Blame Shifting in Presidential Systems: Ministerial Terminations' Corrective Effect on Approval

Codebook

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Abstract

How do ministerial terminations affect presidential approval? Presidents face unexpected challenges related to stochastic events such as scandals, policy failures or economic crises. We argue that the termination of ministers who have received calls for their resignation presents an opportunity for the president to send signals to the electorate in the expectation of a corrective effect on popularity through a blame-shifting dynamic. The central argument is that this dynamic only occurs in coalition governments where political responsibility may be more easily attributed to the coalition's different parties and factions, weakening personalisation centred on the president and facilitating blame-shifting and the corrective effect. The expectation of a corrective effect on approval is tested using instrumental variables (IV) regressions applied to novel data on ministerial terminations and resignation calls in 124 governments in 12 presidential democracies. The data were gathered by combining data mining, machine learning techniques and survey marginal time series based on the dyad ratios algorithm for approval. The main findings support the expectation that individual terminations of tainted ministers generate a corrective effect of nine points on presidential approval in coalition governments, which decreases in the medium and long term.

Keywords: cross-national research; Latin America; presidential popularity; presidents

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A File Description

- **blame_shifting_dataset.csv** (encoding UTF-8).
- Number of rows in the dataset: 1,905
- Number of columns (variables): 23

B Dataset

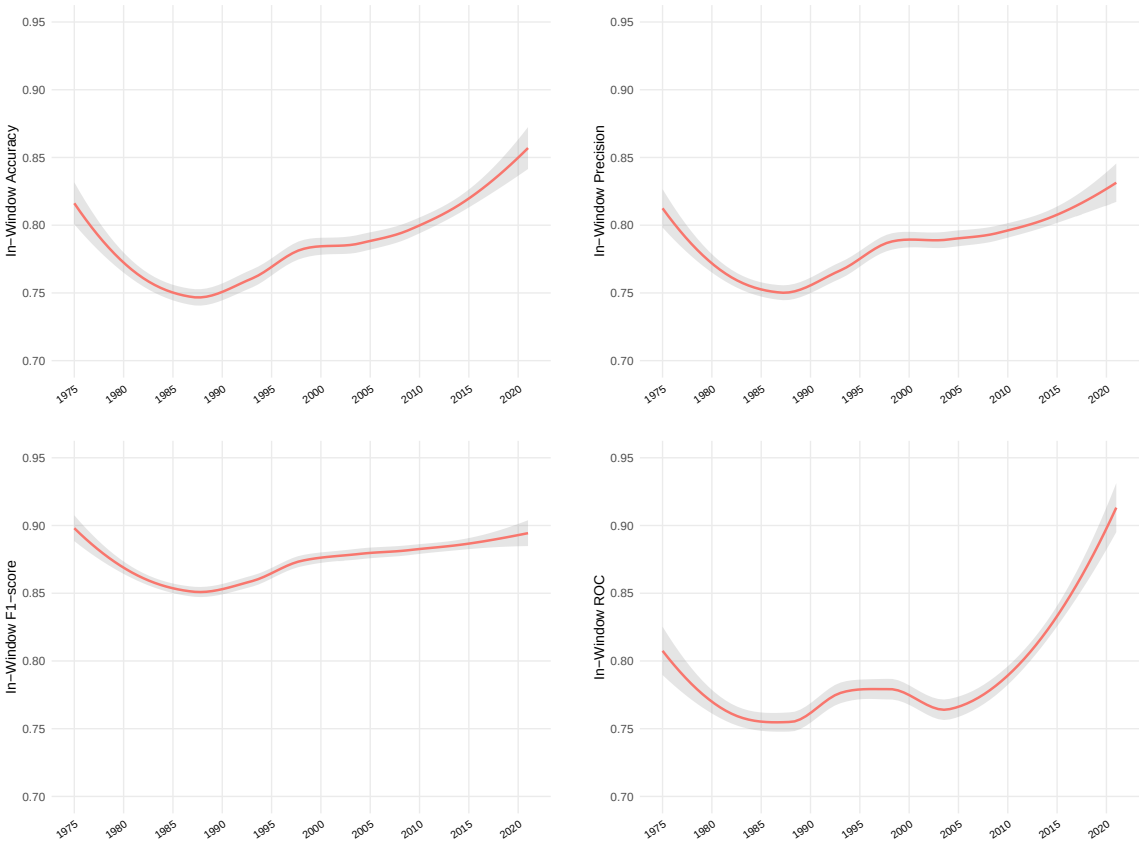
The dataset was built through an archival review of almost 50 years of numbers of the Latin American Weekly Report (LAWR). This involved digitalising with an optical recognition algorithm over 28,000 pages covering a 41-year period (González-Bustamante, 2025). To this, we added a batch of pre-processed data from the 1970s to complete the period studied. With this information, we trained semi-supervised Random Forest algorithms with 500 trees to identify calls for the resignation of cabinet members. We used a fixed five-year rolling window similar to Greene et al. (2019). This procedure enabled us to develop a novel indicator of monthly questionings that was cross-validated and subjected to manual review of low-confidence predictions (between 50% and 59%). In addition, the information on ministries and ministers' tenure was manually validated using official sources, such as libraries of Congress and ministerial archives, and was correlated with other similar information, such as that of Camerlo and Martínez-Gallardo (2020), obtaining goodness-of-fit indicators around 90%.[1]

The indicator of calls for ministers' resignation is based on the identification of events related to personal or financial scandals, public policy failures or internal disagreements in the cabinet, in line with the categorisation used by authors such as Berlinski et al. (2010) and Dewan and Dowding (2005). In a limitation, this indicator is binary because the training of a multiclass classification model yielded accuracy levels below 50%. However, the trained binary classification algorithm has high performance and accuracy indicators, reaching above 70%, depending on the year. The main performance indicators of the algorithm can be found in the figure S1, also available in the Supplementary Material.

The first stage of the data-gathering process sought to identify observations in a dyadic relationship composed of ministers and ministries; therefore, if a minister held more than one portfolio, the observation was coded as a different one. With these individual-level indicators, a database of governments with quarterly observations was constructed. Consequently, the dataset contains i-th observations of governments defined in time intervals that correspond to the four quarters of each year. In this way, the time-varying covariates are coded over the closed interval of the quarter or, in other words, at the end of

[1]For more information, see the convergent validation by González-Bustamante (2025), also available in Assessing Measurement Validity.

Figure S1: Goodness-of-Prediction of the Ensemble Semi-Supervised Algorithm to Classify Ministerial Resignation Calls

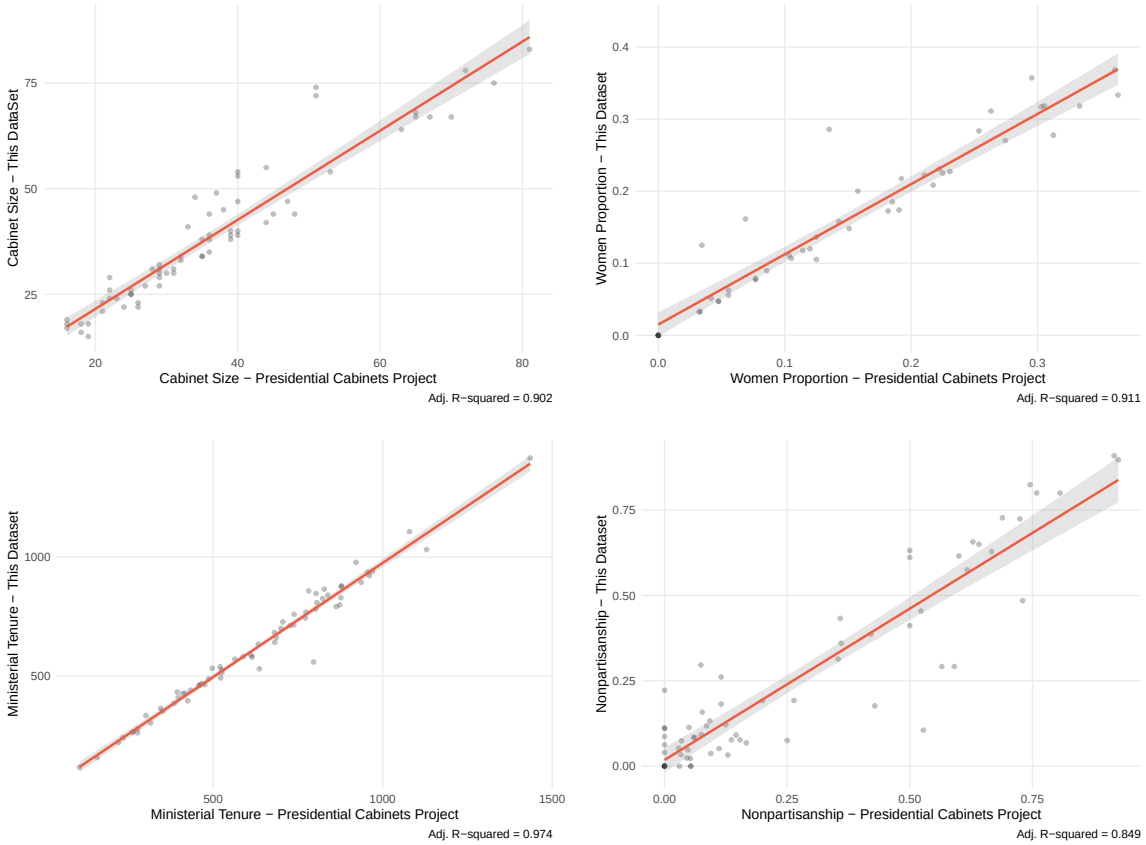


Note. Accuracy reports the proportion of correct predictions; precision is the proportion of positive predicted values; the F1-score reports a combination of precision and sensitivity (i.e., the fraction of correct predictions among true-positive cases); ROC (Receiver Operator Characteristic) shows the inverse relationship between sensitivity and specificity (i.e., the proportion of correct predictions among true-negative cases). For further details see González-Bustamante (2025).

the respective quarter. This permitted the incorporation of time-varying indicators such as the smoothed quarterly presidential approval of Carlin et al. (2019). This approval indicator contains marginal time series surveys of approval calculated with the dyad ratios algorithm of Stimson (2018). During this process, we also added indicators for the econometric controls and the exogenous variables in the IV regressions, such as macroeconomic indicators from the World Bank (2022), political systems indicators from the Inter-American Development Bank (IDB; Cruz et al., 2021) and the WhoGov dataset (Nyrup and Bramwell, 2020).

C Assessing Measurement Validity

Figure S2: Convergent Validation against Similar Datasets



Note. Concurrent presidential terms were used for comparisons. In the case of Camerlo and Martínez-Gallardo's Presidential Cabinets Project (2020), a merged dataset from Argentina, Chile, Colombia, Costa Rica, Ecuador, Peru and Uruguay was used. For further details see González-Bustamante (2025).

D Variables

country. This variable indicates the name of the country corresponding to the quarterly observation.

honeymoon_1q. Dummy variable indicating whether the observation falls in the first quarter of a newly inaugurated presidential term (1 = yes; 0 = no).

honeymoon_2q. Dummy variable indicating the second quarter of a presidential term's honeymoon period (1 = yes; 0 = no).

honeymoon_3q. Dummy variable indicating the third quarter of a presidential term's honeymoon period (1 = yes; 0 = no).

preelection_1q. Dummy variable indicating one quarter before a scheduled presidential election (1 = yes; 0 = no).

preelection_2q. Dummy variable indicating two quarters before a scheduled presidential election (1 = yes; 0 = no).

dismissal_tainted. Number of ministers who were dismissed after receiving calls for their resignation (i.e., "tainted" ministers).

age. Average age of all cabinet members at the end of the quarter.

nonpartisan. Proportion of ministers in the cabinet who are not affiliated with any political party.

inflation. Quarterly inflation rate as reported by the World Bank (2022) data.

gdp. Gross domestic product (GDP) metric obtained from World Bank (2022) data.

allhouse. Binary indicator reflecting whether the president's party holds an absolute majority in the legislative houses with law-making powers (1 = yes; 0 = no). Obtained from IDB (see Cruz et al., 2021).

govfrac. An index measuring the probability that two randomly selected government deputies belong to different parties (0 to 1, with higher values indicating more fragmentation). Obtained from IDB (see Cruz et al., 2021).

reelect_last_year. Binary variable indicating whether it was legally possible for the president to run for re-election in the last year of the term (1 = yes; 0 = no). Obtained from IDB and then manually reviewed.

coalition. Binary indicator reflecting the presence of a multi-party governing coalition according to WhoGov data (see Nyrup and Bramwell, 2020) (1 = yes; 0 = no).

lagged_approval. The prior quarter's smoothed presidential approval estimate, as calculated by Carlin et al. (2019), using the dyad ratios algorithm (lagged measure).

approval. The smoothed quarterly presidential approval measure (Carlin et al., 2019), using the dyad ratios algorithm. This is the approval level at the end of the current quarter.

lagged_rc. The aggregate number of calls for resignation received by any cabinet member in the previous quarter (lagged measure).

lagged_dism_tainted. Number of tainted ministers dismissed during the previous quarter (lagged measure).

lagged_age. The average age of cabinet members in the previous quarter (lagged measure).

lagged_nonpartisan. The proportion of nonpartisan ministers in the previous quarter's cabinet composition (lagged measure).

visibility. Binary variable indicating whether calls for resignation concerned high-visibility topics linked to salient policy or economic issues as per Camerlo and Pérez-Liñán (2015) (1 = yes; 0 = no).

qtr. A unique identifier for each quarterly observation, formatted as YYYYqN (e.g., 2001q3).

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