike, when combined with other austerity measures such as reduced government spending, can adversely affect these firms' revenue streams to a greater

extent than the less exposed ones.

strong evidence for this. The coe□cient of 0.245 on the ”Agg. Tax News Attention * Intensity” suggests that for every 1% increase in general tax news attention a firm with a 50% government revenue share would see its stock volatility rise by about 0.12%. By decomposing news attention into tax cuts and hikes, column (2) clearly suggests that volatility at highly exposed firms responds to tax hike news attention much stronger than to cut news, implying that investors may anticipate reduced government spending alongside the tax increase. Darrat (2008) explores the causal relation between government spending and taxation and finds that raising taxes (working primarily through aroused public awareness, which can incite public demands to curtail unnecessary expenditures) provokes spending cuts. This expectation of lower revenue potential can lead to heightened concerns about the financial health and future prospects of these firms, resulting in increased stock volatility. Columns (3) to (7) presents a range of additional robustness results. Columns (3) and (4) add EPU and tax EPU that are interacted with the exposure intensity, yielding similar results on the relationship between attention and volatility but suggesting that none of the EPU measures has a large and statistically significant impact on volatility. Columns (5) and (6) consider realized volatility and 182-day implied volatility, and the results are still robust. Column (7) replaces my aggregate tax news attention with the WSJ-based general tax news attention from Bybee et al. (2023), and still the coe□cient of the attention-exposure interaction term is line with my expectation. While tax news attention is not a major focus of Bybee et al.’s (2023) study, their findings

Table 4: Option-Implied Stock Price Volatility and Tax News Attention

	(1) 30-d imp	(2) 30-d imp	(3) 30-d imp	(4) 30-d imp	(5) Realized vol	(6) 182-d imp	(7) 30-d imp
Agg. Tax News Attention × intensity	0.245						
	(0.0418)						
Federal purchases/GDP × intensity	-32.76	-40.48	-42.12	-41.63	-32.26	-37.52	-24.73
	(13.32)	(13.32)	(12.54)	(12.58)	(15.83)	(12.51)	(8.066)
Hike News Attention × intensity		0.371	0.362	0.366	0.386	0.325	
		(0.0702)	(0.0710)	(0.0718)	(0.0884)	(0.0677)	
Cut News Attention × intensity		0.150	0.123	0.134	0.172	0.123	
		(0.0486)	(0.0568)	(0.0549)	(0.0613)	(0.0478)	
Log(EPU) × intensity			0.0732				
			(0.0774)				
Log(Tax EPU) × intensity				0.0254			
				(0.0423)			
WSJ Tax News Attention × intensity							0.370
							(0.118)
Constant	-1.064	-1.057	-1.061	-1.058	-1.244	-1.074	-0.760
	(0.0136)	(0.0135)	(0.0161)	(0.0140)	(0.0161)	(0.0126)	(0.00638)
Firm and time e□ects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	136578	136578	136578	136578	136578	136578	136578

Note: Standard errors in parentheses. $p < 0:10$, $p < 0:05$, $p < 0:01$. The sample contains 136,578 observations on 5,460 firms from 1996 to 2012. The dependent variable is the

7 Conclusion

This study delves into the intricate relationship between fiscal policies, particularly tax changes, and economic behavior under the prism of ”fiscal foresight.” Utilizing a novel approach based on seeded LDA to

shocks ε_t:

$$AU_t = B\varepsilon_t \tag{14}$$

where $E[\varepsilon_t] = 0$, $E[\varepsilon_t \varepsilon_t'] = I$, and $E[\varepsilon_t \varepsilon_s'] = 0$ for $t \neq s$. The A matrix imposes the recursive structure, while the diagonal B matrix orthogonalizes the effects of innovations. With 14, the structural form of the VAR can be obtained as follows:

$$AY_t = AC(L)Y_{t-1} + AU_t = AC(L)Y_{t-1} + B\varepsilon_t \tag{15}$$

I obtain the reduced-form residuals $U_t = [u_t^T \; u_t^G \; u_t^y]'$ by estimating 13, and then express the reduced-form residuals as:

$$u_t^T = \alpha_y^T u_t^y + \alpha_G^T \varepsilon_t^G + \varepsilon_t^T \tag{16}$$

$$u_t^G = \alpha_y^G u_t^y + \alpha_T^G \varepsilon_t^T + \varepsilon_t^G \tag{17}$$

$$u_t^y = \alpha_T^y u_t^T + \alpha_G^y u_t^G + \varepsilon_t^y \tag{18}$$

where α_y^T and α_y^G measure the automatic effects of economic activity on spending and taxes under the existing fiscal policy, as a

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data, α_y^T and α_y^G measure only the automatic feedback from real GDP to government spending and tax revenue (i.e., automatic output elasticity of fiscal policy). From their estimates, $\alpha_y^T = 2.08$ and $\alpha_y^G = 0$, as they could not find any automatic feedback from economic activity to government spending.

From Equations 16, 17, and 18, it is evident that u_t^T and u_t^G are correlated with ε_t^y. Therefore, Blanchard and Perotti (2002) compute cyclically adjusted reduced-form residuals for the fiscal variables as follows:

$$u_t^{(T;ca)} \quad u_t^T \quad \alpha_y^T u_t^y = \alpha_G^T \varepsilon_t^G + \varepsilon_t^T \tag{19}$$

$$u_t^{(G;ca)} \quad u_t^G \quad \alpha_y^G u_t^y = \alpha_T^G \varepsilon_t^T + \varepsilon_t^G \tag{20}$$

and use them as instruments to estimate α_T^y and α_G^y in Equation 18. However, $u_t^{(T;ca)}$ and $u_t^{(G;ca)}$ may still correlate with each other, though neither correlates with ε_t^y. Hence, to identify the system, the ordering of the fiscal variables needs to be decided. If tax decisions come first, then $\alpha_G^T = 0$. If spending decisions come first, then $\alpha_T^G = 0$. Both assumptions give similar results.

To identify the structural tax news shocks, I augment the original SVAR with my quarterly tax news index, N_t (i.e., the NTNI). Following Leeper et al. (2013)'s strategy, tax news shocks have no contemporaneous effect on tax revenues, government spending, and output. Consequently, the tax change news equation added last to the system of reduced-form errors is as follows:

$$u_t^N = \alpha_T^N u_t^T + \alpha_G^N u_t^G + \alpha_y^N u_t^y + \varepsilon_t^N \tag{21}$$

are used as instruments for estimating α_T^N, α_G^N, and α_y^N, respectively.

Equation 14 can be written in a matrix form, and all the α's can be estimated by the steps mentioned above. The elements on the diagonal of the *B* matrix are the standard deviations of the ′″s (i.e., a 1-standard-deviation shock to each variable). Six restrictions together exactly identify the

endogeneity concern consists of the potential simultaneity bias resulting from the possibility of correlation between the input choice and the productivity. Following Díez et al. (2021), the methodology addresses this concern through the control function approach by assuming that the demand for the variable input, v, depends on productivity: $v_{it} = f(!_{it}; k_{it})$. Inverting it yields $!_{it} = f^{-1}(v_{it}; k_{it})$ and thus the production function can then be written as follows:

$$q_{it} = \beta_v v_{it} + \beta_k k_{it} + f^{-1}(v_{it}; k_{it}) + \epsilon_{it} = \phi(v_{it}; k_{it}) + \epsilon_{it} \tag{24}$$

where ϕ can be estimated using any consistent non-parametric estimator.

In the second stage, the method assumes that productivity follows a first-order Markov process: $!_{it} = E(!_{it} j !_{it-1}) + \xi_{it}$, where ξ_{it} stands for an innovation shock to the productivity process. Then solving for ξ_{it} and replacing $!_{it}$ with the first-stage estimates can have:

$$\hat{\xi}_{it} = \hat{\phi}_{it} - \beta_v v_{it} - \beta_k k_{it} - E\left(\hat{\phi}_{it-1} - \beta_v v_{it-1} - \beta_k k_{it-1}\right) \tag{25}$$

With standard GMM procedures, β_v and β_k can be recovered. By assuming that the variable input v responds to current productivity shocks but its lagged values do not, the following moment condition can be formed: E

$$\mu_{it} = \frac{\beta_s^v}{\alpha_{it}^v} \tag{27}$$

where β_s^v is the output elasticity of the flexible input *v* in industry *s* and α_{it}^v is the expenditure share of flexible input *v* by firm *i* in period *t*. Therefore, price markups are the deviation between the elasticity of output with respect to a variable input and that input's share of total revenue.

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