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A Narrative Approach to Creating Instruments with Unstructured and Voluminous Text: An Application to Policy Uncertainty

Michael Ryan

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Michael Ryan
School of Accounting, Finance and Economics
Waikato Management School
University of Waikato
Private Bag 3105
Hamilton
NEW ZEALAND, 3240

Email: mr169@students.waikato.ac.nz

Abstract

We quantify the effects of policy uncertainty on the economy using a proxy structural vector autoregression (SVAR). Our instrument in the proxy SVAR is a set of exogenous uncertainty events constructed using a text-based narrative approach. Usually the narrative approach involves manually reading texts, which is difficult in our application as our text—the parliamentary record—is unstructured and lengthy. To deal with such circumstances, we develop a procedure using a natural language technique, latent Dirichlet analysis. Our procedure extends the possible application of the narrative identification approach. We find the effects of policy uncertainty are significant, and are underestimated using alternative identification methods.

Keywords

Latent Dirichlet allocation
narrative identification
policy uncertainty
Proxy SVAR

JEL Classifications

C32, C36, C63, D80, E32, L50

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1 Introduction

Uncertainty is a fundamental concept in macroeconomics, as its unexpected movements (or shocks) are generally seen as important for helping explain, among other things, the dynamic behavior of asset prices, investment, and consumption. In this paper, our focus is on the effects of policy uncertainty because, for example, while a lockdown to slow the spread of a disease will reduce economic activity, so will unclear guidance about when such a lockdown will be enacted or retracted. Consequently, firm and household decisions may be delayed until the policy becomes clearer. Our, and others (e.g., Baker, Bloom, & Davis, 2016), interest in the topic, reflects the significance of policy as a source of uncertainty for many firms and households.

However, measuring the dynamic effects of uncertainty (policy-sourced or otherwise) is challenging because of the difficulty in isolating uncertainty's unexpected movements from its endogenous movements arising from the state of the economy. Of the methods proposed in the literature for isolating uncertainty's unexpected movements (i.e., uncertainty shocks), the simplest (and most common) method, the recursive approach, isolates uncertainty shocks by assuming, somewhat unrealistically, that the relationship between uncertainty and macroeconomic variables is not simultaneous. An alternative method restricts the direction (sign) of the impact of uncertainty shocks on the economy; as Ludvigson, Ma, and Ng (2015) note, this seems inappropriate given that the impact of uncertainty on the economy is ambiguous in theory.[1] Other authors such as Angelini, Bacchiocchi, Caggiano, and Fanelli (2019) and Carriero, Clark, and Marcellino (2018a) use heteroskedasticity-based schemes to identify uncertainty shocks or stochastic volatility-based methods (Carriero, Clark, & Marcellino, 2018b; T. Berger, Grabert, & Kempa, 2016), while Ludvigson et al. (2015) employ shock restriction-based methods applied to different historical episodes.

Instrumental variable (IV) estimation, a well-known solution for dealing with simultaneity in econometrics, has been used by various studies to examine uncertainty. For example, Baker and Bloom (2013) examine how uncertainty affects GDP growth by instrumenting their measure of uncertainty (stock market volatility) on a set of disaster events relating to natural disasters, political shocks, revolutions, and terrorist attacks. Carriero et al. (2018a), Piffer and Podstawski (2018), Husted, Rogers, and Sun (2019), and Kim (2019) examine the impact of uncertainty in a wider range of variables than just GDP growth using a proxy structural vector autoregression (SVAR) approach. Kim (2019) uses the military spending variable of Ramey and Zubairy (2014) as an instrument to study government spending policy uncertainty and Husted et al. (2019) construct instrumental variables based on high frequency data from the bond futures market to instrument their text-based monetary policy uncertainty index. Carriero et al. (2018a) use Bloom (2009)'s uncertainty

[1] See Bloom, 2014 for a summary of the channels through which uncertainty can have a positive and negative effect on the economic variables.

shock series as the instrument in their proxy SVAR; Bloom isolates uncertainty events by looking at the months in which the CBOE S&P Volatility Index (VXO) peaks and then assigns a month a value of one if it contains a VXO peak and zero otherwise. As Piffer and Podstawski (2018) note, Bloom implicitly assumes that a high value of uncertainty is due to exogenous causes, and this is not necessarily true. Instead, Piffer and Podstawski (2018) use the variations in the price of gold around the identified uncertainty events as their instrument of uncertainty's unexpected/exogenous movements.

The approach taken here is similar to those of Carriero et al. (2018a) and Piffer and Podstawski (2018) in two ways: we use a proxy SVAR setup to consider the effects of uncertainty on a wide range of variables, and when creating our instrument, we identify our "uncertainty events" based on uncertainty peaks. However, we depart from these studies by using evidence from narratives to identify the quarters in which the movement in uncertainty is unexpected/exogenous, with a focus on policy uncertainty.[2]

Narratives are a powerful approach not only for influencing people's behaviors (Shiller, 2019), but also as a lens through which people perceive the world. We argue that periods in which uncertainty is discussed intensely in relation to macroeconomic and financial conditions are those in which uncertainty should be considered to be endogenous. Conversely, periods in which uncertainty is discussed intensely in relation to other factors, especially policy, are those of exogenous uncertainty. Indeed, there is a tradition of using narratives in other areas of macroeconomics to isolate unexpected/exogenous movements in variables. Romer and Romer (2010) use budget documents and speeches to isolate exogenous changes in tax motivated by ideology or reducing inherited deficits from endogenous changes in tax reflecting the state of the economy. The same authors undertake a similar exercise for monetary policy using Federal Reserve documents (Romer & Romer, 2004). Hamilton (2003) and Kilian (2008) identify historical events with exogenous causes to isolate exogenous oil prices movements. Antolín-Díaz and Rubio-Ramírez (2018) also uses narratives to apply sign restrictions around key historical events in an SVAR.

The narrative approach in these works tends to rely on relatively short and focused texts because of the difficulties inherent in a manual search/identification approach based on reading each relevant piece of text. In the work presented here, our text source, New Zealand's parliamentary record from 1975 to 2017, makes a manual approach infeasible.[3] As a consequence, we use text-mining techniques suited to unstructured and voluminous text. In this regard, we share a similar spirit to Ter Ellen, Larsen, and Thorsrud (2019) who use an alternative text-mining technique, Latent Semantic Indexing, combined with factor analysis to identify monetary policy surprises. Their application requires both digitised newspapers and official documents

[2] Our analysis is conducted on a quarterly basis, whereas Carriero et al. (2018a) and Piffer and Podstawski (2018) conduct theirs on a monthly basis.

[3] New Zealand's parliamentary record is formally known as the New Zealand Parliamentary Debates. Volumes 396 and 726 were kindly supplied to us in machine-readable form by Mubashir Qasim.

(Central Bank communications in their case) to compare to identify policy surprises; we lack a source of digitised newspapers for our country of study, New Zealand, prior to 1995.

It is important to distinguish our study from studies of uncertainty that have used texts to construct measures of overall and topic-specific uncertainty (Baker et al., 2016; Larsen, 2017; Saltzman & Yung, 2018; Azqueta-Gavaldón, 2017; Xie, 2020, Husted et al., 2019). Their focus is measuring uncertainty and their text-based indices reflect both endogenous movements in uncertainty and uncertainty shocks. Consequently, Larsen (2017, p. 22) and Baker et al. (2016, p. 1596) recognize that their results on the dynamic effects of uncertainty cannot necessarily be interpreted as causal. Our focus is on using text to isolate exogenous movements in uncertainty from an uncertainty index constructed using other methods.

Our study's main methodological contribution is to show how a narratively-based instrument can be created when the text is unstructured and voluminous. We see this as important as it extends the scope for the application of the narrative method, which has been shown to have utility in many applications (as evidenced by the publications on monetary and fiscal policy, and oil, cited earlier). One particular application where there appears particular utility is identification in SVARs via external instruments. J. H. Stock and Watson (2018, pg. 918) note the 'research programme [using external instruments] holds out more potential for credible identification than is typically provided by SVARs using internal restrictions' but finding 'instruments is not easy'. Through opening up the possibility of creating narrative-based instruments from unstructured and voluminous text, we hope our method will make finding an instrument slightly easier and thus facilitate more credible identification.

We make three key contributions in terms of results. We confirm the findings of Carriero et al. (2015) and Kim (2019), but in the specific domain of general policy uncertainty, that the recursively-identified SVAR will underestimate effects of uncertainty on the economy owing to attentuation bias. Secondly, we confirm elections can be used as a source of exogenous uncertainty and thereby assist identification of uncertainty's effects (e.g. Giavazzi & McMahon, 2012, Redl, 2020). Further we show changes in the electoral system can be a further source of exogenous uncertainty. Finally, we build on Piffer and Podstawski (2018) who show that news and uncertainty shocks have heterogeneous effects on real and nominal variables, and financial variables. We provide suggestive evidence this heterogeneity extends to the exchange rate. This adds to the recent work by Novy and Taylor (2020) in helping understand the open-economy effects of uncertainty.

The remainder of this paper is organized as follows. In Section 2, we show how we construct our instrument. Specifically, we isolate a number of quarters in which uncertainty is heightened as our uncertainty events and use text-mining techniques to narratively identify which are considered to be unexpected/exogenous. Section 3 outlines the proxy SVAR setup that allows us to use our instrument to identify a set of structural uncertainty shocks. In Section 4, we assess the quality of our uniquely identified exogenous uncertainty events. First, we check them against a commonly understood economic history of our country of interest, New Zealand. We then check whether our series of narratively identified exogenous uncertainty events meet the relevance and exogeneity conditions required of an instrument. In Section 5, we discuss our estimates from the proxy SVAR of the dynamic effects of the structural uncertainty shocks on the economy and compare the results with those from other common methods of identifying uncertainty shocks. Section 6 concludes.

2 Constructing a set of narratively identified policy uncertainty events

2.1 The source of our narrative

New Zealand is the ideal country to illustrate how policy uncertainty shocks can be identified for two reasons. First, policy uncertainty can plausibly be attributed to non-business cycle-related reasons in two recent periods. During the first period, namely, the 1980s and early 1990s, New Zealand undertook a number of economic policy reforms that were ideologically driven and in many respects untested internationally.[4] During the second period, around 1996, a new election voting regime was introduced: the Mixed Member Proportion (MMP) system. Under MMP, there is a coalition of governing parties. Given that each party initially has different policy positions, this system results in more policy uncertainty (than the previous winner takes all system: first-past-the-post) until agreement is reached.[5] If our narrative method identifies exogenous policy uncertainty events correctly, we would expect a high prevalence of such events in these two periods.

Second, New Zealand is an ideal country for our study of policy uncertainty because a high-quality text is available for our narrative identification: the parliamentary record (called Hansard).[6] Hansard is a useful text source for multiple reasons: parliamentary debate is predominately about policy and given that the debate reflects the contemporary issues of the day, it represents a good source of text data to discern when the source of the policy generating the uncertainty can be considered to be exogenous (e.g., policy reflecting ideology) and when the source of the policy generating the uncertainty can be considered to have occurred because of the business cycle. Furthermore, the parliamentary record in New Zealand is continuously electronically available from 1909.

[4] Much has been written about this reform period. For example, Evans, Grimes, Wilkinson, and Teece (1996) and Dalziel (2002) provide contrasting assessments.

[5] In a similar vein, Redl (2020) proposes that close elections can increase macroeconomic uncertainty.

[6] This is particularly important in New Zealand, as newspapers, the usual source of text information in uncertainty studies, are not available electronically historically for any length of time. Ballingall, Dorigo, Hogan, and Lees (2020) create a trade policy uncertainty index for New Zealand and find that the number of articles is too sparse to go back before 1995.

2.2 Identifying events associated with heightened uncertainty

To construct our series of exogenous uncertainty events, we need to identify the quarters associated with heightened uncertainty (following Piffer & Podstawski, 2018, we call these "uncertainty events"). To identify uncertainty events, we first need an uncertainty index. In our application, the index is taken from Ryan (2020). This index is a combination of four (predominately firm-related) uncertainty indicators. The first three indicators are constructed based on firms' responses to questions about the expected direction of firm-level activity variables (as well as broader economic variables). These indicators are

1. An indicator based on the distribution of firms' responses (constructed as per Girardi & Reuter, 2016).

2. An indicator that measures the average error of firms' expected direction at time $t-1$ compared with the actual outcomes at t; this is called the *"average error."* and is constructed as per Arslan, Atabek, Hulagu, and Şahinöz (2015).

3. An indicator that measures how far, on average, individual firms depart from the *average error* calculated in (2); this is called the *"idiosyncratic error."* and is constructed as per Arslan et al. (2015).

4. The stochastic volatility measure of output uncertainty of T. Berger et al. (2016)

We use principal component analysis to combine the indicators above into an overall index.[7]

The first three indicators are constructed a quarterly survey of New Zealand firms conducted by the New Zealand Institute of Economic Research, called the Quarterly Survey of Business Opinion. This survey of firms, which has run continuously since 1961, has two noteworthy features: (i) its respondents are from most industries, except agriculture, utilities, and government and (ii) it uses stratified sampling based on firm employee numbers. However, it excludes all firms with fewer than six employees and includes all firms with more than 200.

Given that the Quarterly Survey of Business Opinion is a survey of firms and that three of our uncertainty indicators are based on this survey, our uncertainty index should be classified as an index of firm uncertainty. The overall index in Figure 1 shows that uncertainty is heightened during recession periods (the pink sections) as well as throughout the 1984 to 1995 economic reform period discussed earlier.

In Figure 1, the red and blue lines show the election dates, with a red (blue) line indicating that the center-left Labour party (center-right National party) was the winner. We also see that uncertainty spikes around elections, particularly after the introduction of the MMP voting system in 1996.

[7] For our five sectors, the first three indicators are created for each of the j questions individually. To create an overall sector version of each indicator, we take a principal component across the j questions. The three sector indicators are then aggregated into a sector-specific index by taking the arithmetic average. An economy-wide index is next created by weighting the sector-specific indices by their GDP weights. A principal component of this index and indicator four is the final index. See Ryan, 2020 for more details.

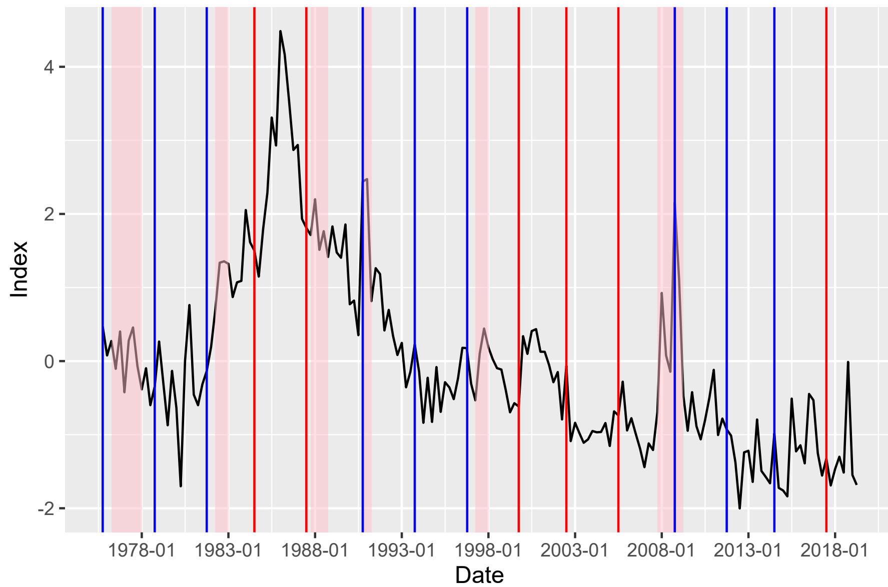


Figure 1: New Zealand uncertainty index

To construct our list of uncertainty events, we convert the continuous uncertainty index variable into a dummy variable that takes a value of one if the index is above its mean value.[8] Otherwise, a value of zero is assigned.

2.2.1 Accounting for the correlation between news and uncertainty

Typically, bad news about the state of the economy is correlated with heightened uncertainty. D. Berger, Dew-Becker, and Giglio (2020), for example, point out the close relation between news and uncertainty, while Piffer and Podstawski (2018) show that news and uncertainty shocks have different effects on financial as well as on real and nominal variables, with news shocks affecting financial variables more. To ensure that we do not confound the two shocks, we thus modify our measure of uncertainty to better isolate our shocks of interest: uncertainty shocks.

Unlike Piffer and Podstawski (2018), who use an estimated series of news shocks from previous research, we need to create our own, as we are not aware of any such studies in New Zealand.[9] D. Berger et al. (2020, p. 42) define first-moment news shocks as "news about the average future path of the economy." The news shock variable we create tries to reflect this definition. Specifically, we take three forward-looking questions from the Quarterly Survey of Business Opinion. The questions relate to firms' investment intentions over the

[8]This is a more relaxed criterion than that employed by Bloom (2009), who identify uncertainty events as when the uncertainty series is 1.65 standard deviations above its sample mean in a given quarter. As noted in the Introduction, Bloom (2009) equates high uncertainty values with being exogenous. As we determine exogeneity in another way, we are more permissive in the quarters we identify as containing uncertainty events.

[9]Kamber, Theodoridis, and Thoenissen (2017) do create a news series for New Zealand, but their work only covers 1989Q3 to 2011Q3.

next 12 months for plant and machinery as well as for buildings and firms' outlook for the general business situation in New Zealand over the next six months. Each of these questions has a time series associated with them, which is the net balance of firms' responses (the percentage of firms expecting an increase minus the percentage expecting a decrease, normalized by a factor that takes into account non-applicable responses). We take the first principal component of these three series and then the first difference, which is our news variable. We hypothesize that a large sudden drop in investment intentions and the outlook for the economy reflects negative news. Reflecting this, from our list of quarters identified as containing uncertainty events, we omit any quarter in which our news variable fell by more than 1.65 standard deviations from its mean values; we term these "bad news" events. We identify the following five quarters as being "bad news" events:

1. 1985Q4: The introduction of a new consumption tax (Goods and Services tax) was announced in the previous quarter.

2. 1987Q4: The 1987 stock market crash.

3. 2000Q2: The bursting of the dot-com bubble.

4. 2005Q4: The close re-election victory of a Labour government (business has traditionally viewed Labour less favorably).

5. 2008Q4: The start of the second, more intense, phase of the global financial crisis.

2.3 Identifying uncertainty events with exogenous causes

Using the above approach, approximately half the quarters in the sample are identified as containing uncertainty events. We now need to distinguish between events in which (i) high uncertainty from policy appears to be in response to the state of the economy and (ii) high uncertainty appears to be in response to non-business cycle factors; our focus is on the latter. To do this, we use the parliamentary record.

The parliamentary record is lengthy (approximately 1.6 million words per year on average in our sample from 1975 to 2017) and unstructured in terms of the topics discussed. The typical parliamentary sitting day includes 12 questions necessitating oral answers as well as the reading of bills on a broad range of subjects.[10] As manually reading the parliamentary record is extremely time consuming owing to its length, we need a method that allows us to structure the text to carry out our narrative classification.

To isolate the topics of regulation discussed in the text on the corporate earnings calls of US companies, Calomiris, Mamaysky, and Yang (2020) take a 41-word window around the term regulation. To identify

[10]For example, on May 27, 2020, the day we first drafted this sentence, the subjects of the oral questions included, but were not limited to the economy, social development, and transport; the subjects of the bills included the budget, smoke-free environments, and the gas market.

about which households and firms may be uncertain, we do the same but apply the 41-word window around any of “uncertain,” “uncertainty,” and “uncertainties.”[11] Figure 2 shows the annual counts of these windows, where the upward trend reflects that Hansard word count is increasing each year.

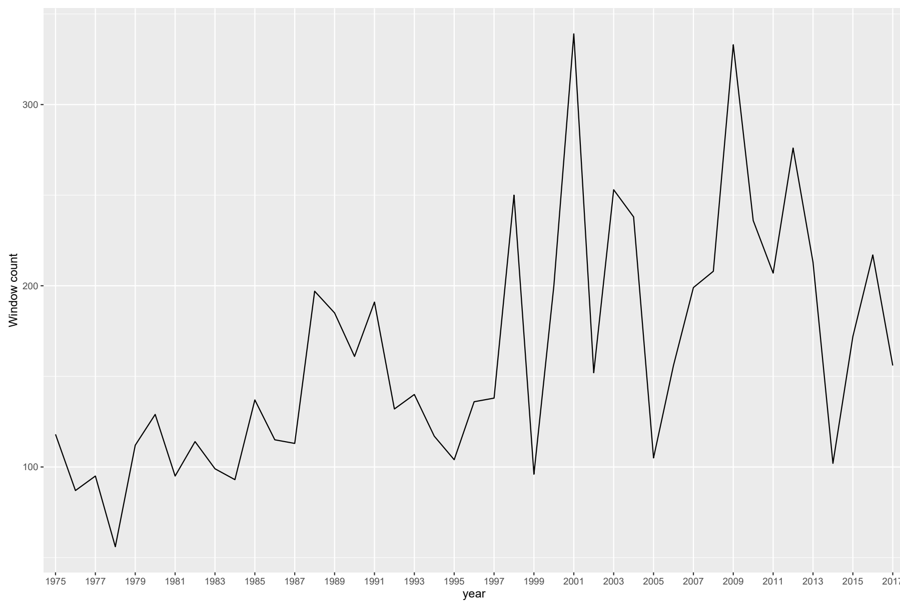


Figure 2: Counts of uncertainty windows per year

The 6,972 identified windows are treated as separate “documents”: each document, in our case, is a mention of uncertainty. We now want to classify each mention of uncertainty based on its theme. Following Calomiris et al. (2020), we use a natural language processing technique called latent Dirichlet allocation (LDA).[12] The LDA algorithm (developed by Blei, Ng, & Jordan, 2003) is based on two ideas. The first is that documents consist of a mixture of different topics, but the proportion of each topic differs by document. The second idea is that each topic is a mixture of words in different proportions (more concretely, for each topic there is a probability distribution across words that varies by topic). For example, a topic about the economy has a high probability of containing the words “GDP” or “inflation,” while a topic about regulation is likely to contain “law,” “compliance,” and so on.

LDA is an iterative algorithm that works by taking a given word in a given document[13] and constructing a conditional probability distribution across topics for the word in that document, with topic k having a

[11] The 41-word window is isolated in the corpus of text that has had a set of common pre-processing steps applied to it (i.e., the removal of “stop” words, punctuation, digits, and one-letter words. In light of the conclusion of Schofield and Mimno (2016) that “stemmers produce no meaningful improvement in likelihood and coherence and in fact can degrade topic stability” (p. 287), we do not stem. Instead, we keep people’s names in the dataset, as these are typically the responsible minister and therefore are useful for defining topics.

[12] Larsen (2017) isolates different topics of uncertainty using LDA on Norwegian newspaper articles and creates topic-specific uncertainty indices, finding that different types of uncertainty have different effects on the economy. However, his study focuses on the measurement of different types of uncertainty rather than using it to identify shocks. See also Gentzkow, Kelly, and Taddy (2019) for an overview of LDA’s application (as well as other techniques for text analysis) in economics.

[13] We use both individual words and bigrams as our units.

higher probability of being associated with that word in a given document if (i) other words in the document are associated with that topic and (ii) the word is associated with topic k in other documents.

The algorithm then samples from this conditional probability distribution to assign the word in the document to a new topic. The algorithm iterates over words and documents. There is no training sample, and the algorithm begins by randomly assigning words to topics. To compute the conditional probability distribution, the LDA algorithm uses Bayesian methods, particularly Gibbs sampling (see the appendix). We implement LDA using R's TextMineR.

One key parameter in the LDA algorithm is the number of topics you ask it to create: if you specify too few, the topics are too general; if you specify too many, the topics become too specific (i.e., the topics will not generalize across documents or mentions of uncertainty). We run the algorithm four times, searching for 50, 60, 70, and 80 topics on each run. We then compare the coherence score for each run and find that 70 topics maximize their value.[14]

With 70 topics identified, we then label each topic based on the top 20 words associated with the topic. Labeling has two components. A less important "specific label" that identifies the specific nature of the topic and a "general" label from the following:

- "Endogenous/economy": the specific topic relates to the state of the business cycle (seven topics).
- "Firm-related policy": the specific topic relates to a policy area likely to affect firms (e.g., regulation, energy, and taxation) (20).
- "Other policy": the specific topic relates to a policy area unlikely to directly affect firms (e.g., education, health, and social welfare) (32).
- "Other/unknown": it is either hard to allocate the topic a label owing to the incoherence of the words associated with it or the topic appears to relate to procedural matters in parliament (11).

Figure 3 shows nine topic examples. The first column shows three examples of "endogenous/economy" topics, the second column three firm-related topics, and the third column three "other policy" topics. Focusing on the first row, the first topic has a combination of words related to the economy ("economy," "growth," "financial." and "crisis") and is therefore allocated the specific label "economy" and, more importantly, is given the general label "endogenous/economy[15]The second topic relates to the cost of regulation; given that this affects firms, we allocate this the general topic label of "firm-related policy." The final topic relates

[14]Intuitively, at a topic level, a topic receives a higher coherence score if the top words associated with it are also usually found together in the documents/mentions of uncertainty. The overall coherence score is the average of the coherence scores across K topics. The specific coherence score we use is probabilistic coherence, as implemented in R's TextmineR package; more information is available at https://github.com/TommyJones/textmineR/issues/35.

[15]Regarding the references to Bill English in figure (g), he was the Minister of Finance using the Global Financial Crisis

to education (e.g., "schools," "children") and is allocated the specific label "education" and the general label "other policy." We focus on firm-related policy topics, as our uncertainty index is constructed using (predominately) firm survey information (see Section 2). Table 6 in the appendix provides more information on firm-related policy topics.

LDA provides each document—in our case, mention of uncertainty—a probability distribution across the range of possible topics; for a given document/mention of uncertainty, all these probabilities sum to one. Figure 4 shows the probability distribution of the first mention of uncertainty in our dataset (although all topics with a probability of less than 0.01 are excluded for readability). We see that topic 20—a topic perhaps related to drinking laws —has the highest probability of being associated with this uncertainty mention.

To assign a topic to each document/uncertainty mention, we first find the topic for that document/uncertainty mention with the highest probability. However, in line with Calomiris et al. (2020), we only allocate a topic to a document/uncertainty mention if the topic with the maximum probability has a probability over 0.5. Only in this case can we be confident that the topic with the maximum probability is representative of the theme of the uncertainty mention; otherwise, the mention is likely to be a relatively even mixture of a number of topics. In our dataset, we originally identify 6,972 mentions of uncertainty; however, after applying the probability threshold, we have 2,736 (40 percent of the original dataset). This is our potential first source of measurement error, as some of these omitted mentions of uncertainty may have helped us better identify the reason for the uncertainty event. To check the robustness of this step—the assignment of the topic to an uncertainty mention—we asked three undergraduate commerce students to check if they agreed with the assessment after manually reading the text in a sample of 100 uncertainty mentions. The average agreement rate was 93 percent.[16]

We also have to omit some uncertainty because not all the uncertainty mentions can be reliably allocated to a quarter, as some of the Hansard volumes span two quarters. This represents a second source of measurement error, and despite our best efforts, we cannot ascribe the mention to a given quarter. The omissions associated with the volume-to-quarter matching issue leave us with 1,881 uncertainty mentions (just over 11 on average per quarter in our sample).

Finally, to identify quarters in which the uncertainty event can be considered as an exogenous event, we calculate the ratio of endogenous/economy-related to firm-related policy uncertainty mentions in each quarter in which an uncertainty event has been identified. We assign a value of one (i.e., identify the quarter as containing an exogenous uncertainty event) to quarters in which the above ratio is zero (i.e., there are no mentions of endogenous uncertainty and at least one mention of firm policy-related uncertainty).[17]

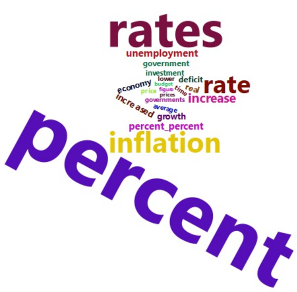
[16]The agreement rate is the number of mentions they agreed with the assessment of divided by the number of mentions they could 'confidently' assess based on their knowledge.

[17]Our instrument is of the style of Boer and Lütkepohl (2020)'s 'sign-proxy'; although we are only focusing on positive

(a) Topic on the economy

(b) Topic on regulation

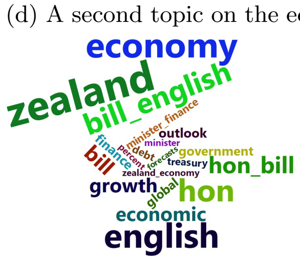
(c) Topic on education



(d) A second topic on the economy

(e) Topic on research and development

(f) Topic on marriage law



(g) A third topic on the economy

(h) Topic on tax policy

(i) Topic on health

Figure 3: Word clouds for nine topics

Note: The bigger the word size, the higher probability it is associated with the topic

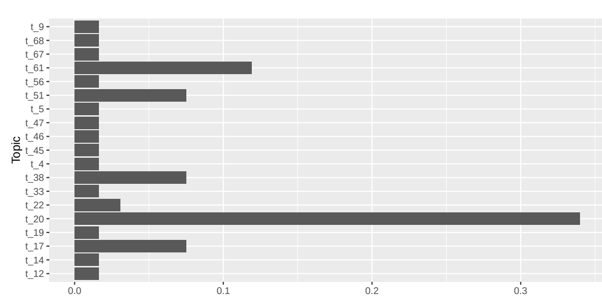


Figure 4: Topic probability distribution for first mention of uncertainty in the dataset

3 Proxy SVAR approach

With a set of uncertainty events reflecting exogenous policy, it is tempting to estimate the effects of policy uncertainty on the economy by regressing the uncertainty events (interacted with the uncertainty index) on GDP and other macroeconomic variables. For example, Romer and Romer (2010) regress their set of exogenous tax shocks on GDP to estimate the dynamic effects of tax changes. However, such an approach has been criticized by Mertens and Ravn (2013), who note that "a concern with the existing literature is that the narratively identified exogenous changes ... are implicitly viewed as mapping one-to-one on to the true structural shocks. In practice there are good reasons to expect that narratively identified shocks suffer from measurement errors as historical records rarely are sufficiently unequivocal that calls of judgment can be avoided" (p. 1213).

Although we do not manually read the text and make judgment calls, as discussed in Section 2, our approach to identifying exogenous uncertainty events/shocks will result in measurement error. Mertens and Ravn (2013) and Mertens and Ravn (2014) propose using proxy SVAR to deal with this measurement error. Under this approach, rather than adding our series of narratively identified uncertainty events into the SVAR directly, we use the events series as an instrument.[18]

Ultimately, our proxy SVAR aims to recover the latent structural uncertainty shock $\epsilon_{t,u}$ from the SVAR model:[19]

$$B(0)\begin{bmatrix} U_t \\ Y_t \end{bmatrix} = B(L)\begin{bmatrix} U_t \\ Y_t \end{bmatrix} + \begin{bmatrix} \epsilon_{t,U} \\ \epsilon_{t,Y} \end{bmatrix} \tag{1}$$

where B(L) is the lag operator for the *1,..,p* lags in the model (p=4 in our case), Y_t is a vector of the k macroeconomic and financial market variables, and $\epsilon_{t,Y}$ is the associated structural shocks. U_t is an observed measure of uncertainty. This is the uncertainty index of Ryan (2020), as discussed in Section 2.2. B(0) is the contemporaneous impact matrix. Our goal is to identify the column of this matrix that relates to the contemporaneous impact of uncertainty on our macroeconomic and financial market variables of interest.

The vector of the k macroeconomic and financial market variables, Y_t, consists of five variables: the quarterly change in the New Zealand share price index, output gap, detrended inflation, detrended nominal 10-year interest rate, and detrended real exchange rate. The output gap is created by applying the method of Kamber, Morley, and Wong (2018) to the real GDP series of Hall and McDermott (2011); inflation and the interest and exchange rates are detrended using the Hodrick—Prescott filter (lambda: 1,600). We detrend inflation and the interest and exchange rates, as the 1980s and early 1990s were a period of large structural

shocks. Boer and Lütkepohl (2020, pg. 1) notes: 'sign-proxies often provide more precise estimates than conventional, more sophisticated proxies that are not strongly correlated with the shock of interest.'

[18] J. H. Stock and Watson (2012) were also early in applying an external instrument approach to identify their SVAR.

[19] The explanation of the proxy SVAR below closely follows that in the online appendix of Mertens and Ravn (2014).

change in the New Zealand economy (e.g., the introduction of inflation targeting, floating of the exchange rate, and opening up of the economy to foreign capital flows). This means that the equilibrium/natural interest and exchange rates are likely to move.[20]

To recover $\epsilon_{t,u}$, we must first estimate the reduced-form VAR:

$$A(L)\begin{bmatrix} U_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \eta_{t,U} \\ \eta_{t,Y} \end{bmatrix} \tag{2}$$

where A(L) is the lag operator for the *1,..,p* lags in the model, $\eta_{t,Y}$ is a vector of the innovation associated with the macroeconomic and financial variables, and $\eta_{t,u}$ is the innovation associated with the uncertainty variable.

Mertens and Ravn (2014) show the relationship between the structural shocks and reduced-form innovations can be written as

$$\eta_{t,U} = \hat{\tau}\eta_{t,Y} + \hat{\phi}\epsilon_{t,U} \tag{3}$$

$$\eta_{t,Y} = \hat{\omega}\eta_{t,U} + \hat{\rho}\epsilon_{t,Y} \tag{4}$$

where $\hat{\tau}$ is a 1xk vector, $\hat{\phi}$ is a scalar, $\hat{\omega}$ is a 1xk vector, and $\hat{\rho}$ is a kxk vector.

We require an instrument, m_t, that meets two conditions:

1. $E[m_t, \epsilon_{t,U}] \neq 0$ (the relevance condition)

2. $E[m_t, \epsilon_{t,Y}] = 0$ (the exogeneity condition)

That is, an instrument is contemporaneously correlated with structural uncertainty shocks (i.e., an instrument that meets the relevance condition) but contemporaneously uncorrelated with the other structural shocks in the model (i.e., an instrument that also meets the exogeneity condition). In Sections 4.1 and 4.2, we test whether our proposed instrument, the narratively identified uncertainty event series, meets these conditions.

The structural uncertainty shocks can be uncovered as follows:

1. In equation 4, m_t can be used to instrument for the reduced-form VAR uncertainty innovation ($\eta_{t,u}$). The instrument "isolates" movements in the uncertainty innovation unrelated to Y_t, thereby providing an unbiased estimate of $\hat{\omega}$.

[20] The share price index is sourced from OECD (2020), Share prices (indicator). doi: 10.1787/6ad82f42-en [Accessed on 15 June 2020], the inflation data are sourced from Statistics New Zealand's Infoshare, the real exchange rate data are sourced from the Bank for International Settlements (narrow version of the real exchange rate): https://www.bis.org/statistics/eer.htm [accessed 20 November 2019], and the nominal 10-year interest rate is from https://www.rbnz.govt.nz/statistics/b2.

2. The residual from equation 4 can then be used as an instrument in equation 3 for the reduced-form VAR macroeconomic variables' innovations $\eta_{t,Y}$, providing an unbiased estimate of $\hat{\tau}$. Intuitively, the residual, $v_{t,Y}$, can be thought of as the movements of $\eta_{t,Y}$ not related to uncertainty and this thus allows for an unbiased estimation of $\hat{\tau}$.

3. The variance of the residual from equation 3 provides an estimate of $\hat{\phi}$.

In their online appendix Mertens and Ravn (2014) show that the estimates of $\hat{\phi}$, $\hat{\omega}$, and $\hat{\tau}$ are sufficient to identify the column of B(0) relating to the impact of uncertainty shocks in our case (tax shocks, in the case of Mertens & Ravn, 2014). This is sufficient to calculate the impulse responses for the response of the macroeconomic and financial variables to structural uncertainty shocks.

We restrict our estimation sample to 1985Q2 to 2017Q4. Although our instrument goes back to 1975Q4, we restrict the starting date of our estimation period for two reasons. First, before 1984, parliament did not sit in the first quarter of the calendar year; this means no text data are available to construct our instrumental variable for these quarters. Second, the New Zealand dollar was floated in 1985Q1 (a significant regime shift for a small economy). Therefore, it is better to start the estimation period after this event.

4 Our narratively identified instrument

Using the methodology discussed in Section 2.2, we identify 17 quarters after 1985Q2 in which exogenous uncertainty events occurred (see Table 1).[21]

As expected, the period of New Zealand's ideologically based economic reform from 1984Q2 to 1995Q4 contained a high number of narratively identified uncertainty events. This is consistent with the economic reforms being a response to perceived economic performance over a number of years, meaning much of the policy change over the period reflected ideological motives, particularly the idea that more economic decisions needed to be made by the market.

Table 1 shows the cluster of narratively identified uncertainty events in 1986 (1986Q1, 1986Q2, and 1986Q4). There were a number of significant events as part of the reform in this year. April saw the introduction of a new Commerce Act to promote market competition for the benefit of consumers; the prospect of increased competition would have increased uncertainty for those firms that had enjoyed protected (particularly from overseas competition) or monopoly status until then. The 1986 budget contained measures to reduce tax evasion and avoidance, while the fourth quarter of 1986 saw the implementation of a consumption tax (GST). That year also saw the corporatization of a number of providers of key business inputs such as

[21]Given we estimate our proxy SVAR from 1985Q2, we focus this discussion on the uncertainty events after this date.

Table 1: Quarters in which exogenous uncertainty events are narratively identified

Year/quarter	Q1	Q2	Q3	Q4
The economic reform period				
1986	x	x		x
1988	x			
1989	x			
1991			x	x
1992		x		x
First MMP coalition government				
1996			x	
1997			x	x
1998	x			
Post-1999				
2000			x	x
2008	x			
2009	x			

electricity and postal services.

Late 1987 saw the re-election of the Labour government, but internal disagreement about how far the reform should go started to show. This disagreement was particularly between the Prime Minister and Minister of Finance; the latter eventually resigned. Indeed, despite the Minister of Finance's flat tax package already having been agreed by the cabinet, the Prime Minister publicly vetoed it in January 1988. Table 1 shows that we narratively identify an uncertainty event in 1988Q1. Tax also appears to drive the event identified in 1989Q1: increased GST and business tax rates were announced in the quarter.

Despite a change in government in 1990, economic reform continued with vigor. Table 1 shows two uncertainty shocks in 1991 (1991Q3 and 1991Q4). This year saw radically new labor and resource management laws. The resource management law (enacted in 1991Q3) had significant implications for planning processes (in terms of both restrictions and costs), affecting the construction industry and other industries where their activities impact on the environment. The new employment law (enacted in 1991Q2) meant anyone could bargain on behalf of workers, which represented a marked change from the system of employer–employee relations in place for nearly 100 years.

Two events are identified in 1992 (1992Q2 and 1992Q4); these quarters border the September 1992 referendum on the electoral system. While the result of the referendum was non-binding, the government committed to holding a binding referendum if there was a majority vote for change. Around 85 percent of voters voted for change with the majority supporting the MMP system.[22] Additionally, immediately before the first election under MMP in October 1996, an uncertainty event is identified (1996Q3).

The potential change in the way those who write the laws are elected appears to have heightened policy

[22]Source: https://www.parliament.nz/en/get-involved/features/25-years-since-mmp-referendum/ [accessed 20 July 2020].

uncertainty. Why so? The previous first-past-the-post system under which the candidate with the most votes in an electorate won the seat and the party with the most seats governed meant the sole winning party could pursue its policy goals unimpeded. By contrast, under MMP, seats are allocated in broad proportion to the party vote, meaning parties need to form coalitions to form a ruling majority in parliament. Coalitions mean compromise on policy but also brinkmanship to obtain policy concessions. Before and immediately after an election, the voting public is not always clear which policies will last the coalition negotiations. During the coalition arrangement, policy might be revisited or reversed, as minor parties seek to appease their voter base. Further, coalition agreements are imperfect like all contracts; it is therefore not always clear which parties' interests will dominate when the coalition faces new issues.

A number of uncertainty events are identified about halfway through the first term of the first coalition government elected under MMP (1997Q3 to 1998Q1). The first MMP government was formed following an election in which the two major parties received an approximately equal share of the vote, and it was left to a party with 8.5 percent of the vote (New Zealand First) to decide who would govern. It was an unstable arrangement with the Prime Minister replaced a year into the parliament (December 1997), as it was felt that he had given New Zealand First too much influence. The coalition ended halfway through the three-year term of the parliament when the new Prime Minister sacked the leader of New Zealand First from the cabinet (August 1998). The uncertainty events we identify in this period (1997Q3–1998Q1) appear to reflect the lead-up and aftermath of the change in Prime Minister. This is unsurprising, as such a change typically alters the direction and focus of policy.

In late 1999, the newly elected center-left Labour-led coalition replaced the perceived more business-friendly National-led coalition. We identify two uncertainty events in the final two quarters of 2000, reflecting changes to labor laws. August 2000 saw the introduction of new employment legalization to, according to Rasmussen, Bray, and Stewart (2019, p. 66), "contain unfair use of employer power" and overcome the "union hostile elements" of the previous employment legislation. December 2000 saw the announcement of significant increases in the minimum wage, with nearly 70 percent rises for those aged 18 and 19 (see Hyslop & Stillman, 2007).

Finally, we narratively identify uncertainty events in 2008Q1 and 2009Q1. The fourth quarter of 2008 saw a change in government as the center-right National government took power. The uncertainty event immediately after the election may reflect nervousness about new coalition arrangements, particularly as two of the coalition partners—the ACT and Maori parties—were new to government. Alternatively, it could reflect uncertainty about the government's response to the global financial crisis.

The narratively identified uncertainty shock in 2008Q1 warrants discussion. It may reflect uncertainty about the policy response to the initial financial shock caused by the downturn in the US subprime mortgage market in the previous year. Importantly, our empirical setup does not require the instrument, which is the narratively identified uncertainty event series, to be orthogonal to the history of the other variables in the model (Mertens & Ravn, 2013; p. 1217) or as J. H. Stock and Watson (2018, pg. 919) put it the instrument does not have to be uncorrelated with past and future shocks. That is, it allows for uncertainty events to reflect uncertainty about government policy in response to a macroeconomic or financial structural shock, as long as the policy response is delayed and given the typical legislative process, most are.

Another possibility is that the identification of 2008Q1 as an exogenous uncertainty event reflects measurement error. After all, Bear Sterns was bailed out on March 17, 2008 and the Federal Reserve cut interest rates by 75 basis points a day later. The Hansard volumes that relate to this quarter ran from February 12, 2008 to March 13, 2008 (volume 646) and from March 18, 2008 to April 17, 2008 (volume 647). As noted earlier, when a volume spans two quarters as volume 647 does, it is difficult to attribute an uncertainty mention to a quarter and this is a source of measurement error. Given the concurrence of the dates spanned by the problematic volume 647 and timing (mid-March) of the Bear Sterns event and interest rate cut, 2008Q1 might be incorrectly classified as an uncertainty shock. However, this illustrates the utility of the approach, as Mertens and Ravn (2013) (p. 1217) note that the instrument does not need to correlate perfectly with the structural uncertainty shocks; some measurement error is allowed.

4.1 Instrument exogeneity

The exogeneity assumption, namely, that our narratively identified measure of uncertainty events/shocks (i.e., our instrument) is contemporaneously uncorrelated with the other structural shocks in the model, is not directly testable, as the true structural shocks are unobserved. Constructing our instrument by including only the quarters in which economy-related uncertainty is not discussed in parliament, we hope to meet the exogeneity assumption by construction.

Piffer and Podstawski (2018) test the exogeneity of their instruments by regressing them against identified oil, monetary, and fiscal policy shocks as well as financial and news shocks from other studies. As such shock series are difficult to source for New Zealand for the period of our study, we adopt a hybrid approach in which regress our instrument on the structural shocks from the estimated recursive SVAR (see equation 5):

$$\epsilon_{R,t,i} = \beta_1 + \beta_2 * m_t + \xi_t \tag{5}$$

where m_t is our instrument and $\epsilon_{R,t,i}$ is the structural shock i from the recursive SVAR.

The recursive SVAR is ordered: the uncertainty index, stock prices, output gap, inflation, interest rate, and real exchange rate; identification is achieved via Cholesky decomposition and the model is estimated with four lags. Table 2 shows that there are no statistically significant relationships between the non-uncertainty structural shocks and our instrument when significance is assessed at either the 5 or the 10 percent level.

As the studies by Bloom (2009) and Carriero et al. (2015) (the latter use the uncertainty series of Bloom, 2009 as an instrument) have been well cited, we compare and contrast our results with those we would have obtained if we had followed the Bloom, 2009 methodology (i.e., if we had equated peaks in the uncertainty index with uncertainty shocks rather than relying on the narrative to identify exogeneity). Following Bloom (2009), we take our uncertainty index (see Section 2.2), detrend it using the Hodrick–Prescott filter ($\lambda =$ 1,600), and then identify quarters as having uncertainty shocks when the detrended series is 1.65 standard deviations above its mean.[23] The "Bloom method" part of Table 2 shows that the instrument based on this method also satisfies the exogeneity condition.

Table 2: Assessing the exogeneity of the instrument

	Dependent variable:				
	Recursive SVAR structural shock				
	Stock price	Output	Inflation	Interest rate	RER
Instrument					
β_2 Estimate	−2.33	−0.14	0.09	-0.13	−0.10
p-value	0.17	0.12	0.65	0.20	0.89
Bloom method					
β_2 Estimate	−3.50	0.01	−0.23	-0.01	−2.20
p-value	0.22	0.94	0.26	0.94	0.14

Note: RER denotes the real exchange rate
P-values are based on heteroskedasticity-robust standard errors.

Our test is not a conclusive test of instrument exogeneity because we regress our instrument against the structural shocks identified using the recursive restrictions we criticized in the Introduction. We assume, however, that even if the identified structural shocks are not the true shocks, they are correlated with the true shocks to some degree.

4.2 Instrument relevance

We conduct two tests of instrument relevance. The first begins by calculating the heteroskedasticity-robust F-statistic from the regression of the reduced-form VAR uncertainty residual/innovation on the instrument. Rüth (2020) notes that instrument relevance can be assessed by testing the null hypothesis that the in-

[23] Bloom (2009) uses the monthly VXO as his uncertainty index; hence, he applies a different lambda.

Table 3: Assessing instrument relevance

Test statistic	Instrument	Bloom method
Wald p-value	0.007	0.000
Lunsford	8.15	7.56

Note: Wald p-value are based on heteroskedasticity consistent standard errors. The Lunsford test uses HAC standard errors owing to the low values of the Durbin–Watson statistic in this equation.

strument is irrelevant using the Wald statistic from the above regression. Both our instrument and the Bloom-based instrument reject the null hypothesis of instrument irrelevance (see the Wald p-values in Table 2).

Another way to assess instrument relevance is to use the rule of thumb of J. Stock and Yogo (2005): the heteroskedasticity-robust F-statistic from the above regression is above 10, which "assures approximately valid coverage of confidence intervals" (Rüth, 2020, p. 6). However, Lunsford (2015, p. 3) argues that the "weak IV rule of thumb that requires an F-statistic to be greater than 10 will lead to tests that are mis-sized." He proposes regressing the instrument on the relevant reduced-form VAR residual and provides critical values that depend on the VAR dimension and bias tolerance. Using a bias tolerance of 10 percent (as Lunsford, 2015 does), the 95 percent critical value for the F-statistic is 7.81. The last row of Table 3 shows that the F-statistic associated with our instruments exceeds the critical value; however, the Bloom-based instrument fails this test.[24] Taken together, this suggests that our instrument does not suffer from the weak instrument problem. The evidence is more mixed, however, for the instrument-based on the Bloom method.

5 Results

We first estimate our proxy SVAR using the narrative-based instrument series. Figure 5 plots the impulse response for a one-unit shock to our uncertainty index (red line). Two (90 percent) confidence sets are also shown, both calculated following Montiel-Olea et al. (2018). The first is the delta-method confidence set based on the plug-in estimator (area bounded by the black dotted lines) with heteroskedascity robust standard errors and the second is the weak instrument robust confident set (blue shaded area).[25] Montiel-Olea et al. (2018) note that the weak instrument-robust confident set being wider than the delta-method confidence set based on the plug-in estimator provides evidence of a weak instrument. As Figure 5 shows,

[24] Our tests are based on HAC standard errors. The Bloom-based instrument does pass if Huber-White-Hinkley standard errors are used; however, an autocorrelation allowance appears necessary according to the Durbin–Watson statistic.

[25] Based on 10,000 bootstrap replications. The weak instrument robust confidence set of Montiel-Olea et al. (2018) is not subject to the criticism of those based on wild bootstrap procedures leveled by Brüggemann, Jentsch, and Trenkler (2016)

we do not generally observe this for our instrument, indicating that it is not weak and thereby confirming our assessment in Section 4.1.

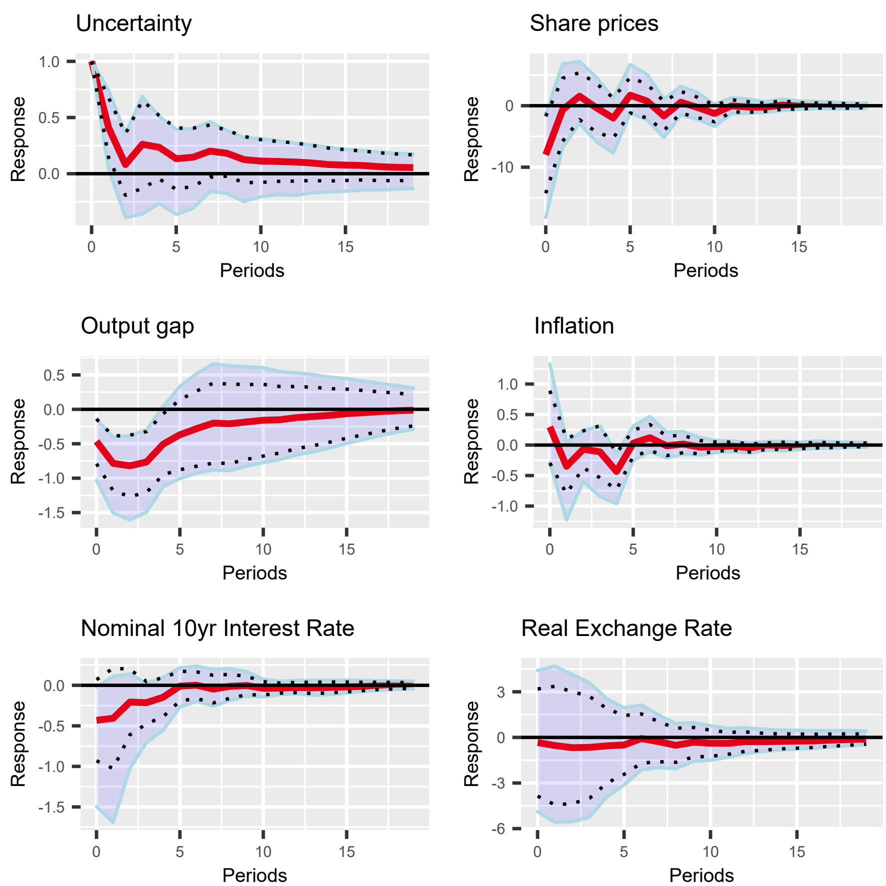


Figure 5: Responses of the variables to a one-unit shock to uncertainty: Proxy SVAR using the narrative-based instrument

Uncertainty shocks have a large negative impact on output and share prices. The fall in output is consistent with declines in investment and consumption. A weaker economy also leads to weaker (non-tradables) inflation (the impact on inflation from uncertainty is statistically different from zero according to both confidence sets in the fourth quarter afer the initial shock), as there is more spare capacity. Although nominal long-term interest rates fall, the impact on interest rates from uncertainty is not statistically different from zero at a 90 per cent level of confidence.

We first compare our results with those from a recursively identified SVAR (see Figure 6).[26] The solid red line in each graph in Figure 6 is the impulse response from our proxy SVAR. The black dot-dash line is the equivalent impulse response from the recursively identified SVAR. Comparing the recursive and proxy SVAR impulse responses in each graph, the impact of attenuation bias owing to improper identification of

[26]The recursive SVAR setup is discussed in Section 4.2.

uncertainty shocks in the recursive SVAR becomes obvious. With the exception of the real exchange rate, the proxy SVAR shows much more pronounced impacts from uncertainty shocks on macroeconomic and financial market variables. Our general finding that the proxy SVAR reduces attenuation bias is consistent with the findings of Carriero et al. (2015) and Kim (2019). The proxy SVAR estimates that a one-unit uncertainty shock has a peak impact of a 0.8 percentage point reduction in the output gap, whereas the recursive SVAR estimates a peak 0.3 percentage point reduction. This 0.3 percentage point reduction is in line with other estimates in New Zealand using a recursive setup. For example, Greig, Rice, Vehbi, and Wong (2018) find a peak impact of between -0.25 and -0.35 percentage points on the output gap three to four quarters after the initial one-unit shock to domestic uncertainty measures.[27]

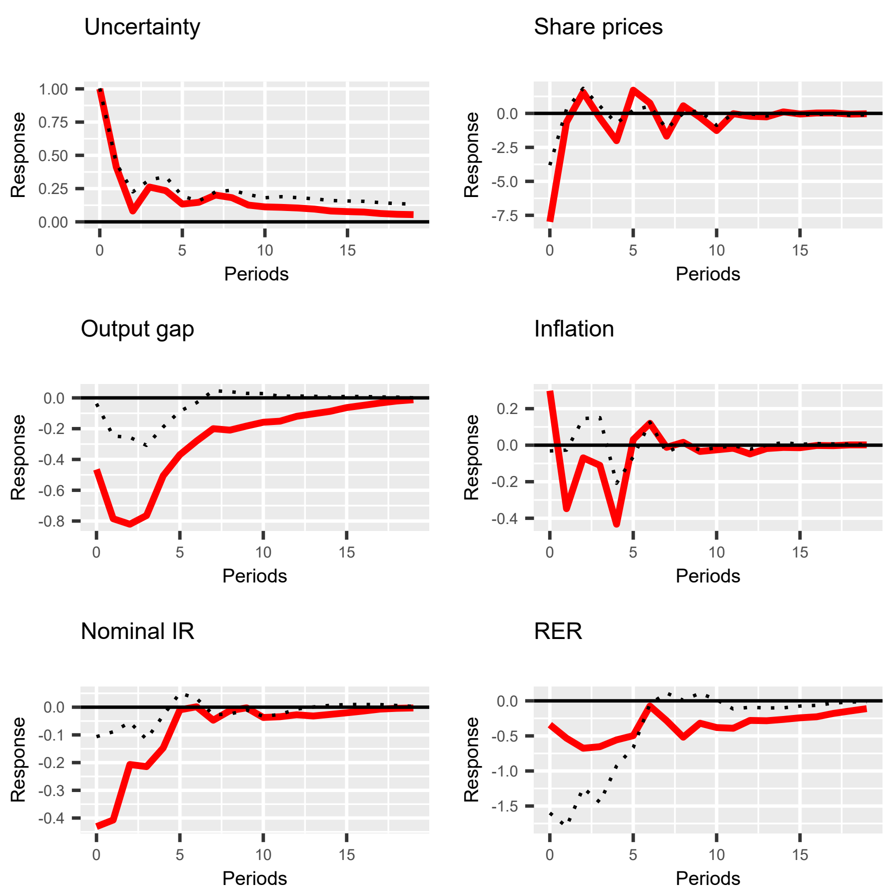


Figure 6: Responses of the variables to a one-unit shock to uncertainty: Comparison of the proxy and recursive SVARs

Note: Proxy SVAR impulse responses are the red line. Recursively-identified SVAR impulse responses are the dotted line.

[27]They find slightly larger impacts from foreign uncertainty shocks. Our results are directly comparable to theirs, as we both normalize the uncertainty series in terms of standard deviations from the mean. Tran, Vehbi, and Wong (2019), using the data rich approach of Jurado, Ludvigson, and Ng (2015), find similar impacts on the output gap as Greig et al. (2018).

The impulse response from the recursive SVAR shows that the impact of uncertainty on the real exchange rate is statistically significant (not shown for readability in figure 6). This is not the case in the proxy SVAR. Given that inflation falls more in the proxy SVAR than in the recursive SVAR, the nominal exchange rate, a financial market variable, must be causing the different results for the real exchange rate in the two models.

Piffer and Podstawski (2018) find that news shocks have larger effects than uncertainty shocks on financial market variables given the fast pricing of news. It makes sense that the New Zealand dollar would be sensitive to news, as it is the 10th most traded currency in the world, despite New Zealand being a relatively small economy by global standards.[28] The differences between the proxy and recursive SVARs suggest that we removed the confounding effects of news shocks when we constructed our instrument for our proxy SVAR. Recall in Section 2.2 we constructed a news variable and in constructing our instrument, we omitted any uncertainty events where the news variable dropped sharply in a quarter. By contrast, in the recursive SVAR, the identified structural uncertainty shocks are confounded by the influence of news shocks. The interpretation of the uncertainty shocks identified in the proxy SVAR as purer uncertainty shocks than those identified in the recursive SVAR is supported by the fact that uncertainty shocks have larger impacts on real and nominal variables in the proxy SVAR, which is consistent with Piffer and Podstawski (2018).

The only challenge to our assertion is that we have successfully isolated uncertainty shocks from news shocks with respect to the other financial market variable: share prices. Piffer and Podstawski (2018) find that the stock market falls by more in response to news shocks than uncertainty shocks; we do not. In the case of share prices, the reduction in attenuation bias in the proxy SVAR, which leads to larger estimated negative impacts on uncertainty in share prices, might dominate the smaller estimated negative impacts one would expect if news shocks are better controlled for. Alternatively, the share market might be more sensitive to policy uncertainty than general uncertainty.

A second comparison is made with a proxy SVAR that uses a Bloom (2009)-type instrument, namely, an instrument that equates exogeneity with high uncertainty values. Figure 7 shows the impulse responses for the proxy SVAR with the Bloom-based instrument.

The proxy SVAR with the Bloom-based instrument finds a statistically significant negative impact on the real exchange rate. Apart from that, however, uncertainty shocks do not appear to have statistically significant effects on the macroeconomic and financial variables in our model at 90 per cent confidence sets. This suggests, at a minimum, the Bloom-based approach is better at identifying uncertainty shocks when the data are at a higher frequency or constructed from financial market data. Alternatively, narrative-based approaches may be better at isolating exogenous uncertainty shocks.

[28]https://www.rbnz.govt.nz/news/2019/09/nzd-remains-10th-most-traded-currency [accessed 20 July 2020].

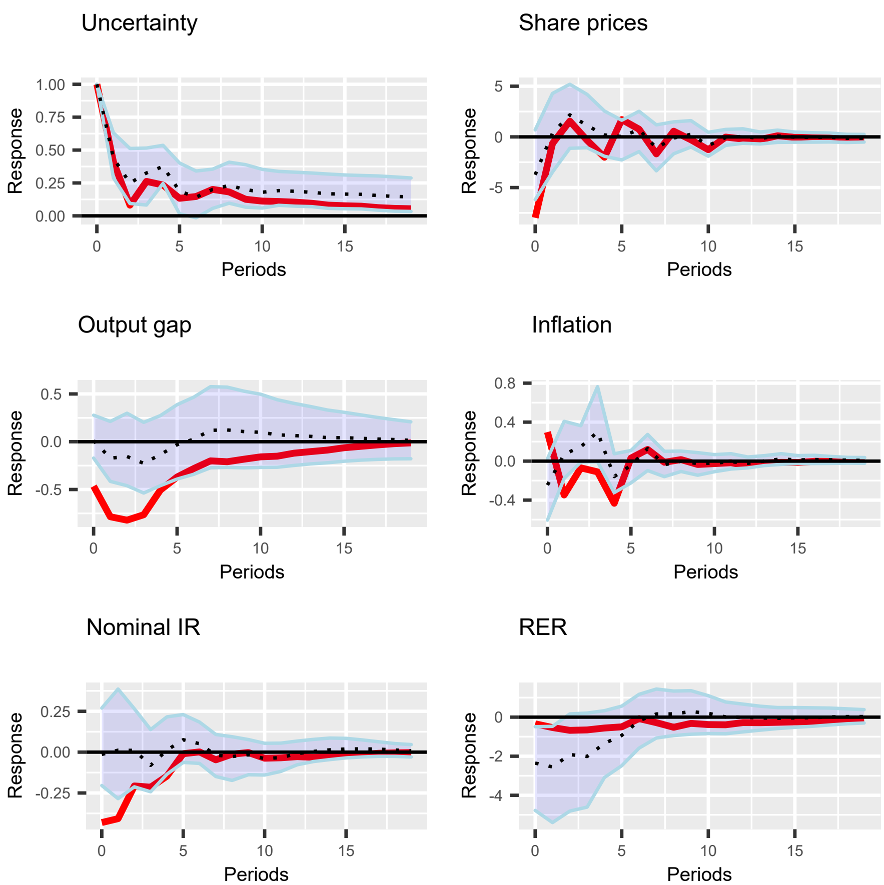


Figure 7: Responses of the variables to a one-unit shock to uncertainty: Proxy SVAR with the Bloom-based instrument

Note: Impulse responses from the Proxy SVAR identified via the narrative instrument are the red line. Impulse responses from the Proxy SVAR identified via the Bloom-type instrument are the dotted line. Shaded area is the 90 per cent weak-instrument robust confidence sets from Proxy SVAR identified via the Bloom-type instrument

Table 4: Forecast error variance decomposition for four quarters ahead

Variable	Recursive	Proxy: Our Instrument	Proxy: Bloom Instrument
Share price	7	15	7
Output gap	9	44	4
Inflation	2	6	8
Interest rate	2	14	0
Real exchange rate	8	1	16

5.1 Forecast error decomposition

Table 4 shows the contribution of uncertainty shocks to the four quarters ahead forecast error variance decomposition. We find that the uncertainty shocks identified using the proxy SVAR and our narrative-based instrument explain a much larger percentage of the variation in output, the share price, and interest rates than the shocks identified using the recursive SVAR and Proxy SVAR identified by the Bloom-based instrument. For example, the uncertainty shocks in the proxy SVAR with our narratively identified instrument explain 44 percent of the variance in the output gap compared with around 9 percent in the proxy SVAR with the Bloom-based instrument and recursive SVAR. The 44 per cent of the variance in the output gap explained by uncertainty may seem high, but it needs to remembered the first half of the sample contained significant economic institution and electoral reform. The uncertainty associated with these reforms is likely to significantly impact on output.

6 Conclusion

This study showed using narrative methods on text data to identify exogenous changes in a variable, such as Romer and Romer (2010) demonstrated with tax changes, can be extended to identify exogenous changes in a variable when the narrative source is unstructured and lengthy such as our source, the parliamentary record. Moreover, although any narrative identification procedure can result in measurement error, the proxy SVAR method deals with such error, which means that the two approaches are ideal complements.

Relative to an estimation strategy based on recursively identifying the SVAR or constructing instruments for uncertainty shocks based on equating the peaks in uncertainty with exogenous uncertainty events (as Carriero et al., 2015 do with the uncertainty series of Bloom, 2009), we find that uncertainty shocks have a larger impact on macroeconomic and financial variables (apart from the real exchange rate) when the shocks are narratively-identified. This reflects the reduction in attenuation bias owing to the better identification of uncertainty shocks using our narrative method.

Given we find policy uncertainty can have large costs on the economy. Policy-makers need to announce and implement policy in such a way to minimise such uncertainty; this will be particularly important during the present policy response to, and eventual recovery from, the Covid-19 pandemic.

This study has some limitations. Although we suggested that news and uncertainty shocks have different effects on the exchange rate, our adjustment to remove the effects of news from the uncertainty shock is ad hoc. Further work, perhaps using the set-identified proxy SVAR of Piffer and Podstawski (2018), could thus investigate our conclusion that news shocks rather than uncertainty shocks drive the exchange rate in a more comprehensive manner. Secondly, the application of natural language techniques to problems in economics is still in its infancy. Our procedure to create the instrument is relatively simple and based on a well-known natural language technique, latent Dirichlet allocation. No doubt more sophisticated techniques can be applied to creating instruments, as can the idea of Ter Ellen et al. (2019) of comparing texts from different sources to identify surprises through differences in the narratives.

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Appendix

Keywords associated with firm-related policy topics

Table 5: Keywords associated with firm-related policy topics

Specific topic label	Word 1	Word 2	Word 3
Agriculture	food	forest	farmers
Industry	industry	review	law
Electricity	electricity	companies	price
ACC	accident_compensation	job	job
Regulations	regulations	law	review_committee
Dairy Industry	dairy	milk	industry
Research and Development	research	science	business_community
Fisheries	fisheries	environmental	protection
Legislation	regulations	provision	bill
Energy	power	water	energy
Tax	tax	income	business
Agriculture	dairy_industry	farming	agriculture
Emissions trading	emissions_trading	price	kyoto
Transport	transport	green	charges
Financial	insurance	financial	auditor
Labour	employment	workers	relations
Energy (hydrocarbons)	energy	oil	gas
Business	investment	australia	rules
Communication sector	commerce	communications	contract
Compliance costs	compliance_costs	regulatory_impact	

Table 6: Firm-specific policy and associated words

LDA

The probability that a word, w, in a given document, d, is associated with topic k is given by[29]

$$\frac{n_{d,k} + \alpha_k}{\sum_i^k n_{d,i} + \alpha_i} \frac{v_{k,w_{d,n}} + \beta_{w_{d,n}}}{\sum_i v_{k,i} + \beta_i}$$

Starting with the left-hand side term in the equation, which seeks to provide a higher probability to topics prevalent in document d, $n_{d,k}$ is the words in document d associated with topic k, which is normalized by the number of words in the document. The α term is a Dirichlet parameter and this allows topics that have not appeared in the document, d, to have a non-zero probability.

[29]This explanation draws on the Video Lecture from the course INST 414: Advanced Data Science at UMD's iSchool by Jordan Boyd-Graber. Available at https://www.youtube.com/watch?v=u7l5hhmdc0M.

The second term in the equation provides the word a higher probability of being associated with a topic if it is associated with that topic in other documents. $v_{k,w_{d,n}}$ is the number of times the word is associated with topic k in other documents normalized by how many times the word is assigned to any topic. The β term is a second Dirichlet parameter and this allows words that have not been associated with the topic previously to have a non-zero probability.

With the conditional probability distribution defined for the word across the K topics, a new topic for the word in document d is sampled (and accepted if the associated probability is higher than a random draw from a multinominal distribution). The process then iterates over words and documents.