Co-sponsorship analysis of party politics in the 20th
National Assembly of Republic of Korea

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Abstract

We investigate co-sponsorship among lawmakers by applying the principal-component analysis to the bills introduced in the 20th National Assembly of Korea. The most relevant factor for co-sponsorship is their party membership, and we clearly observe a signal of a third-party system in action. To identify other factors than the party influence, we analyze how lawmakers are clustered inside each party, and the result shows significant similarity between their committee membership and co-sponsorship in case of the ruling party. In addition, by monitoring each lawmaker’s similarity to the average behavior of his or her party, we have found that it begins to decrease approximately one month before the lawmaker actually changes the party

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1. Introduction

Legislation is a process of cooperation and conflict: To make a law, a bill must be moved to the Assembly by a sufficient number of lawmakers (or in some other ways, e.g., by the government), and the bill will be passed only when approved by a sufficient number of lawmakers. At the same time, lawmakers are divided into parties according to their different views on public interest. Due to its fundamental importance in democracy, this process has been recorded in a publicly accessible form, which makes the data suitable for statistical analysis of human interaction. For example, recent data-driven studies have revealed the role of connectedness in the legislative influence \[1, 2, 3\] and suggested various factors playing behind the scene \[4, 5, 6, 7, 8\] as well as quantitative measures of political polarization \[9, 10\].

In this work, we wish to provide quantitative understanding of party politics by analyzing co-sponsorship of bills moved to the 20th National Assembly of Republic of Korea (May 30 2016—May 29 2020). Although not many bills become laws, such bill data express the sponsors’ ideas most clearly because bills are listed as they are introduced, compared to later stages where the bills are revised and merged to reach a compromise. It has been reported that party membership had the greatest influence on co-sponsorship in the 17th Assembly \[11\], and one may ask how significant it is now, or whether other factors also explain co-sponsorship when viewed from an “orthogonal” point of view. Another related question is if party membership change is a cause or result of the corresponding change in co-sponsorship, which we will attempt to answer after reducing it to a simpler question, asking which one takes precedence.

Our first finding is that the 20th Assembly is best described as a third-party system, i.e., consisting of three wings that represent liberalism, conservatism, and centrism, respectively. Our analysis also confirms that the party influence on co-sponsorship is absolutely dominant, and that political regionalism has coupled lawmakers’ parties to their constituencies and birthplaces. However, if we look at the Democratic Party, which has been the ruling party since May 2017, the most relevant factor in co-sponsorship
among the Democrats turns out to be their standing committees. In addition, we have found that a lawmaker deviates from the average direction of his or her party before leaving it, with a time scale of one month.

2. Datasets

2.1. Bill data

The Assembly started with 300 lawmakers, and the number has been fluctuating between 288 and 300 due to disfellowships and by-elections. If we count all the persons who have ever been a part of the 20th Assembly during the period, the number is 318. We have collected their bills from People’s Solidarity for Participatory Democracy (http://watch.peoplepower21.org), whose original source is Open Data Portal (http://www.data.go.kr). For each bill, we have its date of motion, title, chief author, current status, and co-sponsors’ names and parties. Although the 20th session of the Assembly was seated until 29 May 2020, we had started analysis in the middle of the session, so our dataset ends on June 3 2019, containing 20967 bills. The actual number used for analysis is about 10% less than that because we have to exclude the bills by the government.

2.2. Potential factors behind co-sponsorship

We have also collected various items on individual lawmakers on the Web, including their party membership records (http://ko.wikipedia.org), as well as their constituencies, birthplaces, standing committees, universities, numbers of elected terms, genders, ages, and assets (http://raythep.mk.co.kr). When we have to assign a unique party to each lawmaker, we will use the one at the time of election. Independent lawmakers are classified as a separate cluster. As a consequence, we have $K = 6$ as the number of clusters based on party membership. As for standing committees, if a lawmaker belongs to more than one committees, we choose the first one in the database. The Speaker of the National Assembly is counted as a separate committee because he does not belong to any. As a result, the committee information classifies lawmakers into $K = 18$ clusters. In case of birthplaces, our analysis uses the provincial-level divisions before the foundation of Sejong Special Self-Governing City in 2007, and the resulting number of clusters is $K = 16$. The same applies to constituencies, but this time we have to include Sejong, and proportional representatives, who were 47 lawmakers at the time of election, are also classified into a separate constituency. Therefore, the number
Table 1: List of items collected for clustering analysis on lawmakers. For each item, we show the corresponding number of clusters, denoted by $K$.

| item         | $K$ | misc.                                                                 |
|--------------|-----|----------------------------------------------------------------------|
| party        | 6   | five parties + independent lawmakers, at the time of election         |
| constituency | 18  | provincial-level divisions + proportional representatives            |
| birthplace   | 16  | provincial-level divisions before the foundation of Sejong           |
| committee    | 18  | 17 standing committees + the Speaker of the National Assembly        |
| no. of terms | 8   |                                                                       |
| university   | 66  | If unavailable, high-school information is used instead.             |
| gender       | 2   |                                                                       |
| age          | N/A | $K$ is an input parameter.                                           |
| asset        | N/A | $K$ is an input parameter.                                           |

of clusters according to constituencies amounts to $K = 18$ instead of 16. To capture their academic ties, we have used which universities lawmakers graduated from, with $K = 66$, because high schools are too diverse for clustering analysis. Almost everyone has a bachelor’s degree, but for those who lack it, we use their high schools instead. The greatest number of elected terms is eight ($K = 8$), and gender has $K = 2$. For ages or assets, $K$ is not determined a priori but should be given as an input parameter. All these items are summarized in Table 1.

3. Methods

In this section, we explain how we analyze the above data. Most of the calculations have been done in the python environment [12, 13, 14, 15]. We have also used packages for visualization [16, 17] and clustering analysis [18].

3.1. Principal-component analysis (PCA)

Assume that we have $N$ data points, each of which is $M$-dimensional. The $n$th data point can be denoted by a column vector, $[R_{1n}, \ldots, R_{Mn}]^\top$, where $\top$ means transpose, and the whole data can be represented by an $M \times N$ matrix $R$. In our case, the original data matrix $R$ has $M \approx 2 \times 10^4$ rows and $N \approx 300$ columns. Its element is binary, i.e., $R_{mn} = 1$ if the $n$th lawmaker sponsored the $m$th bill and $R_{mn} = 0$ otherwise. After removing all-zero rows and columns, we standardize the data by using the sample mean $\mu_n \equiv M^{-1} \sum_m R_{mn}$ and standard deviation $s_n =$
\[ \sqrt{\sum_m (R_{mn} - \mu_n)^2 / (M - 1)} \] along the \( n \)th column vector. As a result, we work with the following data matrix:

\[
X = \begin{pmatrix}
\frac{R_{11} - \mu_1}{s_1} & \cdots & \frac{R_{1N} - \mu_N}{s_N} \\
\vdots & \ddots & \vdots \\
\frac{R_{M1} - \mu_1}{s_1} & \cdots & \frac{R_{MN} - \mu_N}{s_N}
\end{pmatrix}, \tag{1}
\]

We then construct an \( N \times N \) symmetric matrix \( Q \) as follows:

\[
Q = \frac{1}{M - 1} X^\top X = \frac{1}{M - 1} \begin{pmatrix}
X_{11} & \cdots & X_{M1} \\
\vdots & \ddots & \vdots \\
X_{1N} & \cdots & X_{MN}
\end{pmatrix} \begin{pmatrix}
X_{11} & \cdots & X_{1N} \\
\vdots & \ddots & \vdots \\
X_{M1} & \cdots & X_{MN}
\end{pmatrix}, \tag{2}
\]

which is called a correlation matrix. Its element \( Q_{ij} \) means correlation between the \( i \)th and \( j \)th data points:

\[
Q_{ij} = \frac{1}{M - 1} \sum_{m=1}^{M} \frac{R_{mi} - \mu_i}{s_i} \frac{R_{mj} - \mu_j}{s_j}, \tag{3}
\]

which takes a value from \([-1 : 1]\) with \( Q_{ii} = 1 \). The key step of PCA is to diagonalize this correlation matrix \( Q \), whereby we get its eigenvalues in descending order together with the corresponding eigenvectors. The eigenvectors are called principal axes, and a reduced representation of the original data is obtained by taking the first few principal axes and projecting the data onto the resulting subspace. Note that the total sum of the eigenvalues equals \( N \) in this standardized PCA. Let us denote the \( k \)th eigenvalue as \( \lambda_k \) and the corresponding eigenvector as \( e_k \). The eigenvectors are normalized so that they form an orthonormal set with \( e_k \cdot e_l = \delta_{kl} \). The correlation matrix can be decomposed in the following way [19]:

\[
Q = \sum_{k=1}^{N} \lambda_k e_k \otimes e_k, \tag{4}
\]

where \( \otimes \) means the outer product.

In performing PCA, it is usual practice to apply the singular-value decomposition as follows:

\[
X = UDV^\top, \tag{5}
\]
where \( U \) is an \( M \times M \) orthogonal matrix, \( D \) is an \( M \times N \) rectangular diagonal matrix with non-negative real numbers on the diagonal, which are called singular values, and \( V \) is an \( N \times N \) orthogonal matrix. The columns of \( U \) are eigenvectors of \( XX^\top \), and the columns of \( V \) are eigenvectors of \( X^\top X \). The singular values in \( D \) are the square roots of the eigenvalues of \( X^\top X \) or \( XX^\top \), and the number of singular values is equal to the rank of \( X \). We have the following identities:

\[
Xv_k = \sigma_k u_k \tag{6}
\]

\[
X^\top u_k = \sigma_k v_k, \tag{7}
\]

where \( u_k \) is the \( k \)th column of \( U \), \( \sigma_k \) is the \( k \)th singular value, and \( v_k = e_k \) is the \( k \)th column of \( V \). Due to Eq. (7), the \( i \)th data point is projected onto the \( k \)th principal axis at position

\[
z_{i,k} \equiv \sigma_k e_{i,k}. \tag{8}
\]

The distance between data points \( i \) and \( j \) on this axis can thus be defined as

\[
d_{ij,k} \equiv |z_{i,k} - z_{j,k}| = \sigma_k |e_{i,k} - e_{j,k}|. \tag{9}
\]

From Eq. (4), it is straightforward to derive the following identity:

\[
d_{ij}^2 = \sum_k d_{ij,k}^2 = 2(1 - Q_{ij}), \tag{10}
\]

where \( d_{ij} \) is called correlation distance between \( i \) and \( j \).

### 3.2. Similarity measures

We examine the collected items one by one in the following way: First, we assume that each given item is a “true” index for classification. We then compare the result with an agglomerative clustering based on the correlation distance [Eq. (10)]. Ward’s method is used for hierarchical linkage throughout this work. For example, in case of gender, \( N \) lawmakers form \( K = 2 \) clusters, one for males and the other for females. Let \( c_1 \) denote this “true” classification. We then perform agglomerative clustering until we end up with two clusters, and denote this clustering as \( c_2 \). The question is how much \( c_1 \) coincides with \( c_2 \). It can be answered with various measures such as the Rand index, the purity index, and normalized mutual information (NMI) [20] (see also [21, 22] for comparative analyses of clustering similarity measures),
• The Rand index measures the fraction of agreements between \( c_1 \) and \( c_2 \). That is, we begin by counting \( n_+ \), the number of pairs of data points that belong to the same cluster both in \( c_1 \) and \( c_2 \), and \( n_- \), the number of pairs that belong to different clusters both in \( c_1 \) and \( c_2 \). To get the Rand index, we divide \( n_+ + n_- \) by the total number of pairs, \( N(N - 1)/2 \).

• The purity index is based on the “true” classification \( c_1 \), and each cluster in \( c_2 \) is given a label according to the class that is the most frequently observed in the cluster. We count the number of data points whose classes match with their cluster labels. The purity index is obtained by dividing this count by \( N \), the total number of data points.

• Mutual information (MI) measures how much information we obtain about the classes in \( c_1 \) by knowing the clusters in \( c_2 \). We normalize MI by the arithmetic mean between entropies of \( c_1 \) and \( c_2 \) to penalize subdividing clusters further into smaller ones.

The statistical significance is estimated with reference to a null model, which is generated by randomly shuffling the values of the item: Specifically, we calculate the \( p \)-values by counting how many of such random samples yield higher values than the real data. If the \( p \)-value is small, observed similarity is unlikely to be an outcome of random chance. Throughout this work, the criterion is \( p \leq 0.05 \) and its Bonferroni-corrected versions, and we have generated more than \( 10^4 \) random samples to estimate each \( p \)-value. This procedure can be used for measuring similarity between two items as well. For example, if we compare constituencies and birthplaces, we construct two clusterings, one based on constituencies \( (c_1) \) and the other based on birthplaces \( (c_2) \), and compute the similarity measures between \( c_1 \) and \( c_2 \). To assess its significance, the \( p \)-value can be measured, e.g., by randomly shuffling lawmakers’ birthplaces. When we compare two one-dimensional number arrays, such as comparing between age and \( z_{i,k} \) with \( k \) fixed [Eq. (8)], we may also use Spearman’s rank correlation coefficient to avoid introducing \( K \) as a free parameter. This measure ranges from \(-1\) to 1, so we have to check its absolute value to compute the \( p \)-value.

4. Results

In Fig. 1(a), we depict a two-dimensional (2D) representation of the bill data by projecting the \( N \) data points onto two principal axes. In this repre-
sentation, they are clearly divided into three wings: The first wing consists of two liberal parties, i.e., the Democratic Party and the Justice Party. The second wing includes conservative ones, i.e., the Liberty Korea Party and the Bareun Party. Finally, the third wing is comprised of the People’s Party, which claims to support centrism. Although this 2D representation explains only 10% of the total variance, the result agrees with common understanding about the Assembly. If we go further to the third and fourth principal axes, which add about 4% of the total variance, the Justice Party separates from the Democratic Party [Fig. 1(b)]. The noticeable segregation in Fig. 1 implies that party membership is an important predictor of co-sponsorship among lawmakers. From this observation, we can ask the following questions: What are the meanings of the principal axes? Which other factors are acting on co-sponsorship? Finally, if party membership is such a critical factor in co-sponsorship, what happens to co-sponsorship when a lawmaker changes his or her party membership? Let us begin by answering the second question.

4.1. Factors behind cooperation

To begin with, we check similarity between each pair of items, that is, how one item is similar to another when used as indices for clustering lawmakers.
Figure 2: Clustering similarity between each pair of items. Nodes are linked when their similarity is significant with respect to all of the following three measures: the Rand index, the purity index, and NMI. If two nodes are linked by a dashed line, their similarity is significant only when the Bonferroni correction is not applied, whereas a solid line means that it is significant even with the correction. The filled rectangle shows a clique, indicating strong coupling among lawmakers’ parties, constituencies, and birthplaces.
Figure 3: Agglomerative clustering based on correlation distance. Each number on the vertical axis means the number of lawmakers belonging to the corresponding branch, and these lawmakers’ party membership is represented by the color of the branch as in Fig. 1. We use Ward’s method for hierarchical linkage throughout this work.
Table 2: Similarity between item-based classification and correlation-based clustering (Fig. 3). The measures are calculated for the whole Assembly and then for three major parties: the Democratic Party, the Liberty Korea Party, and the People’s Party. We write ‘Yes’ if \( p \leq 0.05 \) for the Rand index, the purity index, and NMI, whose values are given as footnotes. The dagger symbol means that the similarity is not judged as significant if we apply the Bonferroni correction (\( p \leq 0.0015 \)). For ages and assets, we have attempted the agglomerative clustering with varying the number of clusters from \( K = 2 \) to 10. If similarity is significant for multiple values of \( K \), we show the case of the smallest \( K \).

| Item     | Assembly | Democratic Party | Liberty Korea Party | People’s Party |
|----------|----------|------------------|---------------------|---------------|
| party    | Yes\(^a\) | N/A              | N/A                 | N/A           |
| constituency | Yes\(^b\) | Yes\(^c\)       | †Yes\(^d\)         |
| birthplace | Yes\(^e\) | †Yes\(^f\)       |
| committee | †Yes\(^g\) |                  |
| no. of terms |      |                  |
| university |      |                  |
| gender    |      |                  |
| age (\(K = 2\)) | †Yes\(^h\) |                  |
| asset     |      |                  |

\(^a\) (0.9, 1.0, 0.8) \(^b\) (0.8, 0.3, 0.3) \(^c\) (0.9, 0.3, 0.3) \(^d\) (0.7, 0.5, 0.3) \(^e\) (0.8, 0.2, 0.2) \(^f\) (0.8, 0.3, 0.3) \(^g\) (0.9, 0.3, 0.4) \(^h\) (0.5, 0.6, 0.01)

As explained in the previous section, we will use three well-known similarity measures: the Rand index, the purity index, and NMI. As shown in Fig. 2, lawmakers’ parties, constituencies, and birthplaces are strongly coupled in terms of all these three measures, and this coupling can be attributed to political regionalism.

Then, in Table 2, we compare each item-based classification with the correlation-based agglomerative clustering (Fig. 3), keeping the number of clusters the same on both sides. If we consider the whole Assembly (\( N = 318 \)), parties show significant similarity to the agglomerative clustering with respect all the three measures. Similarity is also significant when constituencies or birthplaces are used, which is expected from their strong coupling with parties (Fig. 2). In addition, we have found that clusters in the Assembly bears similarity to the age structure (Table 3). If we use \( K = 2 \), for example, the \( p \)-value is estimated as approximately 0.02 for every measure.

At the same time, differences do exist among parties. In Table 2, we have listed the cases within three major parties, constituting the three wings...
Figure 4: Clustering similarity between each item and distance along each principal axis. We perform agglomerative clustering based on $d_{ij,k}$, the distance between $i$ and $j$ on the $k$th principal axis. Each horizontal axis shows $k$, the index for principal axes, and the vertical one shows $p$-values of clustering similarity measures in the logarithmic scale. From (a) to (g), we measure the Rand index, the purity index, and NMI, whereas Spearman’s rank correlation coefficient is calculated for (h) and (i). The horizontal lines represent $p = 1$, $p = 0.05$, and $p = 0.001$ (Bonferroni-corrected), respectively, from top to bottom. We observe $p \leq 0.05$ for every measure in the shaded regions.

4.2. Making sense of principal axes

So far, we have performed the agglomerative clustering based on $d_{ij}$ [Eq. (10)]. Here, we will apply the same method to $d_{ij,k}$ in Eq. (9) across different principal axes with $k = 1, \ldots, 5$. For ages or assets, it is more convenient to calculate Spearman’s rank correlation coefficient with $z_{i,k}$ [Eq. (8)].
As depicted in Fig. 4, the party influence is pervasive along all those principal axes. Considering the strong coupling of parties to constituencies and birthplaces (see the filled rectangle in Fig. 2), it should not be surprising that a substantial amount of overlap exists from Fig. 4(a) to (c). Age is also found significant on the first principal axis [Fig. 4(h)], based on which ‘young’ and ‘old’ parties are separated [Fig. 1(a)]. Also by considering that a lawmaker’s number of terms and assets are correlated with his or her age (Fig. 2), we can explain the reason that these two items are also significant on the first principal axis [Figs. 4(e) and (i)]. We can thus say that the first two principal axes reflect the configuration of parties and other closely related items. For the next two principal axes, on the other hand, we observe significant signal in the number of terms and gender [Fig. 4(e) and (g)], which we have to examine more closely.

If we check how lawmakers are clustered on the third principal axis, we find a nontrivial unimodal structure in their numbers of terms: Among the $K = 8$ clusters for this item (Table 1), the two leftmost clusters consist almost exclusively of the People’s Party [see Fig. 1(b) along the horizontal axis], whose average number of terms is $T \approx 1.9$. The other six clusters on the right are mixtures of the other parties, and the interface between the People’s Party and the rest is occupied by lawmakers elected for many terms, so the fourth cluster in the middle has the greatest number of terms, $T \approx 3.2$ on average. It decreases again as we go across the interface, so the rightmost cluster, on the opposite side of the People’s Party, is composed of newly-elected lawmakers with the smallest $T \approx 1.5$. To sum up, the third principal axis shows statistical significance of a “normal mode”, in which the newly-elected lawmakers in the People’s Party move in an anti-correlated manner with respect to those who are newly elected in the other parties.

As for gender, its significance on the fourth principal axis does not imply any possibility of non-partisan gender politics, as one can still see the party influence there [Fig. 4(a)]. To understand the origin of this significance, one should note that the Justice Party separates from the others on the fourth principal axis [Fig. 1(b)]. The significance of gender is due to the fact that it also has a much higher fraction of female lawmakers (≈ 50%) than those of the other parties (10 ~ 20%). This effect was negligible in clustering the whole Assembly (Table 2) because the Justice Party has a small number of lawmakers. Moreover, if we look closely at the agglomerative clustering on the fourth principal axis (not shown), a female block also exists inside the Democratic Party, but its position is almost on the opposite side of the
Figure 5: Changes in the alignment of parties. A white node means a group of independent lawmakers with no party membership, and a black node means a group of vacancies to be filled by by-elections. Otherwise, nodes are filled with the colors of the corresponding parties. The centrism wing (green in Fig. 1) has undergone substantial changes, among which the biggest one can be written as follows: Bareun Party + People’s Party $\rightarrow$ Bareunmirae Party + Party for Democracy and Peace.

Justice Party. Therefore, we conclude that gender itself is not a meaningful indicator to interpret the position on the fourth principal axis. We can simply say that the Justice Party is a separate entity from the Democratic Party and others, and that its uniqueness is captured only by gender as far as we restrict ourselves to the items of Table 1.

4.3. Party membership change

The wings in Fig. 1 have relatively stable directions throughout the observation period. At the same time, as depicted in Fig. 5, we observe a number of events that lawmakers change their party membership. If a co-sponsorship network also changes with such an event, which is entirely plausible, the
Figure 6: Behavioral readjustment of lawmakers changing party membership. We measure lawmakers’ average cosine similarity in comparison with their respective donor and acceptor parties, together with standard error. The first four principal axes have been used to calculate their directions (Fig. 1). Each error bar contains 60 ∼ 200 points, and the shaded rectangle means the transition region where they change the membership.

This question can be answered by utilizing PCA. For each lawmaker changing the party membership, we take a time window of 100 days, within which PCA is performed to detect the following three vectors (see Fig. [1]): The average direction of the ‘donor’ party, denoted by $d$, that of the ‘acceptor’ party, $a$, and the lawmaker’s individual direction $w$. Let us define cosine similarity between two nonzero vectors $A$ and $B$ as follows:

$$ C(A, B) \equiv \frac{A \cdot B}{|A||B|}. $$

We measure this quantity between $d$ and $w$ as well as between $a$ and $w$ to see how they evolve as the time window moves. The measurement is averaged over membership-changing events. The result in Fig. 6 shows a crossing of $C(d, w)$ and $C(a, w)$ about 20–30 days before the actual event.

5. Summary and Discussion

In summary, we have analyzed co-sponsorship among lawmakers in the 20th National Assembly of Korea to understand how party politics works, such as how lawmakers conform to the directions of their parties and which factors complement the party influence.
Despite the short history and relatively small size, the centrism wing has proved its own identity in legislation [Figs. 1(a) and 3]. As Duverger’s law states [23], such a third-party system had long been regarded as unstable in Korea before the 20th Assembly. Indeed, it was for the first time in 16 years that the Assembly started with three negotiation bodies, and the centrism wing was even broken into two parties in the middle of our observation period (Fig. 5). The two parties nevertheless constituted a single wing, keeping the same direction as before, till the end of our observation. Even with their own political identity, the centrism wing is losing support, and the overall tendency has indicated that it is on the process of disappearance in agreement with Duverger’s law: The size shrank further down to about 20 lawmakers in February 2020, when another party alignment happened in the centrism wing, and they won only three seats in the 21st legislative elections on 15 April 2020.

Besides party membership, we have found that age yields a similar clustering to the one that is based on co-sponsorship (Table 2), but it seems to reflect the age difference among parties. If we look inside each party, the committee membership serves as a significant index in clustering the Democrats. In addition, our clustering analysis, combined with PCA, has detected an anti-correlated mode of newly-elected lawmakers [Fig. 3(e)], and this mode provides possible interpretation for the third principal axis in Fig. 1(b). It is still subject to the party influence in the sense that the mode gives a unique status to the People’s Party, but the shape of the mode suggests how the other parties have collectively responded to the emergence of the centrism wing. On the other hand, the fourth principal axis shows cohesion of the Justice Party in co-sponsorship. Here, we interpret the statistical significance of gender [Fig. 3(g)] as meaning that the Justice Party is uniquely characterized only by gender among our collected items. Such a gender characteristic of the Justice Party is related to the fact that most of its seats were awarded through proportional representation, for which the law stipulates that the fraction of female candidates must be no less than 50%. What is absent can be another meaningful piece of information: We do not observe any significance in academic ties [Fig. 3(f)].

Finally, provided that party membership is tightly bound to co-sponsorship, we have seen that individual change of co-sponsorship comes roughly one month before the actual membership change (Fig. 6). Admittedly, it is hard to establish causal relationship between the two events because one could decide inwardly to go over to another party well before changing the co-
sponsorship. Still, the change in co-sponsorship can serve as an early indicator which tacitly but patently manifests the decision before taking the crucial step.

Legislation exerts far-reaching impacts on the whole society, and understanding its working mechanism is gaining more and more importance in shaping our lives. Our analysis demonstrates that data-driven studies will help us move beyond anecdotes and deepen our understanding of politics in a quantitative way.

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