

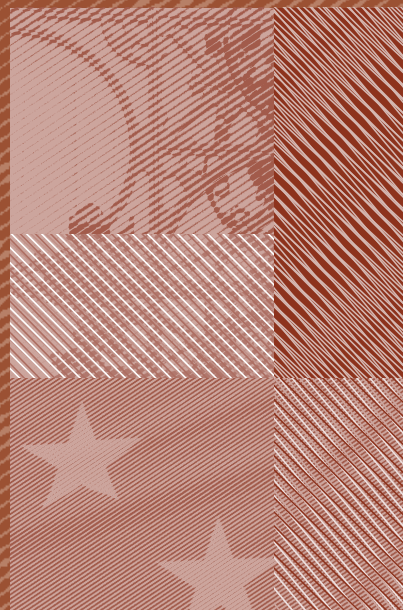
**THE EFFECTS OF TAX CHANGES
ON ECONOMIC ACTIVITY:
A NARRATIVE APPROACH
TO FREQUENT ANTICIPATIONS**

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THE EFFECTS OF TAX CHANGES ON ECONOMIC ACTIVITY: A NARRATIVE APPROACH TO FREQUENT ANTICIPATIONS (*)

Sandra García-Uribe (**)

BANCO DE ESPAÑA

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Abstract

This paper studies the effects of anticipations of tax changes in the USA through the release of tax news in the media. I construct a new measure that captures the anticipation of tax bill approvals by exploiting the content of news in the US television. Since this information typically flows faster than standard measures of GDP, I propose a mixed frequency dynamic factor model to estimate both the economic activity latent factor and the effects of anticipated tax shocks on it. I find that onemonth-ahead media anticipations of tax approvals significantly stimulate current economic activity. This stimulation comes from anticipations of tax cuts.

Keywords: fiscal policy, taxation, mass media, information, beliefs, random forests.

JEL classification: E62, H20, N12, D80.

Resumen

Este artículo estudia los efectos que anticipaciones de cambios impositivos a través de noticias en los medios pudieron tener en la actividad económica de Estados Unidos. Para ello construyo una nueva medida que contiene el nivel de anticipación de la posible aprobación de proyectos de ley fiscal en el Congreso americano explotando el contenido de las noticias que se publicaron en la televisión norteamericana. Dado que esta información fluye más rápido que las medidas estándar de PIB, propongo un modelo dinámico de frecuencias mixtas para estimar tanto el factor inobservable de actividad económica como los efectos de los potencialmente previsibles cambios fiscales sobre él. Encuentro que anticipaciones de cambios en la presión fiscal a un mes vista con la información de los medios estimulan significativamente la actividad económica, siendo las anticipaciones de reducciones en la presión fiscal las que determinan el signo de este resultado.

Palabras clave: política fiscal, impuestos, medios de comunicación, información, creencias, bosques aleatorios.

Códigos JEL: E62, H20, N12, D80.

1 Introduction

Prior to the approval of laws, there is often widespread information about the progress of bills. This information may be valuable for the forecasts that agents make about the economic environment in the future. In the context of fiscal policy, agents may be very attentive to information on these bills if by doing so they are able to anticipate changes that will affect them. This paper provides a way to account for the economic responses to anticipation of tax shocks when there is still uncertainty about the approval of tax bills.

Mass media are a central player in the transmission of public information to society. As reporters and analysts of fiscal bills during their process of elaboration and until approval, they provide information that may be worth to the public's forecast of the success of potential new fiscal policy. This is an anticipation channel that has not been considered before in the literature but one that as this paper shows is relevant to economic activity.

In this paper I introduce a new measure of mass media anticipations of tax bill approvals by exploiting the content of news in the US television during the period 1968-2007. My measure of mass media anticipations is formulated as the predicted probability of a tax bill approval at future periods conditional on the available information in mass media news at the current period. To address this quantification challenge I use a machine learning algorithm from the family of Classification and Regression Trees (CART). CART methods allow the researcher to consider large number of variables for a classification task, whereas standard discrete choice models such as Probit or Logit cannot handle this problem. They are highly non-linear models which help learning the features that better fit the data in a very flexible way. Nonetheless, they suffer from overfitting when the data is very noisy and of bias when there is a high correlation among the features. The news data suffers from all these issues. To overcome them I make use of automatic text analysis techniques to reduce the noise in the data and several extensions of Random Forests to reduce the problem of correlated features.

Time aggregation in the analysis of quarterly economic indicators may mask important anticipation effects, since information through the news may evolve quickly in a matter of days. To circumvent this issue I propose a dynamic factor model to estimate both the economic activity latent factor and the effects of anticipated tax shocks

on it. The empirical basis for this type of study relies on the joint analysis of text data and high frequency indicators of economic activity. In principle, one may want to consider different frequencies, therefore a mixed frequency analysis is appropriate. To my knowledge this is the first paper that exploits a dynamic factor model to account for fiscal policy effects on economic activity. The factor specification considers the dynamics of the factor and the potential effects of tax changes and their anticipation on it. To identify the effects of anticipations on economic activity I take advantage of the variation of estimated beliefs on future tax changes over time. The variation responds to anticipations of approved tax bills but also to ex-post-erroneous anticipations given the information in the media.

In my empirical analysis, I have control of the potential effects of tax changes from the bill initial status to the implementation. This strategy allows measuring implementation effects of tax changes net of other anticipation mechanisms that could be affecting previous levels of economic activity.

My results reveal that one-month-ahead anticipations of tax approvals significantly stimulate current economic activity growth. A ten percent increment in the measure of one-month ahead tax anticipations reduces the monthly growth rate by 1.5%. Two and three month ahead anticipations revert sign but do not have a statistically significant effect on economic activity. After controlling for mass media anticipation, direct implementation effects of tax changes are reduced in absolute value but still have short-run negative significant effects. The results also suggest an upward bias in the previous estimates of the fiscal multiplier proposed by Romer & Romer (2010) due to the omission of anticipation effects. My results are robust to the inclusion of controls for implementation delays, following the strategy of Mertens & Ravn (2012). I also analyze the effects of the anticipation of tax increases versus tax cuts finding that it is the anticipation of tax cuts what stimulates the economy. Anticipating tax increases reduces economic activity by 1,36% while anticipating tax cuts stimulates it by 3,04%.

From Random Forests I learn which text features best predict future tax approvals; I find that those related to the later stages of the bill process are the most relevant covariates for the one-month ahead predictions of tax approvals. The out-of-sample predictive performance of the algorithm reveals we could have predicted four out of twenty tax bill approvals at US Congress by using the television news about taxes.

Relation to the Literature. This paper contributes to the extensive literature of the effects of fiscal policy on economic activity. In particular, it contributes to the narrative approach and the results from the seminal work of Romer & Romer (2010) by providing an empirical strategy, a methodology and evidence of the effects of fiscal policy on economic activity from initial information spills of a tax change to its implementation.

Mertens & Ravn (2012) study the effects of tax implementation delays by exploiting the variation in the implementation horizon of the *exogenous* tax changes in Romer & Romer (2010). They document that tax increases stimulate economic activity prior to implementation while contractions in economic activity come earlier than if implementation was at the time of approval. In this paper, I also control for implementation delays and still find evidence of anticipation effects. Also Coglianesi et al. (2017) provide evidence of anticipation effects of gasoline tax changes in gasoline demand in a framework of policy certainty.

While there is evidence of anticipation effects under certainty of the policy implementation, little is known in terms of behavior under uncertainty. This paper contributes to this literature by considering anticipations of tax changes before bill approvals at Congress, when the media can publish news related to the bill legal process, its economic and political debate. I also distinguish between delayed and on-time implementation of tax changes and find that after considering mass media anticipations of tax approvals, on-time tax changes have no significant effect after implementation in economic activity while delayed tax changes have effects before and after implementation.

This paper contributes to the literature that studies the macroeconomic effects of news content regarding policy announcements by providing a new way of synthesizing many text features of news data into an indicator, in this case of anticipations, and providing a way to estimate its macroeconomic effects. In this literature different works have exploited the number of news mentioning a particular words or dealing with a particular issue to study the macroeconomic effects of news about particular events. Some of these works are Gregori et al. (2016), Bouzgarrou & Chebbi (2015), Caporale et al. (2018), Beetsma et al. (2013) and Gade et al. (2013).

To my knowledge, this is the first application in the literature combining machine learning and forecasting models to study the effects of massive policy-related information from the media on economic activity. Classification algorithms such as Support Vector Machines, Neural Networks or Naïve Bayes have been mostly used for predic-

tion in the field of finance. Manela & Moreira (2017) uses SVM to produce a measures of stock volatility exploiting the information in disaster news. Min & Lee (2005) use it to predict bankruptcy. Arvanitis & Bassiliades (2017) measures investor sentiment using newspaper data and a Naïve Bayes algorithm. Random Forest Classification is a supervised learning algorithm that has been mainly used in fields other than economics such as bioinformatics (Díaz-Uriarte & De Andres, 2006; Yang et al., 2014, June; Khalilia et al., 2011; Saeys et al., 2007; Chen & Liu, 2005) or ecology (Cutler et al., 2007). An application that is closer to economics is the credit scoring study of Van Sang et al. (2016). Recently, there are some economics applications that have exploited Random Forests such as Bajari et al. (2015), Wager & Athey (2017) or Chernozhukov et al. (2018).

This paper also relates to the literature that studies the effects of uncertainty on economic activity. Baker et al. (2016) study the effects of a broad measure of policy uncertainty on economic activity. They offer a specific measure of tax uncertainty constructed with newspapers mentions of economic policy uncertainty keywords. While their aggregate EU index effectively relates to relevant episodes of economic uncertainty, their EPU tax index is not specifically related to the process of tax legislation. It actually contains other sources of uncertainty related to tax policy that are not directly related to the likelihood of tax bills approvals. My measure of tax beliefs differs in that it is meant to capture the likelihood of a tax liability change at a specific date conditional on the current information available, measuring the degree of certainty on a specific policy change. The goal in my empirical strategy is to precisely track the level of predictive information for each potential episode, leaving aside other confounders.

This paper is also related to the literature that studies the effects of media choices on socio economic outcomes. Berg & Zia (2013) and Bursztyn & Cantoni (2016) provide evidence on microeconomic level effects of television content in private consumption and savings and found significant effects. The effects of media news on economic agents have been extensively documented in the field of finance. For example, the works of Tetlock (2007), Tetlock et al. (2008) and Tetlock (2011) have shown how media sentiment and content affects investors or stock market performance.

Methodologically my paper relates to the time series literature that studies the effects of exogenous shocks on macroeconomic indicators. I propose the application of forecasting and nowcasting models to the empirical analysis of policy shocks and

macroeconomic news on economic activity. Using these models one can measure the effects of information shocks that naturally happen at monthly, weekly or daily basis on a latent factor of economic activity, helping us to track closely the effects of economic policy. In earlier work, the study of the effects of tax changes on economic activity has been implemented directly using GDP quarterly data. Mixing frequencies not only gives us the possibility of learning about latent economic activity at other frequencies but also to interpret economic activity in terms of GDP. For this reason, I use Mariano & Murasawa (2003) to estimate the effects of taxes and their anticipation in economic activity.

To some extent this paper also relates to the literature that studies the effects of tax salience on taxpayer behavior. Previous literature has found that consumers underreact to taxes that are relatively less salient. For example, Chetty et al. (2009) shows that when alcohol tax increases are included in posted prices, alcohol consumption drops more than when the same tax increase is applied at the register. Li et al. (2014) document a similar behavior for gasoline taxes. Baker et al. (2017) provide evidence of tax salience in local newspapers for VAT changes but also on the importance of fine-grained time series data to uncover economic activity effects of tax changes. Finally, the salience of taxes may not only affect the reaction of consumers but also of politicians who may see an opportunity to extend particular taxes which are less salient (Finkelstein, 2009; Cabral & Hoxby, 2012; Goldin & Homonoff, 2013).

Section 2 reviews the literature about fiscal policy effects on economic activity. In Section 3, I explain the institutional framework for empirical study of tax legislation in the US. In Section 4, I explain the data I use. Section 5 presents the empirical approach and the measure of beliefs about tax legislation success using mass media news. In Section 6, I discuss the empirical specification that I use to estimate the effects of taxes on economic activity. Section 7 contains the results and Section 8 concludes.

2 Literature Review

The identification of the causal effects of fiscal policy on economic output is complicated by the fact that the observed variation in fiscal policy is partly driven by the economic cycle. There are two strands in the literature on the measurement of fiscal multipliers, the structural VAR approach and the Narrative approach. Under the

structural VAR approach researchers have exploited plausible relations between economic activity indicators and government revenues and spending with the purpose of removing automatic and discretionary components of fiscal changes.

A variety of structural-VAR strategies have been exploited to accomplish this goal. Blanchard & Perotti (2002) stresses the fact that within quarter discretionary responses to output are unlikely and proceed to clean tax and government revenues from automatic responses to output using quarterly data. They make further assumptions on the structure of these relations and find that both increases in taxes and government spending have a negative effect on output. Mountford & Uhlig (2009) contributes with an extension of a sign restriction strategy to identify fiscal shocks. Using the same data as Blanchard & Perotti (2002), they also exploit structural relations between economic and fiscal indicators; government revenues increasing with output a key identifying assumption they use, that is, when both series co-move it must be the case that there has been an improvement in the business cycle. In addition to these sign restrictions, impulse responses of the fiscal variables are assumed to be orthogonal to business cycle shocks identified from the co-movements among a list of indicators. They find that negative tax cuts work the best out of possible linear combinations of tax cuts and spending. These authors also consider the identification of anticipation effects of tax and government changes to output by assuming that one year ahead to the implementation of a tax or government change there may be an effect at the time of announcement which is related to the magnitude of the ex-post shock.

The narrative approach identifies tax and government spending shocks from texts containing information about the political and legislative process of the tax change, which can describe the motivation, size and timing of fiscal shocks. The seminal work in this area is Romer & Romer (2010). They identify a list of tax episodes that can be classified as either endogenous or exogenous to the economic cycle. The classification relies on the narrative analysis of several documents from the legislative and executive power while the bill was under elaboration. A tax change is classified as exogenous if it is known not to offset factors pushing away growth from normal. More specifically, tax changes aimed at improving growth in the long run or those made to deal with inherited budget deficits are considered exogenous. To measure the timing and revenue effects Romer & Romer (2010) rely on documents from the Treasury and the Budget of the Government. Sometimes the conference report on the bill is also a good source

for revenue estimates. Ramey (2011) studies the output effects of government spending but she focuses instead on the three large war episodes and the expected public spending related to those episodes as reported in *Business Week*.

None of these approaches are exempt from criticism. A disadvantage of the narrative approach is the fact that estimates of the magnitude of fiscal shocks obtained from gubernatorial documents may be measured with error if the contemporaneous forecast of the fiscal multiplier by the government in charge is itself biased. This is less of a concern for the structural VAR approach as long as one exploits budgetary fiscal revenue data. The best feature of narrative approach is offering a reduction of the omitted variable problem through controlling for many characteristics of fiscal episodes that are contained in publicly available texts. This is a dimension of the empirical study of these effects to which this paper also wants to contribute.

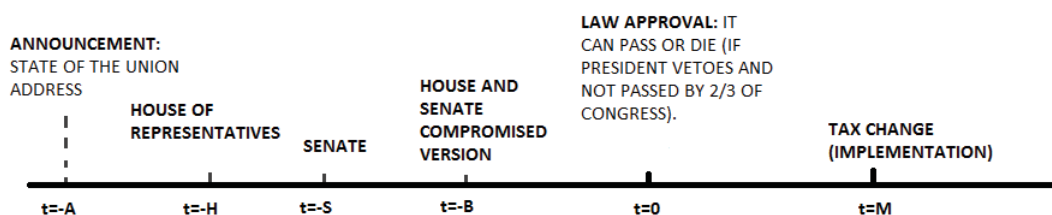
3 Institutional Framework

US federal laws are not passed until they have been discussed, elaborated and approved in different houses of Congress. For the specific case of tax laws, they generally originate as recommendations from the President, which may be announced at the State of the Union Address. However, other House representative may also propose them. If the President proposes a tax change, the Treasury Department will draft it. Usually, this will happen during the first months of the year because the President will only propose one tax bill per year and if not approved within the year it will die, so the process will have to start from scratch. If the proposal comes from another agent, a representative of the House Ways and Means prepares the law proposal or “bill”. All tax legislation in the US must originate in the House of Representatives. When the House of Ways and Means receives the proposal it arranges hearings so that people can testify on the proposal. These people are the Secretary of the Treasury, Administrative officials and other groups of interest. The Committee in charge of the bill will meet in executive session after the hearings. In this session they markup the proposal and discuss it openly in public. They write the proposal in legislative language while simultaneously elaborating a plain language report on the motivation that originate the tax bill.

Once the bill and the report are have been completed, the bill is introduced in the House of Representatives for approval. When the tax bill is passed by the House, the Senate Committee will start a similar process to the one of the House of Representatives, but using the bill and report written by the House of Representatives as the starting point. The Senate Finance Committee usually makes amendments that are written into a new report. The amended bill is debated by the entire Senate, which will decide if it is passed in this house. If there are no amendments and the bill is passed, it is sent to the President to be signed and it becomes law. If on the contrary, there the bill has been amended, the modified bill is returned to the House of Representatives, which will accept it or otherwise appoint a Conference Committee to rewrite the differences with the Senate. The new compromised version is voted by the two houses of Congress, if passed it is sent to the White House for the signature by the President. If the President vetoes the bill, the House and the Senate may try to override the veto by securing more than two thirds of the favorable votes.

Once new taxes are legislated it may take months to their implementation; that is, to the moment when citizens have the obligation to comply with the new tax legislation. However, there are some special cases where tax legislation can be retroactive, which implies an obligation to satisfy tax changes related to economic activity prior to the law approval. A simplified version of the timing structure of the evolution of a tax bill into tax law is depicted in Figure 1.

Figure 1: Evolution of US Tax Bills



Notes: This diagram outlines the institutional stages of a tax bill in the US from its origination in a proposal stage to its implementation. t states for a particular moment in time. A is the announcement time, which generally is made at the State of the Union Address. H is the moment when the House of Representatives passes the bill in the form of a report. S is the moment the report is passed by the Senate. B is the time when the bill achieves a compromised version and is approved by the House of Representatives and the Senate. 0 is the moment when the bill is approved by the president and it becomes a law. M is the moment of implementation of tax changes, which can be divided in multiple periods.

Throughout this process, there are many opportunities for the general public to access information about the state of the bill and its prospective success. In specific cases, journalists can listen to the live discussion. After each stage, there is also a public release concerning the step that has been passed. The media is the most common channel of information about the state of tax legislation for most people. Some groups of interest may obtain first hand information by attending the hearings or through consultation of official documents. The media may not cover all the legislative process in the same manner neither all the tax episodes. The mass media may tend to select some episodes and stages thereby influencing the type of information that spills to the general public. We expect the mass media to cover episodes that affect a large share of the population, but also episodes which are of more interest to their target audience. In the latter regard, if there is a diversity of mass media we can presume that episodes of relevance to all the sociodemographic spectrum will be covered by some media.

4 Data

To estimate the effects of anticipation of tax episodes on economic activity I combine various datasets. I use Romer & Romer (2010) exogenous tax liability changes to identify exogenous tax episodes in the US between 1945 and 2007. To construct the new measure of anticipations through mass media releases of information I use data from US television from the Vanderbilt Television News Archive. Finally, to estimate the mixed frequency dynamic factor model I use economic activity data.

4.1 Romer & Romer (2010) Exogenous Tax Changes

I use Romer & Romer (2010) (RR) dataset on US tax liability changes which comprises information on the implementation date, magnitude and "exogeneity" of each US tax change taking place within the period 1948 to 2007. By reading Congressional Reports and other gubernatorial documents, RR identify the motivation, timing and magnitude of each approved tax change happening in the US during this period. Using this information they manually classify tax changes into more or less related to the contemporaneous economic activity cycle. An *exogenous* tax liability change is one that is classified as unrelated to the economic cycle.

In Table 1, I present descriptive statistics for the time series of all the RR *exogenous* tax liability changes. There were in total forty-two *exogenous* tax liability changes

across the period 1968-2007. The average tax liability change was -0.06 per cent of quarterly nominal GDP (QGDP) in the sample period. The standard deviation of tax liability changes is 0.53. I also manually collect data from Romer & Romer (2009) on the approval dates at US Congress of each tax episode in the US. In Table 1, I also provide descriptive statistics for *delayed* tax liability changes, those that were implemented at least one month after the approval date, *on-time* tax liability changes and those implemented the same month of approval. *On-time* tax liability changes where on average -0.03 of QGDP with a standard deviation of 0.47, while *delayed* tax changes where on average -0.07 of QGDP with a standard deviation of 0.55. In Appendix Table 7, I present the same statistic for the period 1945-2007.

Table 1: Romer & Romer (2010) Exogenous Tax Liability Changes

Variable	Delayed	Mean	SD	MIN	25th-p	Median	75th-p	MAX	Obs
Tax change	No	-0.03	0.47	-1.11	-0.27	0.16	0.29	0.49	10
Horizon	No	0	0	0	0	0	0	0	10
Tax change	Yes	-0.07	0.55	-1.65	-0.15	0.07	0.26	0.76	32
Horizon	Yes	21.44	20.54	1.00	5.00	15.50	30.50	80.00	32
Tax change	All	-0.06	0.53	-1.65	-0.25	0.08	0.29	0.76	42
Horizon	All	16.33	20.11	0.00	1.00	8.00	24.00	80.00	42

Notes: Tax change is the estimated magnitude of the *exogenous* tax liability changes measured in dollars by Romer & Romer (2010) divided by the QGDP and expressed in percentage points. Horizon is the number of months between implementation of the tax change and approval of the tax episode. The summary statistics correspond to time series 1968 to 2007.

In Figure 5, I present the time series of all *exogenous* tax liability changes throughout the period 1968 to 2007. Since an episode may contain more than one tax liability change and they are approved in the same date under the same bill, in Table 2 I provide summary statistics for the magnitude of tax episodes in the US. An average episode is -0.15 of QGDP, with 1.14 standard deviation of QGDP. I also offer the time series of episodes by approval date in Figure 6. In Table 8, I provide the month-of-the-year distribution of tax episodes approval and the implementation of tax liability changes,

showing tax approvals are spread happened in almost all months but are concentrated in the months of June to August and January. Tax changes are implemented mostly on January and October with a less presence in the rest of the months.

4.2 Television Data

According to *www.classictvhits.com*, in 1960, out of 180 million US population, 47 million households had a TV set. In 1998, out of 276 million US population, 99 million households had a TV set. The first most viewed show in 1960 (*Gunsmoke*) had an estimated audience of 17.5 million households. Interestingly, the total estimated audience for the top 10 most rated shows in 1960 was 138 million households, approximately

Table 2: Romer & Romer (2010) Exogenous Episodes

	Mean	Std.	Min.	25th-p	Median	75th-p	MAX	Obs
1945-2007	-0.19	0.96	-4.34	-0.37	-0.04	0.32	1.09	36
1968-2007	-0.15	1.14	-4.34	-0.51	0.05	0.57	1.09	20

Notes: This table describes the size of Romer & Romer (2010) *exogenous* tax episodes which are defined as the aggregate value of tax liability changes approved under the same tax bill as a share of month of approval GDP.

the same as in 1998. Television reaches a large share of the US population since the mid twentieth century. Finding out whether information funnelled through this channel regarding future tax changes had any impact on economic activity before they even become approved is a question of interest.

I use the Vanderbilt Television News Archive (VTNA) which has collected all evening news shows aired at CBS, NBC, ABC from 1968 to the present and CNN from the 1995 to the present. The evening news shows last for 30 minutes and are broadcast at 6.30pm in the Eastern Zone¹. I collected data on a brief title description, an abstract of text describing the news, the number of seconds it occupied in the screen and its order of appearance for each broadcast piece of news. I collect these data from their website for shows aired from August 1968 (first available data point) to December 2007 (last observation in Romer & Romer (2010) data). These news programs are an interesting

¹Simultaneously broadcast in Central and Eastern Zones and three-hours tape-delayed broadcast in the Pacific Zone. While CNN has single feed that airs in all time zones.

piece of data to study since they are narrowed to 30 minutes everyday, aired to the whole of the US simultaneously and informative of events which are interesting for large section of the US population. Another good aspect of this data is providing data for at least three major television channels through the sample period.

I define the universe of television news relevant to the study of anticipations of tax changes by selecting those pieces of news that contain the stem 'tax' and the surname of any congressman in charge of an *exogenous* Romer & Romer (2010) episode. I use the Congressional Bills Project: 1947-2007 (Adler & Wilkerson (2007)) to find the names of the congressmen in charge of the *exogenous* bills passed at US Congress. Filtering for 'tax' mentions limits and guarantees that the information set contains those news dealing with taxes. The alternative strategy would be to use all the available news published in these media where tax news would be a small fraction that would hardly survive to text processing algorithms. Using the congressmen surnames filter I can produce a measure of tax anticipations restricted to the *exogenous* tax episodes. This strategy helps to the identification of the effects of tax changes and their anticipations on economic activity.

There are on average 5.36 pieces of news per month in the series of tax news. The standard deviation is of 6.48 pieces. The months with tax news had a minimum of 1 and a maximum of 44 pieces. The average piece of tax news has 137.7 words and 754.6 characters. The standard deviation among the pieces of tax news is 80.8 words and 440.6 characters.

In Table 3, I present summary statistics of the salience of tax news in the media measured by total seconds per month. The median space that these news occupy in the TV is 510 seconds per month, but the variation of minutes across months is large. In Figure 7, I depict the monthly time series of seconds, which highlights that there will be differences of coverage across different tax episodes.

Table 3: VTDA Tax Salience

	Mean	Std.	Min.	25th-p	Median	75th-p	MAX	Obs
Tax Salience	970.42	1353.30	10	240	510	1100	12630	337

Notes: Tax salience is measured as the month total of seconds that tax news were broadcast during the period 1968 to 2008. Tax news are defined as those news that mentioned a congressmen in charge of any Romer & Romer (2010) *exogenous* tax bill and the stem 'tax'.

4.3 Economic Activity Data

I use the same economic activity indicators as the ones used in Mariano & Murasawa (2003), namely quarterly real GDP (QGDP) and four monthly coincident indicators, which are detailed in Table 9. I take the first difference of the natural log of each series, multiplied by 100, and construct the growth rates. Table 4 shows descriptive statistics of the growth rate of each series for the period 1968-2007.

Table 4: Descriptive Statistics of Business Cycle Indicators Growth Rates

	Mean	Std.Dev.	Min.	Max.
GDP	0.75	0.82	-2.05	3.82
EMP	0.21	0.71	-3.59	2.38
IPI	0.15	0.21	-0.77	1.23
MANU	0.24	0.99	-3.21	3.54
RPI	0.24	0.54	-3.21	4.00

Notes: This table presents summary statistics for the five economic indicators defined in Table 9 for the period 1968 to 2007. Mean states for the sample average, Std. Dev. for the standard deviation, Min. for the minimum sample value, Max. for the maximum sample value. Economic indicators detailed in Table 9. Source: Federal Reserve Economic Data.

5 A Narrative Measure of Tax Anticipations using Media Data

Next, I turn to present a novel narrative approach to measure the level of anticipation of fiscal changes using media data. Our goal is to find a measure that captures meaningful contributions to beliefs about a potential tax bill approval in a future period through the information released in the news. The beliefs may be those of a representative economic agent that watched TV news and saw different tax episode approvals. People may also gather information from sources other to the mass media. An advantage of exploiting the information provided through the TV channel is that it exposes a large share of the population to the same information shocks simultaneously.

There are different dimensions of a tax episode that could be relevant to the anticipated economic response of agents. In this work, I measure on the anticipation of a tax bill approval at Congress because of its first order importance to the study of economic responses to anticipations. However, other dimensions could be explored such as the sign, magnitude, the progressive nature and the different characteristics of the tax base. Tax episodes with different signs may lead to different kinds of anticipation effects, that is, an anticipation of increases in VAT may induce individuals to increase consumption but one of a tax cut may induce individuals to reduce it. I also study the effects of anticipation of episodes of different sign but learning aside other characteristics is left to future work.

The objects of interest are the beliefs about a tax change happening today and some periods ahead conditional on the information today. Let me denote these objects $p_{t+j|t}$ for $j = 0, \dots, J$, where J is the maximum predictable horizon. I define the relevant information set to predict j -months ahead tax changes as the collection of pieces of tax news released at a particular month t . To estimate the measure of beliefs I exploit the variation of the frequency of relevant text features in the tax news across months. It is key to restrict the focus to *exogenous* tax changes since otherwise fiscal changes may be related to other unobservable variables affecting economic activity, contaminating any empirical results relating tax changes and economic activity.

5.1 Data Processing

To construct measures of beliefs, I created a balanced time series variable of aggregate monthly tax news to which I apply automatic text analysis techniques for pre-processing. The pre-processing stage consists of removing english stopwords², deleting punctuation characters, digits and words of less than three characters and transforming to lower case format all words. Finally, I lemmatize and stem³ the data to reduce the dimension of the vocabulary.

The corpus is the collection of texts of the pre-processed variable, where each text is the collection of stems used at each month. Using the bag-of-words approach, we

²I also remove all names of the congressmen in charge of the tax bills to avoid the problem of overfitting through these text features.

³This first step implies singularizing words and lemmatizing verbs. The second part consists of keeping the stem of each word and removing the rest of information.

represent a month observation t by a vector of stem frequencies, $\mathbf{f}_t = (f_1, f_2, \dots, f_v, \dots, f_V)_t$, where V is the maximum size of the vocabulary of the corpus and $f_{v,t}$ is the absolute frequency of stem v in month t . Hence, we can represent the corpus as $\mathcal{C} = \{\mathbf{f}_t\}_{t=1, \dots, T}$ where T is the total number of months in the sample. Under this approach, I do not consider word ordering and the matrix \mathcal{C} is a rather sparse matrix of tokens. \mathcal{C} is a matrix of T Months by V features that belong in the corpus.

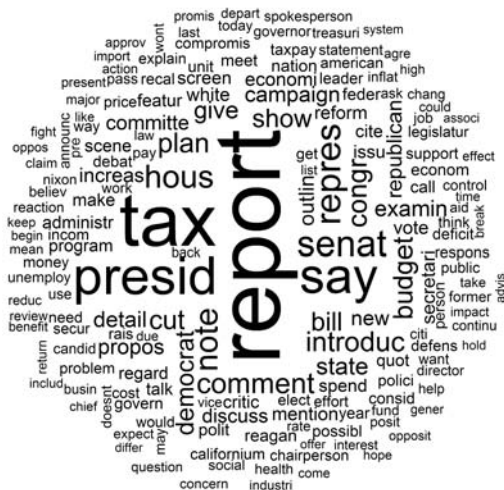
A final processing step is done into the corpus features to further reduce the dimensionality of the problem; I delete those features that appear in less than 10% of the months in the sample. The purpose of this dimensionality reduction is to eliminate month-specific words that can overfit the data. The size of the resulting dataset is 177 text features with a sparsity of 82%. The time series dimension of the data is of 477 observations.

Figure 2 describes the processed series of tax news by means of a *wordcloud* that represents the relative frequency of all resulting terms in the series. As shown, these news mostly speak about the different stages of the bill process until being signed. Table 10 presents summary statistics for frequency of the top 20 text features in the corpus. The most frequent text feature in the universe of tax news is 'report'. It occurs on average 8.39 times per month with a standard deviation of 18 and is not present in only 263 months. Its maximum monthly frequency is 142 times in a month. It is also very frequent to hear talking about 'tax', it is present in 295 months⁴. The stem for president and other text features representing House or Senate are very frequent. It is also very common to see 'bill' or 'note', 'examin', 'detail', 'comment', or 'introduc', suggesting that the most common text features in the tax news sample refer to the process of introducing a new tax bill in the US.

This is an instance in which there are more regressors than data points, so that standard econometric models of discrete choice, such as Multinomial Logit or Probit, cannot deal with this problem. To address this quantification challenge I use a machine learning algorithm from the family of Classification and Regression Trees (CART). In particular, I borrow the Random Forest Classifier to predict a tax episode being approved in the future conditional on the information on television tax bill news.

⁴The difference between the number of months with tax news and the number of months with a mention of the tax stem is due to the fact that some tax words such as 'taxpayers' or 'surtax' have stems 'taxpay' and 'surtax', respectively, instead of 'tax'.

Figure 2: Tax News Universe



Notes: This figure is a *wordcloud* that represents the relative frequency of text features in the cleaned sample of tax news. Larger font size implies more frequency in a ratio 4:0.5. Tax news are defined as those news that mentioned a congressman in charge of any Romer & Romer (2010) *exogenous* tax bill and the stem 'tax'.

5.2 Random Forest Classifier

The Random Forest (RF) was introduced by Breiman (2001). It is an algorithm that applies bootstrap aggregation to multiple decision trees. A decision tree (in a classification tasks) is a representation for a classifying possibility where there are nodes representing the features we want to use for prediction and branches that can combine the nodes and lead to leafs where there are the classes. This method partitions the feature space and fits a model to each partition. The algorithm has to learn the criteria to split the nodes and pruning the trees; in this way it learns how variables fit the data and which variables are more relevant to fit the data. Two differences distinguish RF from classical decision trees. The first is that within each decision tree of the forest the variables considered to split a node are a random subspace of all the features in the sample. A second important difference is that a RF draws a number of random samples from the training set and estimates a decision tree for each random sample, averaging the results over all the estimated trees. This strategy helps reducing the variance of the estimation and works better in cases where each decision tree has limited bias. Comprehensive discussions on RF are presented in Hastie et al. (2009) and Murphy (2012).

To construct a measure of beliefs on future tax approvals of different signs I estimate a RF where the dependent variable is an indicator variable that has value 1 if at a particular month in the future there was a tax approval at Congress. The independent variables are those in the matrix of text features, \mathcal{C} . I implement the estimation with the R package 'randomForest' by Liaw & Wiener (2002).

In contrast with a traditional prediction model, such as logit or probit, RF solves the problem of having too many variables. To exploit the text in a traditional model one would have to drastically reduce the dimensionality of the text to a few features according to some arbitrary criteria whereas using RF there is statistical learning on which features better predict among a large list of features, what also improves model fit. It is also attractive in the situation of many predictors because it performs variable selection in a flexible way. RF is one approach among several approaches that have been recently developed to deal with large covariance spaces. For example, Lasso techniques and other penalized flexible regression methods are a popular alternative in econometric application (Belloni et al., 2013). However, Caruana et al. (2008) show that RF classifiers perform better than other models such as SVM, neural nets or boosted trees.

RF were developed in computer science as black-box predictive algorithms. Their properties from a statistical point of view are an active area of research. A recent contribution is the work of Wager & Athey (2018). This paper develops normal asymptotic theory to a random forest model and confidence intervals for random forest predictions. They apply the theory to causal inference of treatment effects with unconfoundedness. As the authors point out, it is the first step in the direction of making random forests tools for statistical inference instead of black-box algorithms. Providing standard errors for the predictions of beliefs produced by RF is out of the scope of this paper.

Text features in the tax news dataset tend to co-occur many times within the series, i.e. the number of months that two different terms are published together is large. For example, words like "new" and "tax" are mentioned together in 291 months, "approval" and "house" in 113 months. This is common across many pairs of words. In addition, some words are likely to be redundant for the prediction of a tax approval and even obscure the prediction power of others if the correlation among them is not properly accounted for. There are two interesting departures from the classical RF algorithm that I explore in this section and enhance model performance to the specific data issues that appear in this paper.

Fuzzy Random Forests I explore the Fuzzy Random Forests (FF) introduced by Conn et al. (2016) in the R implementation 'fuzzyforest'. This approach consists of estimating different classical RF to predict the target variable using different groups of covariates. The groups of covariates can be proposed by the researcher as the outcome of some correlation analysis, such as the proposed Weighted Gene-Coexpression Network Analysis (WGCNA). From each group-level RF the least important variables are discarded by setting a drop parameter. There is a selection RF run using all the screened covariates resulting from the group-level RF. From this last RF the researcher can set another final number of selected covariates to which a final RF is fit. Depending on the number of iterations made into each group-level and the selection RF the computation burden of the algorithm can be large. In the following I show that this algorithm is more suitable for the prediction of tax approvals since it is the case that there are many redundant words in the vocabulary.

5.3 Estimated Beliefs

In this section, I describe the empirical measures of tax anticipations that exploit TV data and Random Forests. In Figures 8 and 9, I present the OOB (out-of-bag) predictions from RF and FF which, in this case, are predicted probabilities of tax episode approvals at $t + 1$ conditional on the information set at t (computed using the bootstrap samples that the algorithms did not use to estimate the model, so these are out-of-sample predictions of the models). We can note that there are 5 episodes which are predicted by the FF, from the most predicted to the less predicted, we find, the Economic Recovery Act of 1981, the Omnibus Budget Reconciliation Act of 1990, the Omnibus Budget Reconciliation Act of 1993, the Tax Reform Act of 1969 and the Revenue Act of 1971. The RF has lower predictability than the FF because it predicts less episodes. For the rest of the paper we focus in FF results as estimated measures of tax anticipations.

The FF fitted probability of tax approvals at $t + 1$ conditional on information released at t is presented in Figure 10. Summary Statistics for this measure are presented in Table 5. As we can see, for one-month-ahead anticipation of tax approvals the median belief in the time series is a 0,4%, however, the 95% is 9,7% and the standard deviation is 12.7%. The two-month-ahead and three-month-ahead measures of anticipation have a smaller 95th percentiles and slightly smaller standard deviations. In Figure 11, I

Table 5: FF Summary Statistics

	$P(\text{approval}_{t+1} \text{News}_t)$	$P(\text{approval}_{t+2} \text{News}_t)$	$P(\text{approval}_{t+3} \text{News}_t)$
p25	0	0	0
p50	0.004	0.005	0.005
p75	0.021	0.022	0.021
p95	0.097	0.061	0.070
SD	0.125	0.107	0.114

Notes: This table contains the 25th-percentile (p25), the median (p50), the 75th-percentile (p75), 95th-percentile (p95) of the estimated measures of beliefs for tax approvals at $t + 1$, $t + 2$ and $t + 3$ respectively in each column. SD states for standard deviation.

show which are the text features that have more predictability for one-month-ahead tax anticipations. 'tax', 'presid', 'consid', 'bill' and vocabulary related to the the approval of tax bills at the US Congress are in this top ranking. In Appendix C I expose other results from Fuzzy Forest which might be of interest to the reader.

On the shadow side, the estimated models present relatively poor predictive performance. Using out-of-bag (OOB) samples none of these models predicted the event of a tax change next month with more than 50% probability, however FF was closer at some events. One explanation for this result relates to the limited number of *exogenous* tax episodes to learn from in the sample period, 20 versus the 457 months. Whereas it may seem that a TV viewer watching a news report about tax legislation would likely be able to predict very well a tax approval in the next month, this does not need to be the case because viewers receive different levels of information across episodes.

In Table 11, I provide a comparison of the two models across different measures of goodness of fit. Accuracy and Lift AUC is slightly larger for Classical RF but Gain AUC is larger for FF, however, all the accuracy measures are pretty similar across the two models. However, Log-Loss, MSE, RMSE, PRAUC, RMSE, PRAUC and Zero One Loss are smaller for FF. The two models are pretty similar, slightly higher accuracy for RF while lower loss for FF, what allows us to conclude that FF predictions are better than those of Classical RF.

The anticipatory information contained in the measure of anticipations is a combination of salience of the tax news and the likelihood of approval of the tax bill given the political context. Disentangling between these two channels is challenging given

the interconnection between the political decisions and the media. I also estimate measures of tax anticipations for two and three months ahead of potential episode approval. It is also important to note that the current implementations in R were released very recently, so further testing is warranted.

6 A Model for the Effects of Taxes and Anticipations on Economic Activity

In this section, I develop a time series approach to measure the effects of tax changes and their short-term anticipations on economic activity. I start by introducing the general framework and incorporate the different shocks to a dynamic model of economic activity.

6.1 A Model for Monthly Economic Activity

Traditionally, the measure of economic activity used to account for the effects of tax changes has been quarterly GDP. One concern with the use of quarterly GDP is that time aggregation may mask important anticipation effects; after all information disseminated through the media may evolve quickly in a matter of days or weeks. Here, I target a monthly frequency which is economically relevant for the question at hand and empirically feasible, given the indicators of economic activity at my disposal.

Stock & Watson (1991) provided a methodology to construct an index of economic activity exploiting the co-movements of monthly indicators. Later, Mariano & Murasawa (2003) provided a mixed frequency dynamic factor model that allows to exploit quarterly GDP jointly with indicators that have other time frequencies. I borrow their mixed frequency dynamic factor model (MFDFM) which allows me to incorporate data at different frequencies by modeling missing observations corresponding to lower frequency indicators, quarterly GDP in particular. For the purpose of this paper, mixing frequencies has two different advantages. Not only it profits from the quarterly GDP variation to construct the coincident indicator of economic activity but it also recovers an index of economic activity that relates to latent monthly GDP. For all t , a one factor model for $y_t^* = (y_{1t}^*, y_{2t})$ is such that:

$$\begin{pmatrix} y_{1,t}^* \\ y_{2,t} \end{pmatrix} = \beta f_t + e_t \quad (1)$$

$$\phi_f(L)f_t = \omega_t \quad (2)$$

$$\phi_e(L)e_t = \epsilon_t \quad (3)$$

$$\begin{pmatrix} \omega_t \\ \epsilon_t \end{pmatrix} \sim NID \left(0, \begin{bmatrix} \sigma_\omega^2 & 0 \\ 0 & \Sigma_\epsilon \end{bmatrix} \right) \quad (4)$$

where $\beta \in R^N$ is a factor loading vector, f_t is a scalar stationary sequence of a common factor, e_t is an N -variate stationary sequence of idiosyncratic shocks or factors, L is a lag operator, $\phi_f(\cdot)$ is a p th-order polynomial on R , $\phi_e(\cdot)$ is a q th-order polynomial on $R^{N \times N}$. The left-hand side variable in the first equation, $y_{1,t}^*$, is monthly GDP which is a latent variable in our model. The second outcome, $y_{2,t}$, is a $N - 1$ vector of observable indicators of economic activity at monthly frequency. σ_ω^2 is the variance of the error term in the model for the common factor. Σ_ϵ is the variance covariance matrix of the error term in the VAR model for the idiosyncratic shocks. For identification of this model we normalize the first element of β (the one associated with the first economic indicator of the measurement equation) to $\beta_1 = 1$, and we specify Σ_ϵ and $\phi_e(\cdot)$ as diagonal matrices. Since $y_{1,t}^*$ is latent, one cannot estimate model (1)-(4), instead, the proposal of Mariano & Murasawa (2003) is to estimate a model with $y_t = (y_{1t}, y_{2t})$, where y_{1t} is quarterly GDP observable every third period and change the specification for the measurement equation of y_{1t} to one that expresses quarterly GDP as the geometric mean of monthly GDP. Hence,

$$y_{1,t} = \beta_1 \left(\frac{1}{3}f_t + \frac{2}{3}f_{t-1} + f_{t-2} + \frac{2}{3}f_{t-3} + \frac{1}{3}f_{t-4} \right) + \frac{1}{3}e_{1,t} + \frac{2}{3}e_{1,t-1} + e_{1,t-2} + \frac{2}{3}e_{1,t-3} + \frac{1}{3}e_{1,t-4}$$

This expression for $y_{1,t}$ comes from defining latent quarterly GDP as the geometric mean of monthly levels, taking logarithms to GDP and expressing quarterly GDP growth in terms of the factor. The result is that our one factor model implicitly constructs a monthly measure of economic activity according to the following aggregation plan:

$$\begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix} = \begin{pmatrix} \beta_1 \left(\frac{1}{3}f_t + \frac{2}{3}f_{t-1} + f_{t-2} + \frac{2}{3}f_{t-3} + \frac{1}{3}f_{t-4} \right) \\ \beta_2 f_t \end{pmatrix} + \begin{pmatrix} \frac{1}{3}e_{1,t} + \frac{2}{3}e_{1,t-1} + e_{1,t-2} + \frac{2}{3}e_{1,t-3} + \frac{1}{3}e_{1,t-4} \\ e_{2,t} \end{pmatrix}$$

where the left-hand side will contain only observables and β_2 and e_2 will be vectors of the same dimension as $y_{2,t}$.

6.2 Tax Shocks on Monthly Economic Activity

In this section, I propose a methodology for measuring the effects of tax changes on economic activity at monthly frequency. Romer & Romer (2010) provided evidence on the effects of exogenous tax changes on quarterly GDP using a dynamic linear regression model of quarterly GDP on tax liability changes. Not only the magnitude of the effects and its persistence are relevant features of a policy, but also the time at which the effects come into place. From a policy perspective, one may need to choose between two types of policies so having a methodology that measures the effects at higher frequency than a quarter seems an interesting avenue of work. To estimate the effects of tax liability changes on monthly economic activity I suggest estimating a DFM as (1)-(4) where the specification for the factor process (2) is given by

$$\phi_f(L)f_t = \sum_{s=0}^S \theta_s \tau_{t-s} + \tilde{\omega}_t \quad (5)$$

where τ_{t-s} is a tax liability shock to the economy at time $t-s$, θ_s accounts for the effects of a tax liability shock happening at time s before, S is the maximum number of lags to allow for the effects of tax liability changes on GDP. $\tilde{\omega}_t$ is the new error term for the factor. For causal validity it is key to satisfy the identification assumption that $\tilde{\omega}_t$ and τ_{t-s} are independent for all t, s , and this is the reason why the narrative approach uses RR exogenous tax liability changes instead of all types of tax liability changes during this period.

6.3 Media Anticipation on Monthly Economic Activity

There is considerable amount of information prior to the approval of a tax bill that spills through the mass media and has prediction power on tax bill approvals, as documented in Section 5. Does mass media anticipation have any effects on economic activity prior to the approvals? To answer this question, I measure the effects of the media-based anticipation measure of tax approvals at $t+i$ conditional on the information released at t by specifying the following model for my latent factor of economic activity:

$$\phi_f(L)f_t = \sum_{s=0}^S \theta_s \tau_{t-s} + \sum_{i=0}^I \delta_i p_{t+i|t} + \bar{\omega}_t \quad (6)$$

where $p_{t+i|t}$ is the media-based anticipation measure for a tax approval happening at $t+i$ conditional on the information at t . δ_i is the effect of unit changes in the beliefs for rises and cuts approvals respectively. This model traces the effects of taxes from initial information releases by the media to the public. It will capture if there is any effect of tax anticipations under uncertainty of the bill being legally approved. Obviously we do not observe the true value of the beliefs, these beliefs are estimated in a previous step as detailed in Section 5. Hence, the factor model with estimated beliefs is

$$\phi_f(L)f_t = \sum_{s=0}^S \theta_s \tau_{t-s} + \sum_{i=0}^I \delta_i \hat{p}_{t+i|t} + \hat{\omega}_t \quad (7)$$

where $\hat{p}_{t+i|t}$ is a proxy for the true beliefs on tax legislation approval and $\hat{\omega}_t$ is the new error term. Hence it is crucial that the error term is unrelated not only to implemented tax changes but also mass media beliefs on future tax approvals.

Anticipation of tax approvals associated to tax liability increases are likely to have different effects of those implying tax liability cuts. The joint prediction of sign and approval of a tax episode is challenging given the available data. However, it is not far from reality that people know the sign before the approval of a particular episode. To provide light on the differential effects of anticipations of tax rises with respect to tax cuts I construct an indicator variable that takes the value of 1 when there is a mention of "increase" or "rise" among the tax news. Let denote this indicator s_t .

$$\phi_f(L)f_t = \sum_{s=0}^S \theta_s \tau_{t-s} + \sum_{i=0}^I \delta_i^- \hat{p}_{t+i|t} + \beta s_t + \sum_{i=0}^I \delta_i^+ \hat{p}_{t+i|t} s_t + \hat{\omega}_t \quad (8)$$

where δ_i^+ and δ_i^- are the effects of anticipated tax approvals conditional on the mention of tax increases in the news or the absence of mention, respectively. β captures the marginal effect of mentioning tax rises in economic activity. $\hat{\omega}_t$ is the new error term.

6.3.1 Controlling for Implementation Delays

In the time between a tax approval and its implementation there is knowledge that a tax liability change is going to take place at a given point in time and this knowledge may affect economic activity. Mertens & Ravn (2012) document that there are significant anticipation effects of tax changes during the months between approval and

implementation of the tax liability changes. Their notion of anticipation refers to the information that makes the economic agent certain of a tax implementation at a given point in time in the future. In contrast, this paper studies anticipations where the agent still has uncertainty about the event of a tax approval at Congress. To avoid confusion here I refer to Mertens & Ravn (2012) classification of tax liability changes according to information as *on-time*, when they refer to changes that are implemented at the same time they are approved at Congress, and *delayed*, when there is one or more periods between the time of approval of the tax change and its implementation.

The omission of this intermediate period of information may contaminate the estimates of the implementation effects of tax changes because previous levels of economic activity may be affected by the knowledge of a future tax change implementation. In addition, this fact potentially may contaminate the effects of media anticipation of taxes if there is some correlation in the data between *delayed* tax changes and the measure of mass media beliefs on a future tax approval. To control for these potential intermediate period effects I follow Mertens & Ravn (2012) strategy to account for the potential effects of *delayed* tax changes versus *on-time* tax changes. In contrast to their work, I use measures of implementation delays computed at monthly frequency. The specification for the factor (2) that controls for all uncertain and certain anticipations on top of the direct implementation effects is,

$$\phi_f(L)f_t = \sum_{s=0}^S \theta_s^o \tau_{t-s}^o + \sum_{j=0}^J \theta_j^d \tau_{t-j,0}^d + \sum_{m=1}^M \lambda_m \tau_{t,m}^d + \sum_{i=0}^I \delta_i \hat{p}_{t+i|t} + \omega_t \quad (9)$$

where τ_{t-s}^o are *on-time* tax shocks which are implemented at $t - s$, τ_{t-j}^d are *delayed* tax shocks which are implemented at $t - j$, $\tau_{t,m}^d$ are cumulative *delayed* tax shocks at t to be implemented at $t + m$. *On-time* tax shocks are only part of the information set when implemented, that is at $t - s$. *Delayed* tax shocks are part of the information set when the laws are approved but they are implemented m periods ahead, thus we track the effects of implementation and the effects of the tax being part of the information set since the law approval using this distinction. Finally ω_t is the new error term. This specification controls for the effects of tax changes since the first spills of information captured by the mass media beliefs until their implementation and posterior dynamics. The identification of these effects is achieved if the error term is uncorrelated to implementation, delayed and anticipation tax shocks. A final specification is the one combining the effects of s_t as in (8) to model (9).

While Romer & Romer (2010) estimate a dynamic regression model for GDP, Mertens & Ravn (2012) estimate a VAR model on quarterly economic activity indicators. Meanwhile, I estimate effects on a latent measure of monthly economic activity that is identified through the MFDFM.

7 Empirical Results

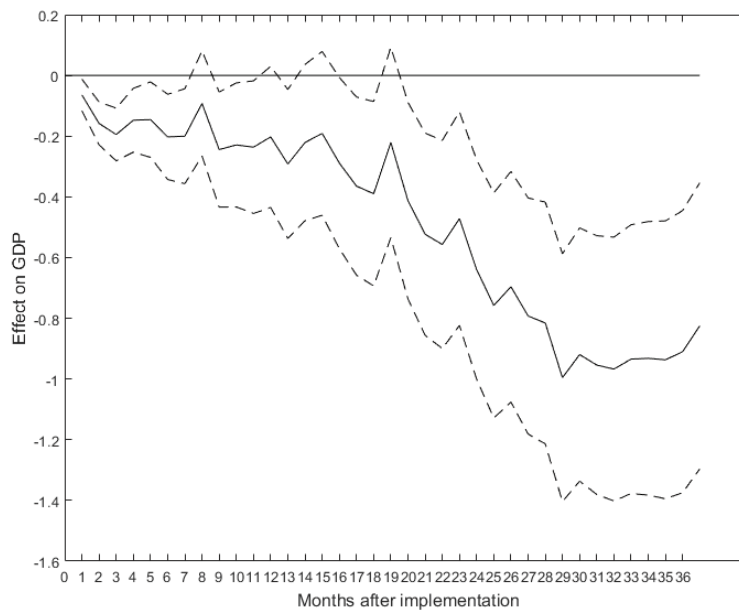
In this section I provide evidence on the effects of *exogenous* tax changes and their anticipations on economic activity. The estimates are the result from the estimation of the MFDFM detailed at Section 6.1 for various specifications of the factor process (2). To do so I use the Kalman Filter and Maximum Likelihood Estimation. Economic activity series are expressed in first differences of the natural log multiplied by 100, i.e. in growth rates. Table 4 describes the series of economic indicators. Romer & Romer (2010) *exogenous* tax liability changes are expressed in percentage points of monthly GDP. Table 7 describes tax liability changes in the period 1968-2007 as a whole and disaggregated into unanticipated and anticipated using the definition of Mertens & Ravn (2012) (on-time and delayed in the terminology of this paper). I demean all the series so that the models are estimated without constant terms. I do not standardize the growth rates of the indicators neither the tax and information shocks, so that I can identify the common factor as the latent monthly real GDP growth. Before estimation, I follow Mariano & Murasawa (2003) and substitute missing observations of the every-third-period observable y_{1t} with random draws from a standard normal distribution.

7.1 Implementation Effects of Tax Changes

Figure 3 presents the implementation effects of *exogenous* tax liability changes on economic activity, in the period 1948 to 2007, following model (5) for the factor. I control for up to $S = 36$ period dynamics, that is, for three year dynamics as in Romer & Romer (2010). The figure shows the cumulative effects in terms of an increase in tax liabilities of a one percent of QGDP together with the one-standard-error bands. The maximum effects are achieved 29 months after implementation of the tax changes when monthly economic activity growth drops by 99.56%. Given that average monthly GDP growth

was approximately 0.29% in 1948-2007, the maximum implementation effect of a 1% of QGDP increase of tax liabilities is a reduction of monthly economic activity growth of 0,28%. There are also immediate effects of the tax changes on monthly GDP growth. For example, two months after implementation tax increases reduce monthly economic activity growth by 15.8%. The monthly dynamics and magnitude of the effects are comparable to the baseline results of Romer & Romer (2010), which are expressed on a quarterly basis and with respect to the level of GDP.

Figure 3: Tax Changes on Economic Activity



Notes: This figure shows the cumulative effect of a one percent increase in tax liabilities over monthly GDP of the Romer & Romer (2010) *exogenous* tax changes.

For the period that we dispose of television data, 1968 to 2007, immediate implementation effects are -6.6% for monthly economic activity growth. Two months after implementation the effects are -10.7%. Maximum effects are a -69.1% and happen 25 months after implementation.

7.2 Media Anticipation on Economic Activity

This section presents evidence on the effects of mass media anticipations of tax bills approvals on economic activity. The effects are captured by the parameter δ_j for $j = 1, 2, 3$ of model (7); that is, the effects of a marginal change in the probability of a

tax approval happening one to three months ahead on current economic activity conditional on all the relevant information of tax news in the media. Baseline results use the estimated measure of anticipations from the FF algorithm. Mass media induced beliefs about a tax approval next month significantly affect current economic activity as documented in Table 6. I quantify that a ten percent probability of a tax approval at the following month increases the growth rate by 1.5%. Beliefs on tax approvals happening two or three periods ahead revert sign and are poorly significant.

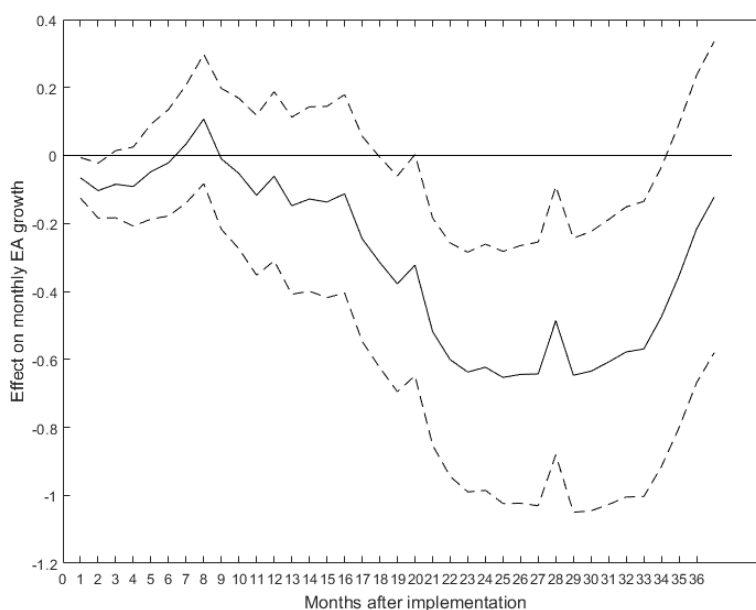
Table 6: Media Anticipation Effects on Current Economic Activity

	(1)	(2)	(3)	(4)
P(Tax Approval at t+1)	0.155 (0.099)	0.1698 (0.097)	0.304 (0.125)	0.303 (0.122)
P(Tax Approval at t+2)	-0.039 (0.115)	-0.0008 (0.115)	-0.050 (0.156)	-0.025 (0.155)
P(Tax Approval at t+3)	-0.026 (0.109)	-0.0314 (0.108)	-0.091 (0.117)	-0.101 (0.116)
Tax Increase at t			0.003 (0.034)	-0.009 (0.035)
P(Tax Approval at t+1)*Tax Increase at t			-0.443 (0.209)	-0.407 (0.210)
P(Tax Approval at t+2)*Tax Increase at t			-0.019 (0.234)	0.025 (0.234)
P(Tax Approval at t+3)*Tax Increase at t			0.486 (0.306)	0.523 (0.298)
Observations	471	471	471	471

Notes: This table contains the effects of one to three month ahead media anticipation of tax approvals on current economic activity using the estimated beliefs of a FF. Column (1) presents the results from the factor model affected by RR exogenous tax implementations plus beliefs on tax bills approvals. Column (2) presents the results when the factor is differentially affected by *on-time* and *delayed* tax liability changes and implementation delays on top of media anticipation. Columns (3) and (4) present of model () and () but it distinguishes the effects of anticipations of net tax cuts from net tax rises.

Figure 4 presents the cumulative implementation effects of a one percent increase in tax liabilities after controlling for mass media anticipation of tax bill approvals up to three months ahead, together with one-standard-error bands. There are some quantitative differences with respect to the results presented of Section 7.1. The one-month implementation effects become -6.6% of monthly EA, two months after implementation tax changes reduce monthly EA by 10.35% and the maximum implementation effect is -65.32% of monthly EA, smaller in absolute value to the maximum effect of tax changes if one does not consider media anticipations. However, maximum effects are also reached 25 months after implementation. After considering the measures of tax anticipations, the direct implementation effects of tax changes are reduced in absolute value suggesting an upward bias in previous estimates.

Figure 4: Tax Changes on Economic Activity controlling for Media Anticipations



Notes: This figure shows the cumulative effect of a one percent increase in tax liabilities after controlling for the new measure of media anticipations of the Romer & Romer (2010) *exogenous* tax episodes.

As documented by Mertens & Ravn (2012), in some tax episodes, there is a lapse of time between the approval and the implementation of tax changes, which I define as implementation delay. To the purpose of this paper, I use the term anticipations only for predictions of taxes under uncertainty while these authors refer to anticipations once it is certain the future implementation date. I estimate the model for $M = 18$, as in

Mertens & Ravn (2012). In column (2) of Table 6 I also present the results of estimating MFDFM with specification (9) for the factor. I distinguish between delayed and on-time tax liability changes and include tax implementation delays. The absolute value of the effects of media anticipation slightly increase in this specification, so not controlling for the Mertens & Ravn (2012) does not confound the effects of media anticipations. In Figures 12 and 13, I show that implementation effects of on-time tax changes are not significantly different from zero and they are reduced in absolute value. The effects of delayed tax changes are significant and larger than the original implementation effects of tax changes of Figure 4. Up to seven month implementation delays of tax rises have a positive and significant impact on economic activity of 40% of monthly EA. Longer horizon implementation delays are poorly estimated as shown in the Figure.

7.3 Heterogeneous Effects of Tax Anticipations

In this section, I provide evidence of the differential effects for anticipation of tax cuts and tax rises. Conditional on the media release of information about a potential tax approval, it is likely that people is aware of what is the net tax liability change associated to the potential approval since media also makes reference to terms like "increase", "rise" or "cut". There are 20 episode approvals in the sample and learning how to predict the sign joint to the approval based on 10 approvals per sign resulted in something unfeasible. I construct an indicator variable that captures the mention of "increase" or "rise" within the tax news to approximate the possibility of a tax rise approval. The average of this variable is 0.23 and the standard deviation is 0.42, it takes the value 1 in 10% of the months approximately.

In columns (3) and (4) I control for this indicator and its interaction with media anticipation of tax approvals for the classical Romer & Romer (2010) and the Mertens & Ravn (2012), respectively. A 10% probability of tax approvals conditional on the tax news at t not mentioning tax increases significantly stimulates current monthly economic activity growth by 3.04%. In the case of the media mentioning tax increases the effect is a reduction of monthly economic activity growth by 1.36%. In column (4) the effects are 3.03% and 1.12% respectively what implies that controlling for implementation delays slightly reduces the magnitude of the effects of anticipation of tax increases, however the effects are still statistically significantly different from zero. The implementation effects of tax changes for the results of column (3) are -6.14%, -10.19% and

-67.11% for one-month, two-month and maximum effects respectively, hence they are similar to those corresponding to the results of column (1).

8 Conclusions

This paper introduces a new empirical measure that captures the level of anticipation of tax bill approvals in the US for the period 1968-2007. I combine text data and machine learning techniques to construct a measure that enables the study of anticipation effects of tax changes on economic activity following the steps of the narrative approach.

Since time aggregation in the analysis of economic indicators may mask important anticipation effects and information may evolve quickly in a matter of days, the paper proposes a mixed frequency dynamic factor model to estimate both the economic activity latent factor and the effects of anticipated tax shocks on it. To my knowledge this is the first paper that exploits a dynamic factor model to account for fiscal policy effects on economic activity.

This work contributes to the study of the macroeconomic effects of available information of different policies prior to their legal approval by providing a strategy that exploits information in the news and combines it with other lower frequency economic indicators using a well-established methodology.

My results reveal that one-month-ahead anticipations of tax approvals significantly stimulate current economic activity. A ten percent increment in the measure of onemonth ahead anticipations reduces the monthly growth rate by 1.5%. Two and three month ahead anticipations revert sign but do not have a statistically significant effect on economic activity. After controlling for mass media anticipation, direct implementation effects of tax changes are reduced in absolute value but still have short-run negative significant effects. I also analyze the effects of the anticipation of tax increases versus tax cuts finding that it is the anticipation of tax cuts what stimulates the economy.

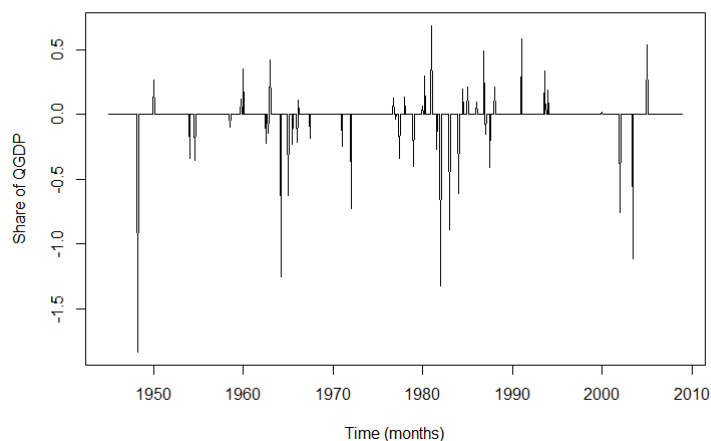
Media coverage of tax episodes at particular dates may be related to unobservable factors that relate to economic activity. I overcome this concern by aggregating the news in a month and assuming that tax announcements can be postponed but not replaced within the month. Finally, there may have been anticipation of eventually not-approved tax bills. In principle, my measure of beliefs can capture them as long as congressmen in charge of those where also in charge of some approved bill. Capturing

the effects for this sort of episodes may be worth as a piece of evidence of unconventional fiscal policy but I do not dispose of data that allows me to identify those specific episodes.

The measure of tax anticipations captures both information about tax salience and that of the likelihood of approval of a tax bill at Congress. The strong relation between both channels of information challenges the study of their separate effects, postponing this question to future work. Finally, Random Forests, as other machine learning algorithms, were developed in computer science as black-box predictive algorithms and their properties from a statistical point of view are currently an active area of research. Providing standard errors on the output of Random Forests is something I hope could be addressed in future research.

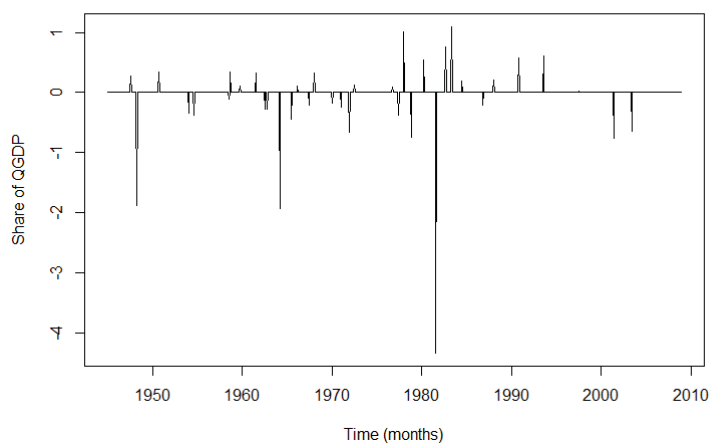
Appendix A Additional Figures

Figure 5: Exogenous Tax Liability Changes



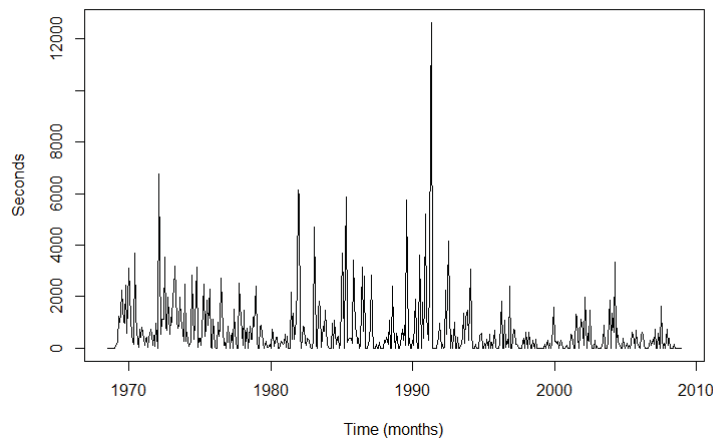
Notes: This figure shows the time series of Romer & Romer (2010) *exogenous* tax liability changes as a share of quarterly GDP (percentage points) at implementation months. The time series starts at January 1945 and ends at December 2008.

Figure 6: Tax Episodes



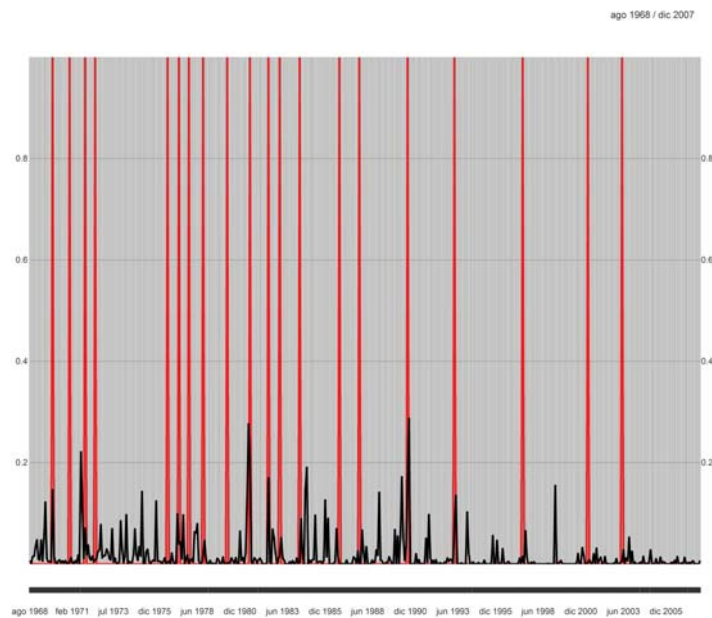
Notes: This figure shows the time series of Romer & Romer (2010) *exogenous* tax episodes as a share of quarterly GDP (percentage points) at approval months. The time series starts at January 1945 and ends at December 2008.

Figure 7: Tax News VTDA Saliencia



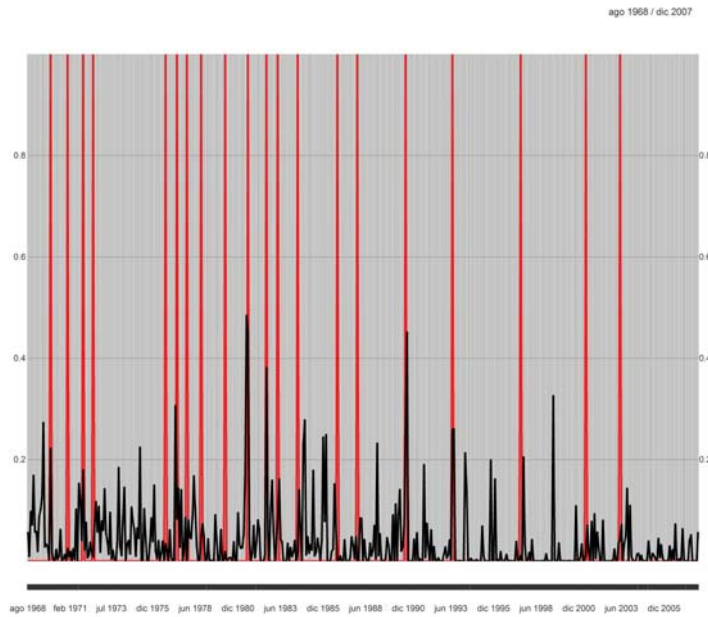
Notes: This figure shows the time series of television salience of tax news expressed in seconds using the VTDA sample of news. The time series starts at August 1968 and ends at December 2008.

Figure 8: RF OOB Predicted Probability of a Tax Approval at $t + 1$



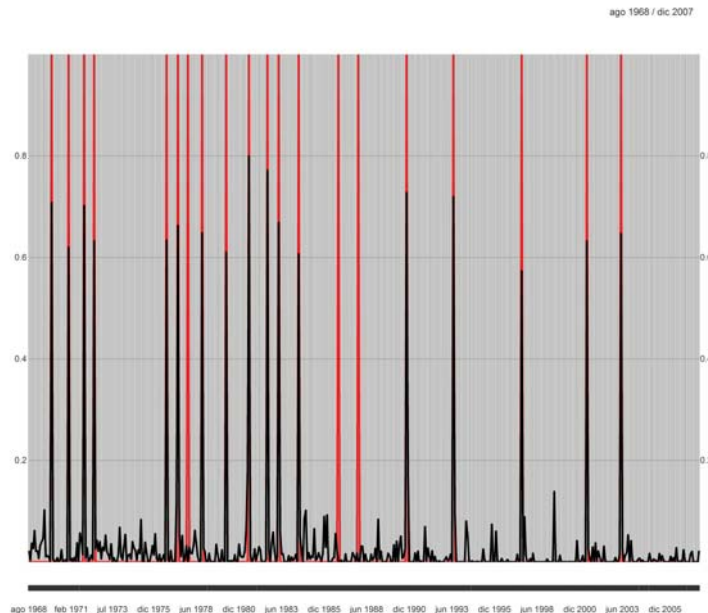
Notes: This figure shows the OOB predicted probability of media anticipations for tax bill approvals at Congress at $t + 1$ conditional on VDTA Tax News at t for the period July 1968 to December 2007 and using standard Random Forests.

Figure 9: FF OOB Predicted Probability of a Tax Approval at $t + 1$



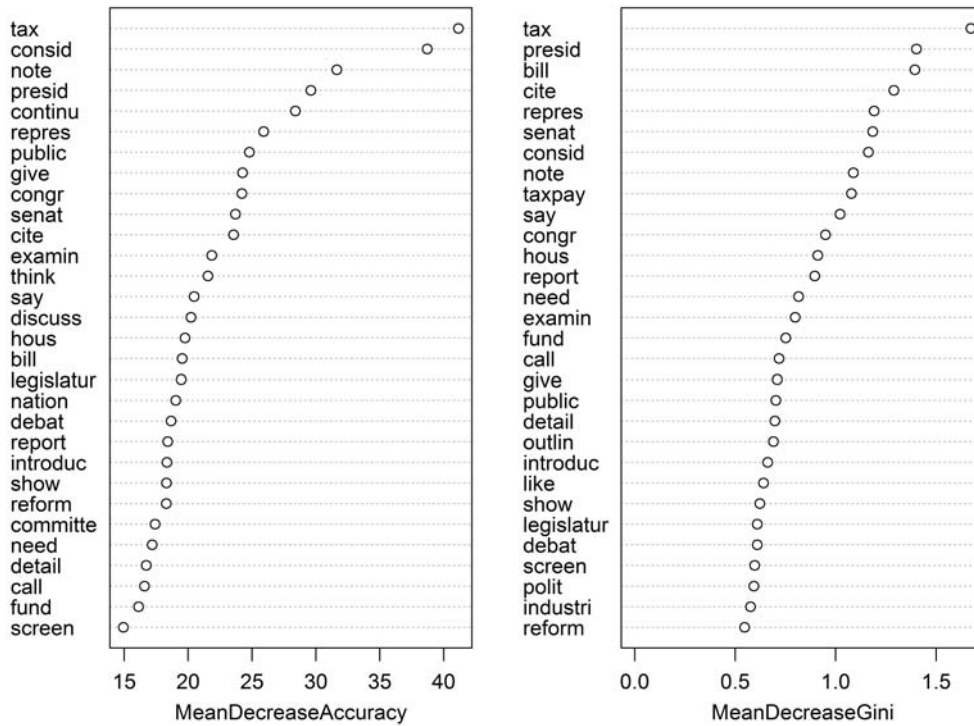
Notes: This figure shows the OOB predicted probability of media anticipations for tax bill approvals at Congress at $t + 1$ conditional on VDTA Tax TV News at t for the period July 1968 to December 2007 using Fuzzy Forests.

Figure 10: FF Predicted Probability of a Tax Approval at $t + 1$



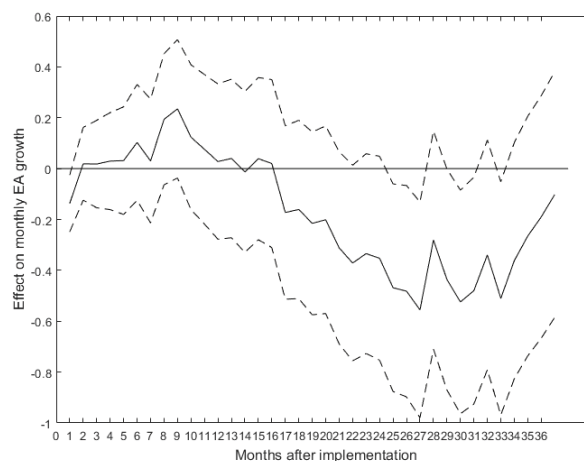
Notes: This figure shows the fitted predicted probability measure of media anticipations for tax bill approvals at Congress at $t + 1$ conditional on VDTA Tax TV News at t for the period July 1968 to December 2007 using Fuzzy Forests.

Figure 11: Feature Importance in the one-month-ahead Fuzzy Forest



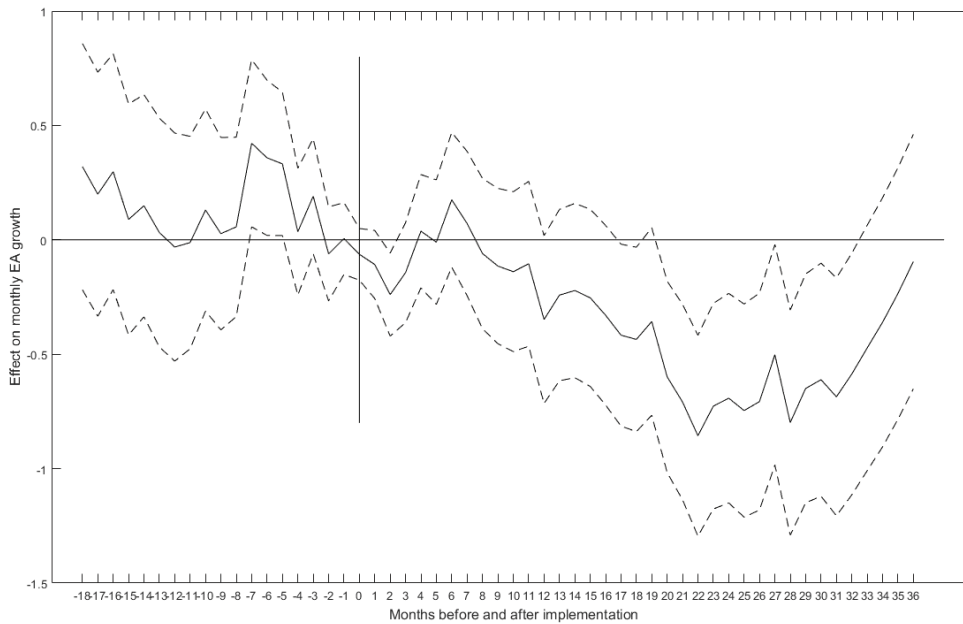
Notes: This figure describes the ranking of feature importance for classification of one-period-ahead months as months of tax approvals in US Congress conditional on VDTA Tax TV News at current month. The right-hand-side figure uses Mean Decrease Gini while the left-hand-side figure uses Mean Decrease Accuracy to measure feature importance for prediction. From the top to the bottom, more to less relevant features.

Figure 12: On-time Tax Changes on Economic Activity



Notes: This figure shows the cumulative effect of a one percent increase in on-time tax liabilities of Romer & Romer (2010) *exogenous* tax changes, distinguishing between on-time and delayed tax changes as in Mertens & Ravn (2012) and also controlling for media tax anticipations.

Figure 13: Delayed Tax Changes on Economic Activity



Notes: This figure shows the cumulative effect of a one percent increase in delayed tax liabilities of Romer & Romer (2010) *exogenous* tax changes, distinguishing between on-time and delayed tax changes as in Mertens & Ravn (2012) and also controlling for implementation delays (as in Mertens & Ravn (2012)) and media tax anticipations.

Appendix B Additional Tables

Table 7: Romer & Romer (2010) Exogenous Tax Liability Changes

Variable	Delayed	Mean	SD	MIN	25th-p	Median	75th-p	MAX	Obs
Tax change	No	-0.23	0.56	-1.83	-0.34	-0.19	0.12	0.49	21
Horizon	No	0	0	0	0	0	0	0	21
Tax change	Yes	-0.04	0.52	-1.65	-0.15	0.09	0.31	0.76	39
Horizon	Yes	20.72	19.33	1.00	5.00	16.00	29.00	80.00	39
Tax change	All	-0.11	0.54	-1.83	-0.26	0.05	0.24	0.76	60
Horizon	All	13.47	18.44	0.00	0.00	5.00	20.50	80.00	60

Notes: Tax change is the estimated magnitude of the *exogenous* tax liability changes measured in dollars by Romer & Romer (2010) divided by the QGDP and expressed in percentage points. Horizon is the number of months between implementation of the tax change and approval of the tax episode. The summary statistics correspond to time series 1945 to 2007.

Table 8: Monthly Tax Activity

Month of Year	Approval Month	Implementation Month
1	16.67	66.67
2	5.56	0
3	0	3.33
4	5.56	3.33
5	2.78	0
6	11.11	5
7	16.67	8.33
8	13.89	5
9	8.33	0
10	8.33	6.67
11	8.33	1.67
12	2.78	0
Events	36	60

Notes: This table contains the relative frequency for tax approvals (1) and tax implementations (2) in particular months of the year across the sample period 1945-2007.

Table 9: US Business Cycle Indicators

Indicator	Description
GDP	GDP quarterly, seasonally adjusted annual rate, deflated with Implicit Price Deflator of GDP (Index 2009=100, quarterly, seasonally adjusted)
EMP	All employees: total nonfarm payrolls, thousands of persons, monthly, seasonally adjusted
IPI	Industrial Production Index, Index 2012=100, monthly, seasonally adjusted
MANU	Real Manufacturing and Trade Industries Sales, millions of chained 2009 Dollars, monthly, seasonally Adjusted
RPI	Real personal income excluding current transfer receipts, billions of chained 2009 Dollars, monthly, seasonally adjusted annual rate

Notes: Definition of economic activity indicators used in this paper. Source: FRED, Federal Reserve Bank of St. Louis.

Table 10: Top 20 Text Features

	Mean	Std. Dev.	Median	Max	Not null
report	8.39	18	1	142	263
tax	6.61	12.79	2	98	295
presid	4.45	10.29	1	92	240
say	4.18	8.06	1	61	257
senat	2.71	6.53	0	62	190
repres	2.65	7.87	0	78	189
note	2.32	5.94	0	52	187
hous	2.23	6.26	0	70	180
comment	1.86	6.66	0	76	153
introduc	1.79	5.34	0	62	191
congr	1.75	4.14	0	38	161
plan	1.75	4.72	0	46	145
cut	1.68	5.5	0	62	137
budget	1.68	9.01	0	164	109
bill	1.58	5.41	0	67	121
show	1.55	4.6	0	55	182
democrat	1.48	4.62	0	51	129
give	1.43	3.09	0	29	193
state	1.38	3.76	0	54	175
examin	1.24	3.56	0	46	157

Notes: This table describes the absolute monthly frequency of the twenty most frequent text features in the corpus of tax news for the period 1968 to 2008. There are 489 (month) observations in the sample period. Tax news are defined as those news that mentioned a congressman in charge of any Romer & Romer (2010) *exogenous* tax bill and the stem 'tax'. Mean states for the sample average, Std. Dev. for the standard deviation, Median for the median, Sum for the total sample occurrence, Range for the difference between the minimum and maximum value in the sample, Not null for the total months of no occurrence, Obs. for the month observations

Table 11: Goodness of Fit Measures

	Classical RF	Fuzzy Forests
Accuracy	0.958	0.957
AUC	2.067	2.067
Gain AUC	0.507	0.508
Lift AUC	0.714	0.691
KS	91.525	91.525
Log-Loss	0.676	0.358
MSE	0.040	0.039
PRAUC	0.678	0.655
RMSE	0.200	0.199
RMSLE	0.139	0.139
Zero One Loss	0.852	0.686

Notes: This table contains a list of measures of goodness of fit for Random Forests Classifiers comparing the results for OOB Classical RF, Test WSRF, OOB FF results. Accuracy is the share of true positive and true negative predictions made over the total of test samples. AUC is the area under the ROC curve, AUC is the area under the curve and measures the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one, Gain AUC, Lift AUC measures how much more likely a positive responses is received than a randomly chosen response, KS is score/probability band where separate between positives and negatives is maximum. Log-loss is the negative log-likelihood of the true labels given a probabilistic classifiers predictions. MSE is the mean square error of predicted probability of classes versus true classes. PRAUC is the area under the precision-recall curve, RMSE is the root mean squared error of the predicted probability of classes versus true classes, RMSLE is the root mean squared logarithmic loss. Zero One Loss is the normalized classification error loss.

Appendix C Fuzzy Forests Results

In this section I explain the details of the estimation of Fuzzy Forests (FF) to predict a tax approval at the US Congress using media data.

In a first stage, this algorithm suggests the estimation of Weighted Gene-Coexpression Network Analysis to the original set of covariates to identify groups of correlated features. This first stage can be rephrased as estimating an average hierarchical clustering model using as input data a matrix of topological overlap dissimilarities, which is a way of representing the networks of the original data set. Setting a threshold level, the algorithm finds a number of modules (or groups) of variables that would relate more closely. I decide to do WGCNA on the text features alone, since I do not want the algorithm to disregard variables such as past salience or episodes. I chose power of 3 and minimum module size of 20 to avoid having too many groups. The resulting modules are described in Figures 14 to 17 using word clouds that represent the relative frequency of features in the corpus for each modules.

The turquoise module contains words mostly related to 'report', 'hous', 'presid', 'senate', which are institutional features of the process of the bill approval at US Congress. The brown module represents words related mostly to 'introduc', 'comment', 'campaign', 'mention', that is, words that deal with different comments at the initial debate of a bill. The blue module is a group of words related to other issues that interact to tax changes in the process of debate. Finally, the grey module is a small group about some government departments and past vocabulary.

For each module, a Recursive Feature Elimination Random Forests (RFE-RF) is estimated to screened out the least predictive features. The researcher has to decide how many features are eliminated at each iteration and how many features wants to keep. I set to eliminate 1% of the features at each iteration until having dropped 75% of the original number of features in the module. After the screening step, the algorithm runs a final RFE-RF using all the screened features from the different modules to predict the dependent variable. In this stage, the interaction between the different features is taken care of. Here, I also eliminate a 1% of screened features until I keep the best 50 features according to the algorithm. Figure 18 presents the relative importance before and after the screening of features. The most present module is the turquoise followed by the blue and the brown. The red part of the bars is the amount of words finally selected from each module after feature selection. The grey module

almost disappears after feature selection. This selection of features is consistent with the predictability of the features since the turquoise group is more related to the event of approval of a bill while the brown module relates to the initial process of bill approval where there is considerable uncertainty about the potential approval. Finally, I estimate a classical RF using the 50 selected features.

Figure 14: Blue Word Cloud



Figure 15: Brown Word Cloud



Figure 16: Grey Word Cloud



Figure 17: Turquoise Word Cloud

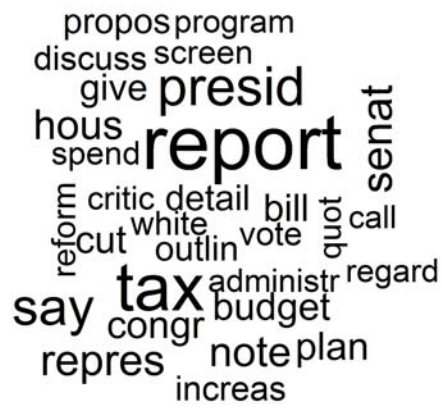
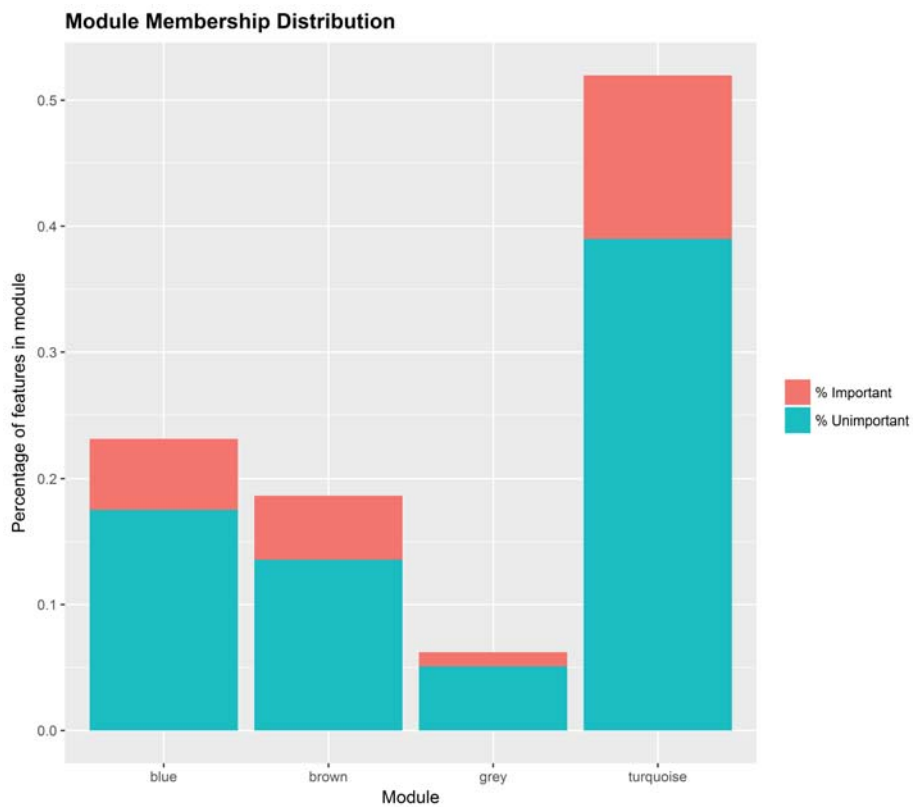


Figure 18: Modules Distribution



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