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Time-Series Topic Analysis Using Singular Spectrum Transformation for Detecting Political Business Cycles

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ABSTRACT

Herein, we present a novel topic variation detection method that combines a topic extraction method and a change point detection method. It extracts topics from time-series text data as the feature of each time and detects change points from the changing patterns of the extracted topics. We applied this method to analyze the valuable albeit underutilized text data that contained the Japanese Prime Minister's (PM's) detailed daily activities of over 32 years. The proposed method and data provide novel insights into the empirical analyses of political business cycles, which is a classical issue in economics and political science. For instance, as our approach enables us to directly observe and analyze the PM's actions, it can overcome empirical challenges encountered by previous researchers owing to the unobservability of the PM's behavior. Our empirical observations are primarily consistent with recent theoretical developments regarding this topic. Despite limitations, by employing a completely novel method and data, our approach enhances our understanding and provides new insights into this classic issue.

KEYWORDS

Topic variation detection; Political business cycles; Latent Dirichlet allocation; Singular spectrum transformation; Japanese politics

1 Introduction

An increasing number of studies in political science and economics are adopting advanced text mining methods to analyze large-scale text datasets. Many of them have successfully provided novel insights into classical issues in those fields. This study aims to contribute in a similar scope. By extending our earlier paper (Kato et al. [15]), We herein propose a new topic variation detection method and apply it to analyze a valuable albeit underutilized text dataset containing the Japanese Prime Minister's (PM's) detailed daily schedule of over 32 years. We aim to enhance our understanding of the empirical analysis of the political business cycle (PBC), which is a classic issue that economists and political scientists have been addressing for over four decades (Dubois [5]).

Research on the PBC was initiated with the pioneering work of William Nordhaus [27]. The PBC theory posits that an incumbent government will stimulate an economy immediately before an election to increase its chances of being reelected. Earlier theoretical and empirical studies on the PBC, including that of Nordhaus, focused on presidential democracies, where the date of election is exogenously fixed. However, the majority of the present democratic states have a parliamentary system, in which the election date is endogenously determined by the PM's decision to dissolve the legislature and call for an early election (Shleiter & Travits [33]). In parliamentary democracies, the PBC is a more complex issue. To increase his chances of winning an election, the PM can either "manipulate" the economy prior to an election, as the standard PBC theory indicates (*manipulative hypothesis*), or call an early election to "surf" on favorable economic conditions (*surfing hypothesis*) (Inoguchi [9]; Kayser [16]).

Past empirical analyses of the PBC with endogenous election timing (EET) that examined whether the manipulative or surfing hypothesis is valid have encountered several empirical challenges. The core of the challenges was the unobservability of the PM's behavior. For example, even when an apparent correlation exists between election timing and favorable economic conditions (e.g., low unemployment, high income growth), researchers encounter challenges in determining whether the PM has manipulated or surfed.

In this study, we used a novel dataset and method to overcome the empirical challenges encountered by previous researchers. The primary dataset we used in this study was a text dataset that tracked the Japanese PM's schedule—where he went and whom he met—365 days a year for over 32 years. Known as *shushō dōsei* [the PM's movement] in Japanese, it is compiled by reporters who are officially permitted to record the PM's detailed daily activities (Nippon Hōsō Kyōkai

[26]). This dataset provides researchers a rare opportunity to directly and systematically observe the actions of the head of the Japanese government, who is generally the concurrent leader of the ruling party. However, its use has been limited to sporadic references in qualitative research, owing to inadequate advanced research into the Japanese politics by utilizing textual data. This study is the first to extensively apply machine learning techniques to this highly valuable dataset.

We present a new topic variation detection method to analyze the *shushō dōsei* dataset. The new method combines a topic extraction method with a change point detection method. This enables us to extract topics from time-series text data as a feature of time and detect change points from the patterns of the topics simultaneously.

We used the method to empirically examine whether the PM has manipulated or surfed in past elections. This approach enabled us to overcome challenges encountered in past empirical studies regarding the PBC with EET because it could directly be used to observe and analyze the actions of the PM. Furthermore, it enabled us to empirically assess the PM's complex and strategic decision making implied by recent theoretical arguments regarding this topic.

The main contributions of this study are as follows:

- We proposed a new topic variation detection method for a time-series text data. Our proposed method comprises a feature extraction represented as topics and a change point detection focusing on the topic patterns.
- Using our proposed method, we empirically examined whether PBCs occur in Japan by analyzing time-series text data that recorded the Japanese PM's daily activities. This approach could be used to examine the PM's actions directly and enabled us to overcome empirical challenges encountered in past studies.

The remainder of this paper is organized as follows: In Section 2, we present a problem definition of the PBCs in parliamentary democracies. An overview of related studies is presented in Section 3. In Section 4, we present our method—a topic variation detection method for time-series text data. In Section 5, we apply our method to the *shushō dōsei* dataset. In Section 6, we empirically assess if and how PBC occurs in Japan. We conclude in Section 7 by indicating the scope for future research.

2 Problem Definition

Past empirical analyses of the PBC with EET to examine whether the PM has manipulated or surfed are accompanied by several problems. The first is a causal relation problem. Notwithstanding a coincidence between the election timing and favorable economic conditions for the incumbent, it is challenging for researchers to determine whether the economic conditions have motivated the PM to call for an early election (surfing hypothesis) or whether the PM has manipulated the economy to realize favorable conditions at the time of election (manipulative hypothesis) (Rogoff & Sibelt [31]).

The second empirical problem is a measurement problem. How can one measure the PM's manipulation? In earlier studies on the PBC, researchers used macroeconomic outcomes, such as the Gross Domestic Product (GDP) growth, unemployment, and inflation rates as proxies for manipulation. However, it is uncertain whether the PM can control similar macroeconomic outcomes using manipulation tools at his disposal. More recent studies measure manipulation through use of economic policy tools, such as taxes (Yoo [18]) and government spending (Rogoff & Sibelt [31]; Kohno & Nishizawa [19]). Although the PM has more direct influence over similar policy tools than over macroeconomic outcomes, it is still uncertain whether he has complete control over them. Various studies regarding policy processes, including those of the Japanese politics (e.g., Johnson [13], Mabuchi [21]), revealed that the PM's action and actual use of those policy tools are not directly linked. For example, bureaucratic autonomy should severely hinder the PM's influence over those tools. Therefore, there should exist cases when the PM attempts to manipulate but fails to actually activate macroeconomic tools or influence macroeconomic outcomes. However, past empirical studies could not identify such cases.

The root cause of these empirical problems arises from the challenge of directly observing the PM's actions. As indicated in Figure 1, lack of data that directly tracks the PM's actions motivated previous researchers to gather political and economic data near election times and infer the PM's actions—whether he has manipulated or surfed. The method and data of this study, as indicated in Figure 1, is advantageous over those of previous studies in terms of their capability to directly track and analyze the actions of the PM who is the primary decision maker near election time. It is a novel approach to a classic issue in political science and economics, which can overcome a few serious empirical problems encountered in past empirical studies.

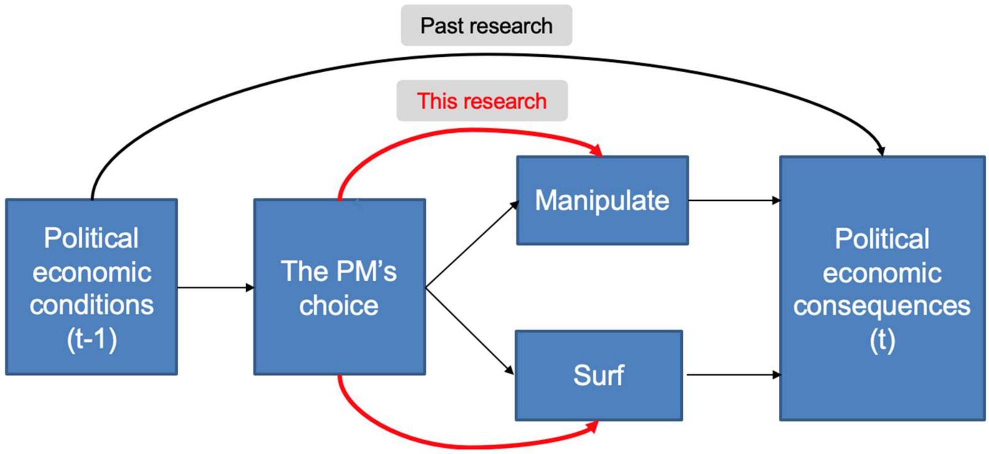


Figure 1: Diagram of previous and the current studies

3 Related studies

3.1 Related Studies on PBC

Previous empirical studies of the PBC with EET have attempted to investigate whether the manipulative or surfing hypothesis is valid in parliamentary democracies, such as those in Japan (Ito & Park [10]; Ito [11]; Kohno & Nishizawa [19]; Cargill & Hutchison [2]), the UK (Smith [34]; Smith [35]), and India (Chowdhury [1]). They used macroeconomic indicators and policy tools as proxies for the PM's action and analyzed the relations between the proxies and electoral timing. Although the results are varied, they primarily support the surfing hypothesis. That is, a typical PBC in line with the manipulation hypothesis is often not observed in parliamentary democracies.[1]

On the theoretical side, a limited number of formal analyses have been conducted regarding this topic. Recent theoretical analyses such as those by Kayser [16] modeled the PBC with EET as a dynamic optimization problem of the PM and examined when the PM has manipulated or surfed. In contrast to previous empirical studies that implicitly

[1] A few empirical studies have indicated that both manipulative and surfing hypotheses can co-exist (e.g., Cargill & Hutchinson [2]).

assumed that the PM has *always* manipulates *or always* surfed in every election, recent theoretical developments illustrate that the PM strategically opts to manipulate or surf depending on the political or economic conditions encountered (Saito [32]; Kato & Inui [14]).

This study is the first attempt to analyze a text dataset that directly observes the PM's behavior. It overcomes a few of the empirical problems that encountered in previous studies. Furthermore, it can examine, in contrast to previous studies that naively assumed that the PM has always manipulated or always surfed, when and why the PM has manipulated or surfed in each election.

3.2 Related Studies on Topic Variation Detection

Text segmentation segments texts into topically related units (e.g., Hearst [7], Sun et al. [36], Eisenstein [6], Riedl & Biemann [30], and Jameel & Lam [12]). The method regards a text as a sequence of subtopics, and when it detects a change in the subtopic within a text, it creates a new segment. Therefore, text segmentation can be considered as a detection method to determine where segments should be placed within each text. Meanwhile, our method focuses on each subtopic and detects a change in pattern in the appearance of each subtopic.

Studies on topic bursts are related to the method introduced herein. Mane & Börner [22] used Kleinberg's burst detection algorithm to identify topics that experienced an abrupt increase in usage. They named such abrupt increases as "topic bursts." Their method can be considered as an approach for the anomaly detection of topic usage, focusing primarily on when the topic share increases. By contrast, our method seeks to detect not only the increase in topic share, but also patterns in the appearance of a topic.

4 Topic Variation Detection Method for Time-Series Text Data

In this section, we propose a new method—topic variation detection (TVD) for time-series text data. We applied it in our analysis in this study. This method detects changes in patterns of contents in text data delivered in time series. It first extracts topics from time-series text data as features of each time using latent Dirichlet allocation (LDA). Subsequently, it detects a change point where patterns of the extracted features change using singular spectrum transformation (SST). TVD enables us to detect changes in the semantic patterns of topics in time-series text data.

We first describe the fundamental concept of TVD in Section 4.1. In Section 4.2, we briefly explain LDA and SST, i.e., the two methods we used for TVD.

4.1 Basic Concept

Our new method—TVD—combines LDA (Blei, Ng, & Jordan [3]) to extract topics from text data and SST (Ide & Inoue [8]) to detect changes in topic patterns. It seeks to detect change points in the pattern of events written in text data delivered in a time series, such as daily reports. A simple method to achieve this is to tabulate the frequency of occurrence of certain keywords in a time series. This approach is effective when text data delivered in a time series consistently expresses similar contents with similar words. However, this is not applicable when the text data delivered in a time series include various keywords and content. Another challenge is to visually verify word frequency oscillations on a graph. By combining LDA and SST, TVD enables us to more systematically and clearly detect patterns of events from time series text data with varieties of keywords and contents.

4.2 LDA and SST

In this section, we briefly summarize LDA and SST, which we combined in the TVD method.

4.2.1 LDA.

LDA (Blei, Ng, & Jordan [3]) is a topic model that extracts topics from a document set. In an LDA, documents can be represented as combinations of latent topics, where each topic is characterized by the distribution of words. LDA assumes that documents are generated in the process of selecting topics according to the topic distribution within a document and selecting keywords according to the word distribution within a topic. Let N be the number of words in a document. The variable names are defined as follows: α is the K-th dimensional hyperparameter of the topic prior to distribution, β is the parameter of the word distribution, θ is the topic distribution, z is the topic set, and w is the word set. When α and β are specified, the mixed distribution θ of topics, topic set z, and word set w are represented as follows:

$$p(\theta, \boldsymbol{z}, \boldsymbol{w} | \alpha, \beta) = p(\theta|\alpha) \prod_{n=1}^{N} p(z_n|\theta) p(w_n|z_n, \beta).$$

Here, θ and β are potential parameters. When the document is observed, one can estimate the topic(s) the document by estimating θ and β.

4.2.2 SST.

SST (Idé & Inoue [8]) detects change point(s) by calculating the changing point score $z(t)$ in each time. SST can be considered as a transformation from a time series T to a new time-series T_c.

For a more formal description, first, let the time series data $S = \{x(1), x(2), x(3)...\}$. SST is realized using the following procedure:

1. w past data for time t are prepared and vector $\boldsymbol{s}(t-1)$ is expressed by arranging them. Therefore, $\boldsymbol{s}(t-1) = \left(x(t-w), \ldots x(t-1)\right)^T$. These column vectors are arranged to form a matrix H_t. Here, $H_t = [\boldsymbol{s}(t-n), \ldots, \boldsymbol{s}(t-2), \boldsymbol{s}(t-1)]$.
2. Similarly, matrix H_{t+L} is formed by shifting the time series by L toward the future. $H_{t+L} = [\boldsymbol{s}(t+L+w-1), \ldots, \boldsymbol{s}(t+L+w+m-2), \boldsymbol{s}(t+L+w+m-1)]$. The SVD for each matrix H_t and H_{t+L} is calculated to determine the left singular vector.
3. The changing point score $z(t)$ in [8] is calculated, which represents the degree of difference between the two left singular vectors calculated in step 2.
4. The changing point score $z(t)$ of each time is calculated by the sliding the time and executing steps 1–3. A point with a high value of $z(t)$ is regarded as a change point.

5 Applying the Topic Variation Detection Model

In this section, we first introduce the primary dataset we used in this study, *shushō dōsei*. Subsequently, we apply TVD to the data.

5.1 Data

The primary dataset to which we applied the TVD method for analysis in this study was time-series text data called *shushō dōsei*. It tracks the Japanese PM's schedule daily (see Figure 2 for a sample). Whereas the list was launched around 1970, this paper focuses on the period from July 1, 1986 to November 30, 2018, for which electronic data from the Nihon Keizai Shimbun (Nikkei) is currently available. This valuable dataset has been severely underutilized because few studies regarding Japanese politics have employed advanced machine learning techniques.

首相官邸 27日

▽9時32分 公邸から官邸。▽10時7分 河野外相、谷内国家安全保障局長、外務省の秋葉次官、森外務審議官、正木欧州局長。▽11時12分 国家安全保障局長、槌道防衛省防衛政策局長。▽12時2分 山口那津男公明党代表。▽15時26分 二階幹事長、林幹事長代理。▽16時31分 兵庫県養父市主催の国家戦略特区シンポジウム向けのビデオメッセージ収録。55分 渡辺復興相、復興庁の加藤次官、末宗統括官。▽17時18分 国家安全保障会議の4大臣会合。37分 麻生財務相。▽18時3分 高橋防衛次官。41分 公邸。茂木友三郎キッコーマン名誉会長、中原伸之元日銀審議委員ら財界人と会食。▽21時2分 全員出る。宿泊。

Figure 2: Prime Minister's schedule

(source: Shushō kantei in *Nihon Keizai Shimbun*, 2019, February 27.)

Shushō dōsei is a highly succinct summary (frequently missing verbs) of the PM's activities that accurately lists the names and affiliations of those he meets and the places he visits. For example, the entry for January 21, 2009 reads as follows: "8:31 Upper House Budget Committee. Brief exchange later with committee's Chief Director Iwanaga." Nouns are the most important elements of these entries, and "latent semantic features" can be discerned from the co-occurrence of certain names and topics. This study analyzes similar occurrences by grouping the entries into documents encompassing a period of seven days each.

Because the PM's schedule is extremely tight, the daily allocation of his time should *ex ante* reveal his strategic priorities. The right to dissolve the Diet is an exclusive prerogative of the PM, and selecting the election date may be "the most important single decision" by the PM (Newton [25]). We thus assume that indications for crucial decisions, such as pre-electoral macroeconomic stimulations closely related to the call of early elections, can be detected by analyzing the PM's daily schedule. Hence, an analysis of the PM's daily schedule offers researchers an invaluable opportunity to directly observe the PM's manipulating or surfing behavior while declaring an early election.

5.2 Realization of Topic Variation Detection

We applied TVD to the *shushō dōsei* dataset. Because days (e.g., holidays) when no political action is undertaken exist, we organized one week (seven days) of text data as a set of data and let $D = \{d_1, d_2, d_3, \ldots, d_n\}$ be a time-series of textual documents. Each document d_i comprises the PM's seven-day schedule, which appears in *shushō dōsei*.

By applying TVD to *shushō dōsei*, we aim to detect change points of the PM's behavioral patterns that appear in the PM's weekly schedule D. The formal procedure to realize TVD are as follows:

1. By extracting K topics of all the documents in D through LDA, we obtained K-dimensional multivariate time-series $V = \{v_1, v_2, v_3, \dots, v_n\}$. Here, each element of vector v_i is a share of the topics of document d_i.
2. Considering a target element of all the vectors v_i in V, we constructed a real-valued time-series $x = \{x(1), x(2), x(3), \dots, x(n)\}$. Here, x corresponds to a time-series of the share of an extracted topic.
3. We transformed x to change point scores $s = \{s(1),\ s(2),\ s(3),\ \dots,\ s(n)\}$ through SST.
4. By setting and applying the criteria to assess the change point scores of each peak point, we detected the topic variation.

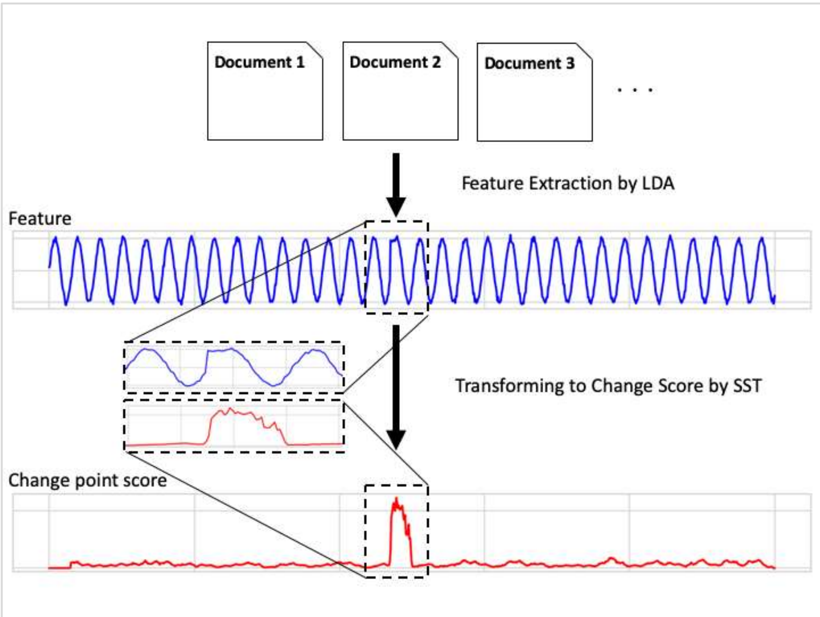


Figure 3: Overview of topic variation detection (TVD) method for time-series text data

Figure 3 displays an overview of TVD. Procedures 1 and 2 are performed to extract topics from documents and display the time-series share of the topics. In this study, we extracted the PM's behavioral patterns as a real valued time-series on K topics. The remaining procedures 3 and 4 are performed to detect changes in the topic patterns. When the extracted real-valued time-series exhibits high oscillation and superficial random movements, it is difficult to detect a change in the topic patterns. SST transforms the real-valued time-series of topics to a time-series of change point scores, which reveals the extent of change in the topic patterns. By generating change point scores, SST enables us to create a more systematic criterion to detect the changes. For example, in the later section of this paper, we describe a criterion that we created to assess whether the PM has manipulated the economy.

When employing TVD, it is necessary to be cognizant at every step of the preprocessing and hyperparameter setting. During step 1, topic extraction consistent with LDA is performed. To clear the topics before affecting the LDA, the words that appear frequently and the stop words are deleted from the documents. In an LDA, since K topics and the two parameters of β (the word distribution parameter) and θ (the topic distribution parameter) significantly affect the topic extraction, further adjustments are necessitated. If the topic extraction is successful in step 1, then the topics of interest can be determined in step 2. In step 3, to detect the change accurately, hyperparameters that appear via SST are selected carefully. In step 4, the criteria are confirmed according to the problem, and the robustness of these criteria are verified. In subsequent sections, we will further investigate these steps with greater precision as we engage in an empirical assessment of detecting PBCs.

6 Empirical Assessment

In this section, we assess the empirical results obtained by applying TVD to the *shushō dōsei* dataset. In Subsections 6.1 and 6.2, we extract 11 topics using LDA and identified topics that represent the PM's use of the economic policy. In Subsection 6.3, we transform the topic share to change the point score by SST. Finally, in Subsection 6.4, we create a criterion based on both the change point score and the increased rate of topic share to assess when the PM has manipulated. Using the criterion, we categorized each Japanese national election held during the time span of the data as either "manipulation," "surfing," or "other." We compared and assessed our results with previous empirical and theoretical studies regarding the PBC with ETT.

6.1 Topic Extraction

We first extracted nouns from *shushō dōsei* using Python with MeCab (Kudo, Yamamoto, & Matsumoto [20]) and mecab-ipadic-Neologd. We used Python 3.5.6, Mecab 0.996, gensim 3.6.0, and mecab-ipadic-Neologd with seed file v0.0.6 for our implementation.

6.1.1 Adjusting hyperparameter for LDA

Our corpus was created using Python with Genism (Rehurek & Sojka [29]). We excluded stop, rare, and high frequency words and conducted stemming before applying LDA to the dataset. Having conducted a morphological analysis using MeCab, the words obtained from the list of Japanese stop words developed in the SlothLib project were deleted from the documents.[2] Both words with high frequency that appeared in over 30% of documents and words with extremely low frequency that appeared in less than 10 documents were removed. To determine the number of topics K, we used the perplexity and coherence values. The perplexity index is widely used to evaluate the predictivity of models. The coherence index signifies the human interpretability of models (Mimno et al. [24]). We used UMass Coherence from among several different indexes for evaluating coherence. However, perplexity and coherence indexes do not necessarily match with each other. Therefore, we selected topics that are regarded to have a definite meaning while considering the balance between the two indexes. It is important to adjust β and θ because topics are affected by both word and topic distributions. We first set β and θ to auto, with only K topics allowed to change. However, because we could not obtain clear topics, we subsequently conducted a grid-search to obtain the appropriate values for K, β, and θ that exhibit good perplexity and coherence. To realize a balance between perplexity and coherence, we examined actual topics sequentially and selected $K = 11$, $\beta = 2$, and $\theta = 0.09$. Figure 4 shows the perplexity and coherence scores for each K.

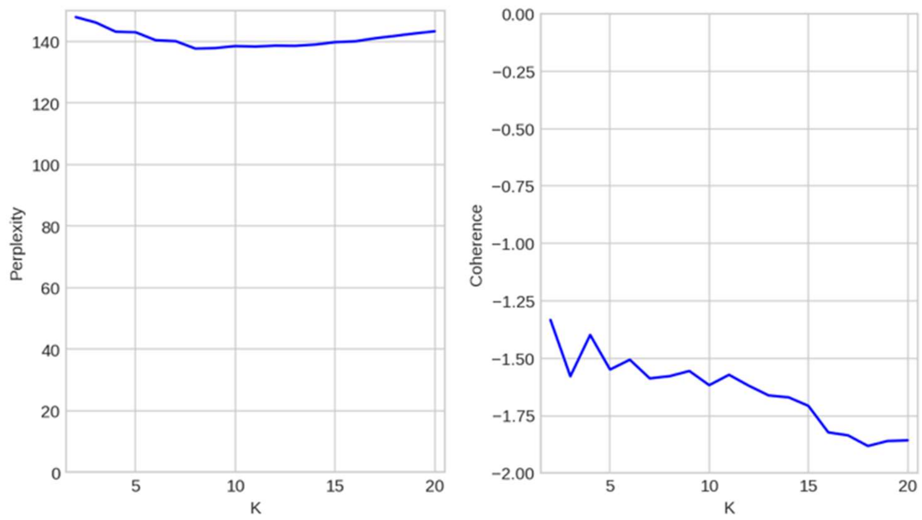


Figure 4: Perplexity and coherence indexes with different numbers of topics K

[2] The list of Japanese stop words created by Slothlib can be downloaded at the link below:
http://svn.sourceforge.jp/svnroot/slothlib/CSharp/Version1/SlothLib/NLP/Filter/StopWord/word/Japanese.txt

6.1.2 Election related topics and their appropriateness

Before starting our main empirical analysis, we first evaluated the appropriateness of the model generated using LDA. Hence, we examined whether the frequency of an election-related topic matched with the actual election dates. Among the 11 topics, we selected a topic that consisted of words related to the last-minute election campaigns. The word cloud of this topic is shown in Figure 5. It presents the frequency of words, such as "outdoor speech," "street speech," "TV program," "Tokyo Station," "ANA," "JAL," and "TV appearance."[3]

Figure 5: Word cloud of election topic 1 (last-minute election campaign)

Figure 6 illustrates variations in the share of this topic through the timespan of the dataset we used. The dotted lines represent the dates when the Lower House elections occurred. As shown in Figure 6, a large share of the topic matches with the Lower House election dates. Other high-share points matched with other election dates (e.g., the Upper House and local elections).

[3] The English keywords in the word clouds displayed in this paper were translated by the authors from the original Japanese terms. ANA is the largest airline company in Japan and JAL is the second. A highly frequent mention of them together with "Yamabiko" and "Nozomi," the nicknames of bullet trains, and "Tokyo Station" reveals how the PM travelled around the country during the electoral campaign.

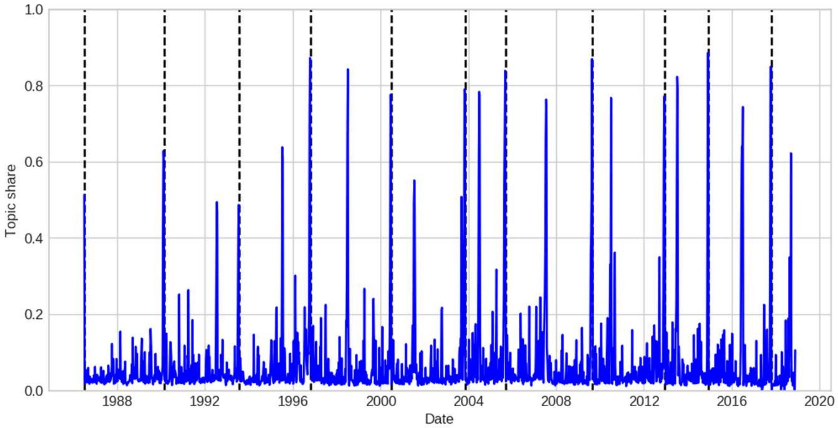


Figure 6: Topic share of election topic 1 (last-minute election campaign)

The next election-related topic extracted by LDA consist of words related to electoral preparations. Figure 7 shows the word cloud of this topic, including words such as "candidacy," "electoral affairs office (of the party)," "campaign office (of the party)," and "support group.[4]" The share of the topic of each document is shown in Figure 8. As shown, the topic share increases slightly differently from the election dates. Such a movement of the shares implies that the topic contains information that differs from that of the last-minute election campaign topics. From these results on election-related topics, we can be reasonably certain that LDA has appropriately extracted topics from *shushō dōsei*.

Figure 7: Word cloud of election topic 2 (Electoral preparations)

[4] It is called "*koenkai*" in Japanese. Because of its unique structure and role within Japanese politics, it is typically denoted as "*koenkai*" instead of "support group" even in political science literature written in English.

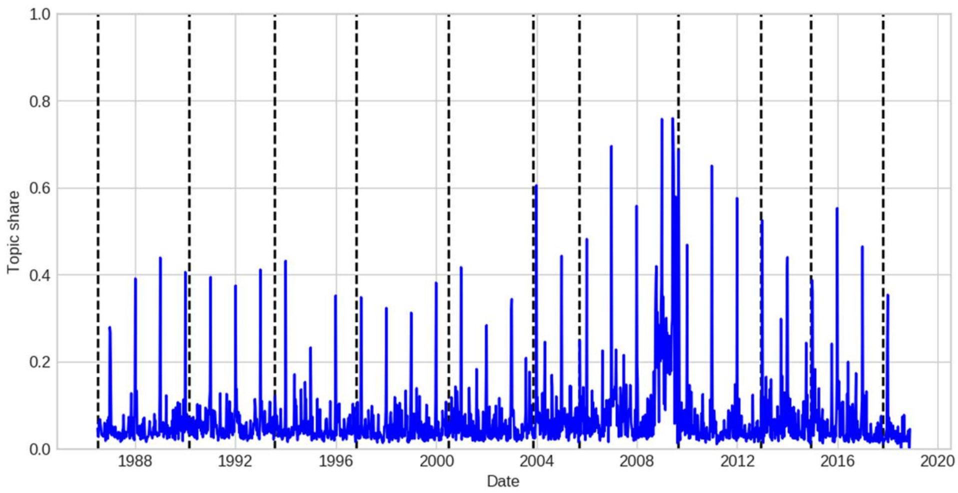


Figure 8: Topic share of election topic 2 (Electoral preparations)

6.1.*3 Other topics*

Among the 11 topics that we extracted by LDA, two were the election-related topics that we described and five were topics related to economy and finance, which we will analyze in detail in the next subsection. Figure 9 shows the word clouds of the other four topics, i.e., "internal affairs," "national security," "Western diplomacy," and "Asian diplomacy." Words in each topic are primarily coherent and each topic represents important policy areas of the Japanese government. We believe that these four topics, which are reasonable, further confirm that LDA has appropriately extracted topics from *shushō dōsei*. The next section presents our main analysis, in which we examine whether the PM has surfed or manipulated prior to the election.

Figure 9: Word clouds of other topics

6.2 Economic Policy Topic

When the PM seeks to manipulate the economy prior to an election to increase the incumbent's chance of winning, he is likely to allocate his limited time to activities related to economic and fiscal policy. Among the 11 topics extracted by LDA, five were topics related to economy and finance. Because it was challenging to distinguish among the five topics, we merged them into one topic by following the procedures adopted by past political science research using LDA (Martin & McCrain [23]) and termed it "economic policy topic."

Figure 10 shows a word cloud of economic policy topics. Words such as “finance,” “Cabinet Office,”[5] “Council of Fiscal and Monetary Policy,” “financial services,” “Ministry of Finance,” and “Ministry of Economy, Trade, and Industry” appear frequently.

Figure 10: Word cloud of economic policy topic

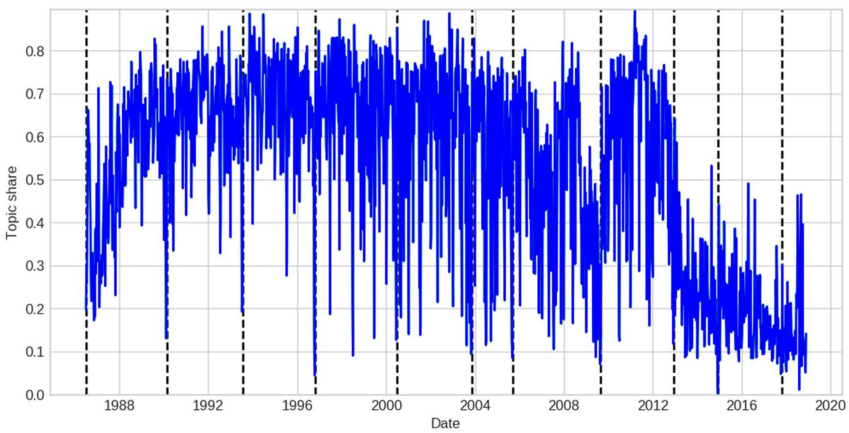


Figure 11: Topic share of economic policy topic

[5] The Cabinet Office, where the Council on Economic and Fiscal Policy is placed, is in charge of macroeconomic policymaking in the Japanese government.

Figure 11 shows the share of the economic policy topic within documents for the timespan of the dataset. Because the variance of the share of economic policy topics is extremely high, it is challenging to visually detect the change patterns of the share toward the election dates.

6.3 Change Point Score

We applied SST to detect the PM's manipulation through the pattern changes in the economic policy topic. As stated previously, the change point score is marginal when the change is negligible compared with past patterns and is large when a pattern differs substantially from those of the past.

To apply SST, we must first adjust the hyperparameters of SST. When we select a small value for the parameter w, known as the window size, the sensibility of SST becomes higher. Such a model with a small w is suitable for investigating changes over a short time span. By contrast, when the parameter w is set as a large value, the sensibility becomes lower and the model is suitable for measuring changes over a more extended period. Section 6.1 shows that, as an election date approaches, the share of election-related topics increased significantly, with the share of other topics suppressed. We adjusted the SST parameters to observe changes in topics other than election-related ones at the time of elections.

Figure 12 shows the share and change point scores of the economic policy topic before and after the Lower House election that was held on February 18, 1990. As shown in Figure 12, near the points where the share of the economic policy topic is relatively stable, the change point score is marginal. Conversely, when the share varies substantially, the change point score is large. Because the change point score quantifies the share variation of the economic policy topic, we can define an objective criterion of likely economic policy manipulation. Appendix shows the topic share of economic policy topics for other periods near elections.

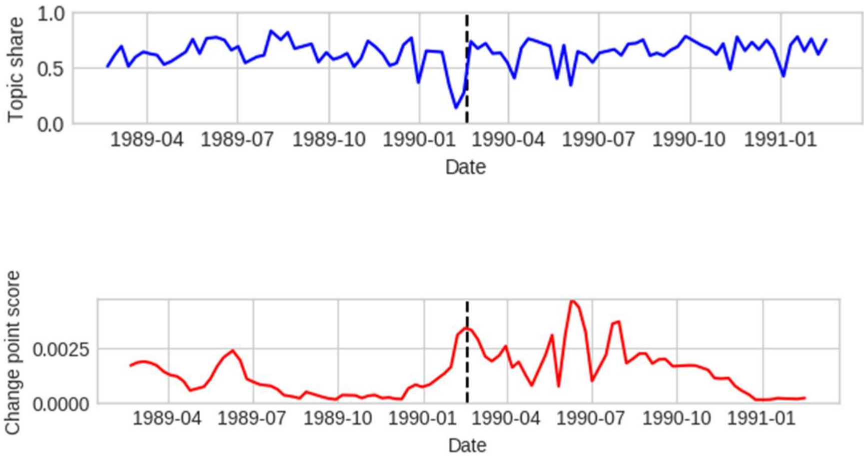


Figure 12: Topic share and change point score of economic policy topics

6.4 Empirical Results and Implications

To empirically assess whether the PM has surfed or manipulated, we first examined, in each election, whether the economic policy topic has changed substantially before it was apparent that the PM would call an early election. If yes, it implies that the PM has conducted a pre-election manipulation of the economy, consistent with the manipulative hypothesis. If no, it implies that the PM has either surfed on favorable economic conditions (consistent with the surfing hypothesis) or that other political economic conditions compelled the PM to call for an early election.

We used a change point score to detect significant changes in the patterns of economic policy topics. By assessing the change point score 45 days prior to the call for an early election was apparent in the media, we checked whether peak point(s) existed in the timespan. When it did, we also examined whether the share of the economic policy topic increased near the peak point(s). With this assessment, we categorized 10 elections into the following two groups: 1) Elections where the economic policy topic increased at peak point(s) (manipulation group); 2) Elections where peak point(s) did not exist or the economic policy topic decreased in the peak point(s) (non-manipulation group).

More formally, our criterion for categorizing elections with prior manipulation and non-manipulation is as follows:

Criterion. Let day t be less than N days prior to the call for an early election in the media, let $f(t)$ be the share of economic policy topic on day t, and let $g(t)$ be the change point score on day t. We categorize an election as "manipulation" if the following three conditions are satisfied on day t:

1. $g(t) > g(t - 1)$ and $g(t) > g(t + 1)$.
2. $g(t) > k_1 g(t - 1)$ or $g(t) > k_1 g(t - 2)$, where k_1 is the threshold value.
3. $f(t) > k_2 f(t - 1)$ or $f(t) > k_2 f(t - 2)$, where k_2 is the threshold value.

Condition 1 implies that the change point score $g(t)$ is a peak point. Conditions 2 and 3 show that the rates of change of $g(t)$ and $f(t)$ are relatively large near day t. These conditions require day t to be the time when the pattern of the economic policy topic changes substantially and the share of the economic policy topic increases substantially. The entire procedure of TVD for PBCs is summarized as a pseudocode in Algorithm 1.

Algorithm 1: TVD for Detecting PBCs.

Input: List D of the PM's daily schedules

Output: List M that are detected as days when manipulation occurred

Extract K topics of each d in D through LDA in Section 4.2.1
Use a topic share time-series $\{f(1), \ldots, f(N)\}$ of D
for each t **do**
    Calculate change point score of $f(t)$ by SST in Section 4.2.2
end for
Create empty list M
for each t **do**
    if t satisfies manipulation condition in Section 6.4
        Append t to M
end for

Subsequently, we set the following values: $N = 45$ and $k_1 = k_2 = 1.5$. We will examine the robustness of these parameters later. After categorizing the Lower House elections into "manipulation" and "non-manipulation" groups by applying the criterion, we extracted the 1993 election from the non-manipulation group and included it in the "other" category. This is because the 1993 election was a rare case in Japanese politics when a non-confidence motion of the cabinet passed the Diet, compelling the serving PM Kiichi Miyazawa to dissolve the Lower House.[6] Hence, in the 1993 election, the PM could not strategically opt to surf or manipulate, rendering this case an evident outlier. Subsequently, we named the remaining non-manipulation group as the "surfing group." Table 1 presents the categorization of the 10 elections.

Although the earlier empirical studies of the PBC with EET assumed that the PM always opted to manipulate or surf in every election, recent theoretical and empirical studies of the topic assumed that the PM strategically opted to manipulate or surf depending on the political and economic conditions encountered. Therefore, how do the classifications presented in Table 1 fit with or differ from recent empirical and theoretical analyses of PBCs with EET? To assess this, we used three indicators frequently used recently: 1) time spent in office as a percentage of the full term (i.e., four years); 2) GDP growth rate; 3) cabinet approval rate, each measured at the nearest point of each election. The average values of each indicator for each group are presented in Table 2 (detailed data for each election are presented in Table 1).

Table 1: Categorization of Elections from 1986 to 2018

Election day	Group	Percent of time spent within the term (4 years)	Quately GDP growth rate	Cabinet approval rate
Feb-18, 1990	Surfing	0.91	3.10	33.6
Jul-18, 1993	Other	0.85	-0.63	10.3
Oct-20, 1996	Surfing	0.82	0.05	37.7
Jun-25, 2000	Manipulation	0.92	1.88	18.2
Nov-9, 2003	Surfing	0.84	0.40	43.7
Sep-11, 2005	Surfing	0.46	0.97	53.5
Aug-30, 2009	Surfing	0.99	2.11	16.7
Dec-16, 2012	Manipulation	0.82	0.29	18.2
Dec-14, 2014	Surfing	0.50	0.09	45.4
Oct-22, 2017	Manipulation	0.71	0.62	37.1

[6] When a no-confidence motion of the cabinet passes the Diet, the Constitution of Japan requires the PM to either resign or dissolve the Diet.

Table 2: Average Indicators Values for Each Group with Threshold $k_1 = k_2 = 1.5$

	Percent of time spent within the term (4 years)	Quately GDP growth rate	Cabinet approval rate
All	0.78	0.89	31.4
Manipulation	0.82	0.93	24.5
Surfing	0.75	1.12	38.4
Other	0.85	-0.63	10.3

The results presented in Table 2 are primarily consistent with the theoretical and empirical expectations of recent studies. For example, recent studies predicted that the PM would be more likely to surf when the remaining period within the term was longer and more likely to manipulate when the remaining time was shorter (Schultz [17]; Kayser [16]; Kato & Inui [14]). Furthermore, they predicted that the PM would be more likely to surf when his cabinet's approval rate was higher and the economic conditions better (Saito [32]; Kato & Inui [14]). Meanwhile, our results did not support earlier empirical studies on this topic (e.g., Inoguchi [9]; Ito & Park [10]), which assumed that the PM has always manipulated or surfed in every election. Instead, they were consistent with recent theoretical developments, where the PM strategically opted to manipulate or surf depending on the political economic conditions encountered.

We will now examine the robustness of the results above. To set the criterion, the following values were set: number of days before the dissolution of the Parliament was set at $N = 45$, and thresholds were set at $k_1 = k_2 = 1.5$. When we maintained $N = 45$ and substantially increased the threshold values to $k_1 = k_2 = 2$, only one case, namely the 2000 election, moved from the manipulation group to the surfing group. As shown in Table 3, such a change in threshold values does not substantially change the overall results. Whereas the percentage of time spent within the term became indistinguishable between both the manipulation and surfing groups, the values for the quarterly GDP growth rate supported the findings of previous studies more strongly (Saito [32]; Kato & Inui [14]). As for N, none of the elections moved between the two groups when we changed N to 60 or 90 days. Hence, we can conclude that, notwithstanding small sample sizes, our findings are relatively robust.

Table 3: Average Indicators Values for Each Group with Threshold $k_1 = k_2 = 2$

	Percent of time spent within the term (4 years)	Quately GDP growth rate	Cabinet approval rate
Manipulation	0.77	0.46	27.7
Surfing	0.78	1.23	35.5

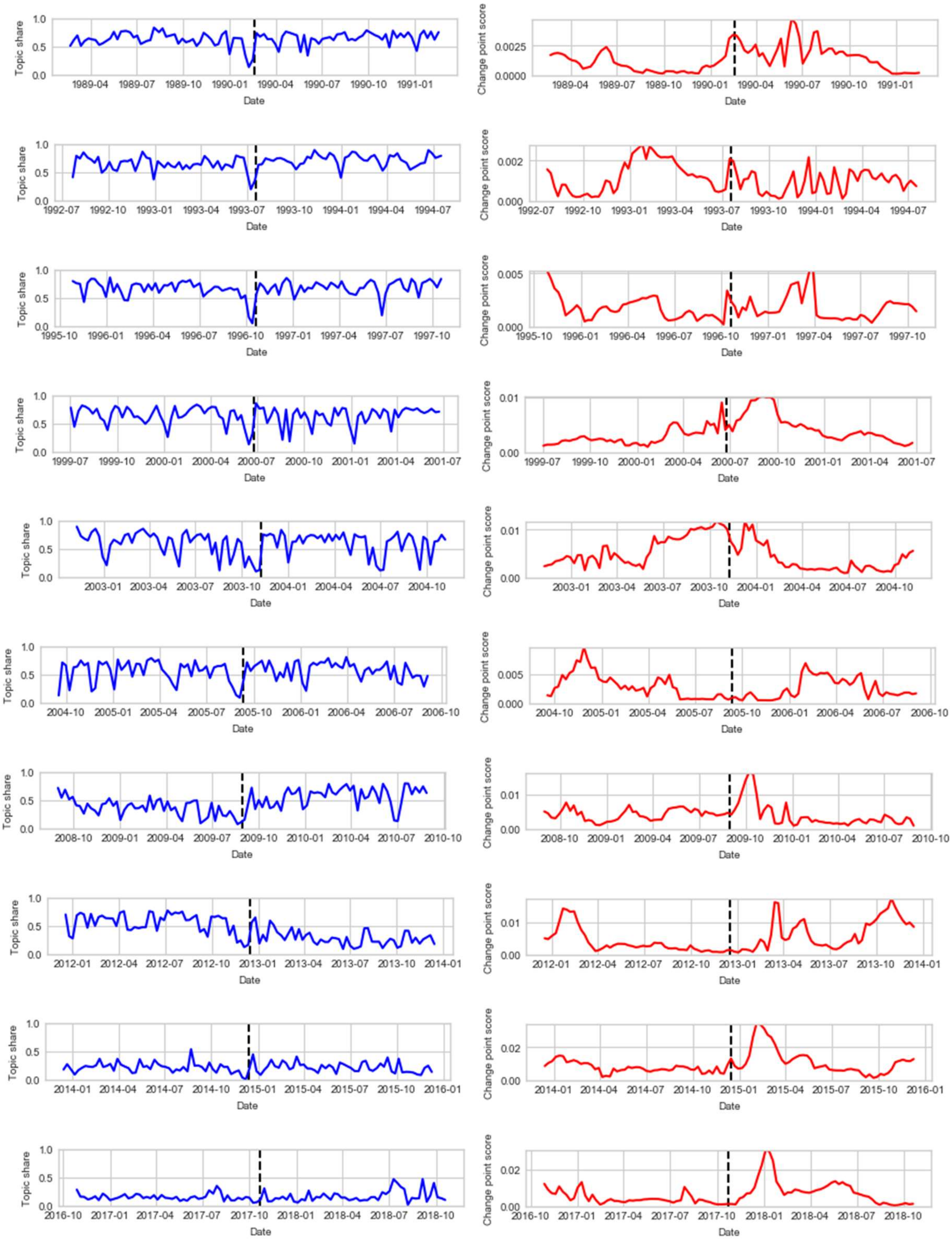
7 Conclusions

We herein introduced a novel dataset and method to empirically assess whether the PM has surfed or manipulated in the PBCs with EET, a classical research topic in political science and economics. TVD was proposed to detect the PM's manipulation by examining his daily schedule.

Our approach enabled us to directly observe the PM's behavior and overcome severe methodological challenges encountered in past empirical research on PBCs with EET. However, our research presents some limitations. For example, because only 10 Lower House elections occurred during the time range of the dataset (i.e., 1986–2018), this study cannot empirically determine whether the surfing or manipulative hypothesis is valid because of the marginal degrees of freedom. Needless to say, past empirical studies regarding this topic also had to address the small sample size problem. However, in our view, our approach enhances the understanding on this classical topic from a new perspective and can at least serve as a strong robustness evaluation of previous empirical studies regarding PBCs with EET.

With regard to future studies, because the number of elections within the timespan of our dataset was severely limited, we must expand the sample size by extending the timespan of the dataset. Furthermore, we can analyze the Upper House election cases, in which the election dates are fixed, to enrich our understanding on this topic. With regard to the method, TVD can be transformed and improved depending on the characteristics of the dataset analyzed. For example, LDA can be replaced by other topic models, such as the dynamic topic model (Blei [4]).

Appendix: Topic Share and Change Point Score of all Lower House Elections from 1986 to 2018



List of Abbreviations:

PM: Prime Minister

PBC: Political business cycle

EET: Endogenous election timing

GDP: Gross Domestic Product

TVD: Topic variation detection

LDA: Latent Dirichlet allocation

SST: Singular spectrum transformation

Availability of Data and Materials

We used the newspaper text data service of Nikkei Media Marketing Inc. The number of text files is 11,242. The total number of characters in the text files is 26,58,687.

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