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Citation: Kladakis, G. & Skouralis, A. (2024). Election cycles and systemic risk (WP-CBR-02-2024). London, UK: Centre for Banking Research, Bayes Business School, City St George's University of London.

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**Centre for Banking Research
Bayes Business School (formerly Cass)
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Election cycles and systemic risk

George Kladakis

Alexandros Skouralis

October 2024

Centre for Banking Research Working Paper Series

WP 02/24

Election cycles and systemic risk

George Kladakis

University of St Andrews Business School

Alexandros Skouralis*

Bayes Business School, City St George's, University of London

September 30, 2024

Abstract: We examine whether election periods are associated with increased systemic risk. Our analysis includes a global sample of banks from 22 advanced economies from 2000 to 2023, covering a total of 147 national elections. The findings indicate that systemic risk increases during election and post-election periods, while it is lower in the pre-election period in the case of end-of-term elections. More specifically, the year in which elections occur is associated with a 3.74% higher systemic risk compared to the overall average. The results can be attributed to the suppression of negative information and expansionary fiscal policies in the period before elections. Notably, the impact is more pronounced for snap elections and when the incumbent government was not re-elected. In addition, we find that macroprudential policies, strong economic growth and trust in the current government and banks' financial health can partially mitigate the impact of elections on systemic risk. Finally, to alleviate endogeneity concerns, we employ two instrumental variables, namely, term times and an election uncertainty index based on Google Trends, in a 2SLS model and the results hold and confirm our previous findings, further validating the robustness of our analysis.

Keywords: *Elections ; Systemic risk ; Political uncertainty ; Financial stability*

JEL Classification: *G02; G32 ; G18 ; D72*

*Corresponding Author: alexandros.skouralis@city.ac.uk

1. Introduction

Politics play a critical role in the structure and development of the financial system, with financial markets being consistently high on policymakers' agenda due to the inherent and unavoidable market failures that often require a government intervention (Beck, 2011). A deeper understanding of this relationship is important, especially in the current context of heightened geopolitical risks. This paper explores the role of election cycles for financial stability and, more specifically, whether elections can be a source of systemic risk. Elections are a fundamental pillar of democracy, embodying the principle of representation and offering voters the chance to shape future government policies. Consequently, when election cycles draw to a close, the intersection between politics and financial stability becomes particularly critical as financial markets react to the uncertainties stemming from potential changes in economic policies, regulatory frameworks, and government spending priorities.

Previous empirical research provides evidence of the influence of political events on stock market returns suggesting that the effect strengthens as the election day approaches and uncertainty increases (Pantzalis et al. 2000 ; Santa-Clara and Valkanov, 2003). In addition, research has focused on the effects of elections and/or political uncertainty on asset prices (Liu et al., 2017), stock price volatility (Białkowski et al., 2008 ; Boutchkova et al., 2012), stock price informativeness (Fulgence et al., 2023), the equity option market (Kelly et al., 2016), investments (Julio and Yook, 2012 ; Gullen and Ion, 2016 ; Jens, 2017), firm valuation (Bekaert et al., 2016) and risk-aversion and leverage strategies (Lee et al., 2017). Despite the body of research underscoring the significance of politics in the financial markets, the impact of political uncertainty on macro-financial stability remains underexplored.

This paper addresses this critical gap by exploring the influence of electoral cycles on systemic risk. To the best of our knowledge, this is the first study to examine the dynamics between politics and financial stability by focusing on whether elections are associated with increased systemic risk. We use a large dataset covering the period from 2000 to 2023, which includes 22 countries, 147 national elections, and 193 banks. Our findings reveal a robust, albeit time-varying, relationship between elections and systemic risk. More specifically, we find a notable decrease in bank systemic risk by 1.95%¹ during the pre-election year and campaign period. This is followed by a substantial surge in systemic risk during the election year and post-election period, with increases of 3.74% and 3.86%, respectively. In addition, we find heterogeneity in the magnitude of the effect on systemic risk depending on the election outcome as the impact is partially mitigated when the incumbent government is re-elected, whereas it is stronger in the case of snap elections. Our empirical analysis also suggests that firm characteristics such as profitability, bank size and low idiosyncratic risk play a role in mitigating the effects of elections on systemic risk.

¹ The percentages are estimated given that the mean value of the dependent variable is 1.737%.

Our results are robust to a series of robustness tests. Firstly, we extend our sample to include different types of financial institutions (697 in total), not only banks, and the results hold across all model specifications. Secondly, we employ alternative measures of systemic risk, namely Marginal Expected Shortfall (MES) by [Acharya et al. \(2017\)](#) and SRISK by [Brownlees and Engle \(2016\)](#), and confirm our findings. Thirdly, we remove year fixed effects from our model and control for the effect of the COVID-19 pandemic, yet our results remain robust. Finally, our results hold when we incorporate monthly data series into our model.

Moreover, this paper aims to shed light on the mechanisms behind the dynamics between election cycles and systemic risk. Following the literature, we observe that government expenditures increase in the period before elections ([Kräussl et al., 2014](#); [Drazen and Eslava, 2010](#)), while stock price informativeness decreases ([Li et al., 2018](#); [Fulgence et al., 2023](#)). Our empirical findings suggest that both factors act as buffers against election cycles and can partially explain the decline in systemic risk in the pre-election period, especially in the case of end-of-term scheduled elections. Conversely, stock market sentiment, measured by annual stock price volatility, indicates distress during the election and post-election periods, especially in snap elections or when a new government is elected. These results align with our previous findings. Interestingly, other social factors, such as trust in the current government, and strong economic growth reduce the systemic importance of election cycles.

These insights not only contribute the theoretical discourse on political finance, but also have significant implications for policymakers and financial regulators aiming to mitigate systemic risks. With regards to the latter, we explore the role of macroprudential policy as an important factor that determines the magnitude of the impact of elections on systemic risk. These policies are designed to strengthen the resilience of the financial system, reducing the likelihood that political and economic uncertainties associated with elections will translate into broader financial instability. To empirically test the role of macroprudential policies, we employ the iMaPP dataset by the IMF and [Alam et al. \(2019\)](#) into our model. Our findings confirm the significant decrease in systemic risk in a year of macroprudential tightening. In addition, we find that in years of macroprudential tightening, the impact of elections on systemic risk weakens significantly and therefore macroprudential policy can play a mitigating role in the face of political uncertainty.

The focus of this paper is on elections, and not political risk or uncertainty indices for two main reasons. First, policy uncertainty and financial distress present a high degree of correlation ([Baker and Bloom, 2013](#)) and to avoid this issue and the endogeneity concerns that arise from that, we use elections, which provide an independent natural experimental framework for studying how political uncertainty affects the financial markets ([Jens, 2017](#) ; [Li et al., 2018](#)). [Redl \(2020\)](#) also uses elections to decompose the effect of political uncertainty and financial stress on the macroeconomy. [Redl \(2020\)](#) argues that these events are associated with political uncertainty, but not with financial stress, and therefore can be used to isolate the two alternative channels. Interestingly, [Redl \(2020\)](#)'s results show that election-

related shocks are more important for GDP compared to financial shocks. Secondly, elections provide a more precise and focused measure compared to Economic Policy Uncertainty (EPU) indicators. The latter, while useful for gauging general economic uncertainty, are not well-suited for capturing specific political cycles or uncertainties because they aggregate a wide range of variables that extend beyond political factors, whereas elections directly represent the potential for political change, including shifts in regulatory and fiscal policies. This is not the first paper that explicitly discusses the difference between the use of national elections and uncertainty indices. For instance, [Pástor and Veronesi \(2013\)](#) argue that policy uncertainty is only a channel through which political uncertainty induces financial markets.

To further alleviate any endogeneity concerns, we employ two instrumental variables, namely, term times and an election uncertainty index based on Google Trends, in a two-stage least squares (2SLS) model. Term times, used also by [Jens \(2017\)](#), serve as an effective instrument with a strong correlation with election timing and no association with systemic risk. In addition, the election uncertainty index is based solely on people's searches on Google, and not on the combination of economic and political variables. Therefore, it reflects the real-time sentiment and anticipation around electoral outcomes, providing an innovative and dynamic measure of uncertainty. A similar measure is constructed by [Castelnuovo and Tran \(2017\)](#) for overall market uncertainty and, more recently, by [Fungáčová et al. \(2024\)](#) to measure election-related uncertainty. The 2SLS approach confirms our findings and mitigates potential biases arising from reverse causality, ensuring a more reliable estimation of causal effects. Finally, as an additional test for endogeneity, we rerun the model excluding years in which banking crises occurred. To ensure comprehensive results, we use two databases on banking crises. The first one is from [Reihart and Rogoff \(2014\)](#) and the Harvard Business School and the second one is from [Metrick and Schmelzing \(2021\)](#). The consistency of our results even after the exclusion of the banking crisis periods confirms the robustness of our analysis, reinforcing the credibility of our empirical strategy.

Our findings have direct policy implications since they highlight the crucial role of political events, such as elections, in systemic risk management and investment decision-making. From the policymakers' perspective, the strong association between elections and systemic risk highlights the necessity for a proactive approach that according to our findings can help mitigate these associated risks and strengthen the financial system. In addition, the close monitoring of political developments and incorporating them into investment strategies is essential for investors to better navigate the volatility that such events often bring.

The remainder of this paper is organized as follows. Section 2 reviews the relevant empirical literature and develops the main hypotheses. Section 3 describes the election dataset, the estimation of systemic risk, and the empirical methodology. Section 4 presents our empirical findings on the

relationship between systemic risk and elections and discusses the mitigating factors and transmission channels. Finally, Section 5 presents the robustness tests, and Section 6 concludes.

2. Literature review and hypotheses development

The paper contributes to the growing literature on the intersection between politics and financial markets. [Białkowski et al. \(2008\)](#) use data from national elections and find that in a sample of 27 OECD countries stock market volatility is double in the week around an election. Similarly, [Boutchkova et al. \(2012\)](#) use national elections as a proxy for political uncertainty and find that some industries are more sensitive to political risk due to their trade exposure, contract enforcement, and labour and thus they exhibit greater return volatility when local political risks are higher. Similar findings have been presented from studies that use indicators of political uncertainty instead of national elections data. [Smales \(2014\)](#) and [Goodell et al. \(2020\)](#) find that political uncertainty leads to an increase in both financial market uncertainty and volatility. Elections-related uncertainty is also linked to investor sentiment. [Jens \(2017\)](#) finds that investments are reduced by 5% around the election, but they quickly return to previous levels if the incumbent government is re-elected. The impact of elections is stronger on developing countries ([Honig, 2019](#)), countries with levels of debt and/or in cases where the results were difficult to predict ([Julio and Yook, 2012](#)).

Similar findings are provided by [Julio and Yook \(2012\)](#) who study elections and corporate investment and they find that the impact can be greater if the result is difficult to predict or in countries with high levels of debt. The decline in investments is driven by the additional lending costs that impact firm-level investment decisions. More specifically, financial institutions face higher costs of equity ([Brogaard and Detzel, 2015](#)) and debt ([Francis et al., 2014](#)) since investors require higher risk premium to account for the election-associated uncertainty ([Gungoraydinoglu et al., 2017](#)). Overall, election cycles affect bank access to finance and their lending strategies ([Koetter and Popov, 2021](#) ; [Kara and Yook, 2023](#) ; [Fungáčová et al., 2024](#)) and economic policy uncertainty alters leverage decisions and bank risk-taking capacity ([Lee et al., 2017](#)).

Despite the extensive research focusing on stock market volatility and corporate strategies, to the best of our knowledge, this paper is the first to explore the impact of elections on systemic risk. This is the second strand of literature to which this paper contributes, i.e., on the determinants of systemic risk. Systemic risk is defined as the risk of a significant disruption within a financial system triggered by significant distress or collapse at the firm or sectoral level. Large financial institutions are often labelled as "*too big to fail*" and are found to be more systematically important ([Varotto and Zhao, 2018](#) ; [Pais and Stork, 2013](#); [Laeven et al., 2016](#)) due to their significant impact on the financial system. Previous studies suggest that systemic risk is also positively associated with leverage ([Acharya and Thakor, 2016](#)) and total lending as a fraction of total assets ([Buch et al. 2019](#)). On the contrary, factors such as bank capital ([Laeven et al., 2016](#); [Anginer et al., 2018](#)) and liquidity creation ([Davydov et al., 2021](#)) reduce

bank-level systemic risk. Systemic risk is also driven by the market developments. [Anginer et al. \(2014\)](#) find that greater competition results in banks taking on more diversified risks, which reduces their exposure to systemic events. On the other hand, [Kladakis and Skouralis \(2024a\)](#) argue that external factors such as credit ratings downgrades reduce banks' access to finance and subsequently lead to increased systemic risk. In addition, the literature provides evidence on the impact of other forms of government interventions, such as capital regulations ([Bostandzic and Weiss, 2018](#)) and government support programs ([Berger et al., 2020](#)).

However, as we mentioned before, there is limited research on the systemic risk induced by elections. One of the papers related to our study is [Matousek et al. \(2020\)](#) who study the impact of economic policy uncertainty on capital shortages. To measure EPU, the authors use the index by [Baker et al. \(2016\)](#) that account for the country's political environment and policymakers and it includes elections and other political factors of various degree of importance. The level of capital shortfall is measured by SRISK, the systemic risk metric developed by [Brownlees and Engle \(2016\)](#). Their findings suggest that higher policy uncertainty induces future capital shortfall increases in periods of market distress. Similarly, [Duan et al. \(2023\)](#) and [Fang et al. \(2023\)](#) find that economic policy uncertainty (EPU) by [Baker et al. \(2016\)](#) increases bank systemic risk. As we discussed before, despite the fact that the index also includes terms related to politics or political uncertainty, it is not an ideal proxy for political uncertainty, because it encompasses a broad range of factors beyond just political dynamics. More specifically, the EPU index captures general economic conditions, policy changes, regulatory adjustments, and macroeconomic developments, all of which may be influenced by but are not exclusively tied to political events. Therefore, our paper aims to fill this apparent gap in the literature and provide empirical evidence on the dynamics between election cycles and systemic risk. Drawing on the aforementioned literature, we hypothesize that systemic risk will be elevated during election periods due to the heightened uncertainty surrounding future government policies and the election-induced financial markets' stress. Our analysis seeks to quantify this impact, providing a clearer understanding of how election-induced uncertainty translates into systemic risk.

H.1: Election periods are associated with greater systemic risk.

However, the impact of elections on financial markets and systemic risk might vary depending on market's expectations ([Boutchkova et al., 2012](#)). Specifically, in cases where there is no candidate with a significant lead, the pre-election stock market volatility is higher ([Li and Born, 2006](#)), whereas the adverse effect of elections is limited in cases of the re-election of the incumbent government or the election of a government with strong majority ([Białkowski et al., 2008](#)). In the latter case, elections also have the potential to enhance financial stability by reinforcing institutional trust and a stable political environment conducive to economic growth. In line with that, [Goodell et al. \(2020\)](#) use election polls and they find that the probability of the current government being re-elected affects drastically both

policy and financial uncertainty. On the other hand, unexpected election outcomes can create rather than resolve the associated market uncertainty. [Cox and Griffith \(2019\)](#) use the 2016 surprise Trump win in the US elections as a case study of such an event and they find an increase in information asymmetries among market participants, reduced liquidity and higher volatility in the post-election period. Therefore, we expect that the impact of elections on systemic risk to be stronger in cases that the winning party is not in the incumbent government and when there is a snap election, not fully anticipated by the markets.

H.2: The impact of elections on systemic risk depends on the election timing and outcome.

Nonetheless, systemic risk exhibits different patterns, not only based on the outcome, but also on the different stages of the election cycles. The time-varying dynamics of financial distress during election cycles have been previously documented in the literature. [Liu and Ngo \(2014\)](#) exploit the exogenous nature of US gubernatorial elections and their findings suggest that bank failures are 45% less likely to occur the year before elections, compared to non-election years. The heterogeneous across time effect is likely driven by two main factors, the suppression of information and the expansionary fiscal policies in the pre-election/campaign period. [Li et al. \(2018\)](#) show that stock prices are more likely to crash in the post-election period since it coincides with the subsequent release of adverse news suppressed or covered in the pre-election period. This is because during this period of high political uncertainty, stock price informativeness declines due to the highly volatile environment in which firms tend to disclose less information ([Fulgence et al., 2023](#)). Similarly, [Boutchkova et al. \(2012\)](#) and [Gungoraydinoglu et al. \(2017\)](#) suggest that during elections, information risk is increased and is overall associated with investors' reduced demand especially for risky assets ([Pástor and Veronesi, 2013](#)).²

Another explanation of the decline in systemic risk in the pre-election period is the adoption of expansionary policies prior to the election day. Political parties often engage in strategic behaviour regarding government spending and tax policies before elections ([Alesina et al., 1991](#)). This pattern, known as political budget cycles, can lead to increased spending, tax cuts, and higher transfers before and during election years ([Rogoff and Sibert, 1988](#); [Rogoff, 1990](#); [Kräussl et al., 2014](#)). [Drazen and Eslava \(2010\)](#) provide empirical evidence from Colombian elections suggesting that the incumbent government might choose to change the allocation of government spending to target specific groups of voters prior to the elections. Looking at the same channel but from a different angle, [Dinç \(2005\)](#), [Carvalho \(2014\)](#) and [Koetter and Popov \(2021\)](#) show that government-owned banks change their strategy and increase their lending in election years relative to independent, private banks. Based on the above we hypothesize that systemic risk should be lower in the campaign period or the year before the election.

² [Piotroski et al. \(2015\)](#) provide empirical evidence based on a study of two visible political events in China. They find evidence of temporarily restricting the flow of negative information on government-affiliated companies and consequently fewer stock price crashes during the examined period, followed by an increase in crashes afterward.

H.3: Systemic risk is lower in the pre-election period.

[Insert Table 1]

Table 1 summarizes our hypotheses regarding the relationship between elections and systemic risk. Overall, we expect that elections will increase systemic risk in the current and following year. However, we aim to examine whether the re-election of the incumbent government mitigates this effect in the post-election period or whether snap elections are associated with greater systemic risk. Conversely, we anticipate that systemic risk will be lower during the campaign period. However, we remain agnostic on whether this mitigating effect holds for unexpected (snap) elections or if the incumbent government wins the elections. Based on the aforementioned literature, we expect that the suppression of information (leading to information asymmetries) and fiscal expansion will act as buffers against the impacts of elections during the campaign period. Additionally, we hypothesize that periods of high economic growth can partially mitigate the impact of elections on systemic risk metrics, as systemic risk is negatively associated with macroeconomic developments ([Giglio et al., 2016](#) ; [Brunnermeier et al., 2020](#)). On the other hand, market sentiment, measured by stock market index annual volatility, caused by political uncertainty is expected to amplify the impact of elections on systemic risk during election years and in the post-election period. Based on the above we test the following two hypotheses:

H.4.A: Expansionary fiscal policies and information asymmetries in the pre-election period can reduce the effect of elections on systemic risk.

H.4.B: Financial market sentiment is driving the negative effect of elections on systemic risk in the post-election phase of the cycle.

Additionally, we control for the role of trust in government as a driving factor in our results. [Pantzalis et al. \(2000\)](#) show that the relationship between political uncertainty and stock markets depends on factors such as the country's political, economic and press freedom. We focus on trust in government, which is strongly associated with macroeconomic development ([Algan and Cahuc, 2010](#)), and we expect that it will mitigate election-related systemic risk. High trust in government reduces political uncertainty during elections, leading to more stable financial markets and implies a consistent and fair regulatory environment, allowing banks to operate with greater predictability and stability. On the other hand, the trust in the government varies during election periods ([Dabros et al., 2015](#)) and thus can work as an additional transmission channel.

H.5: Higher trust in government results in a weaker relationship between election cycles and systemic risk.

Finally, our paper contributes to the growing literature on the effectiveness of macroprudential policies in reducing systemic risk. These policies are designed to strengthen the resilience of the financial system, and by construction they target systemic risk indicators and aim to reduce the

likelihood of systemic events. [Meuleman and Vander Vennet \(2020\)](#) study a large set of European banks for the period 2000-2017 and they find that macroprudential policy announcements have a negative effect on bank systemic risk, with the impact to be greater on distressed banks. Similar findings are presented by [Rizwan \(2021\)](#) and [Apergis et al. \(2022\)](#), who also document the heterogeneity in the impact of macroprudential policies depending on the size of the economy and the market structure and bank characteristics, respectively. In this paper, we empirically test the impact of the adoption of macroprudential policies on bank systemic risk in line with the aforementioned literature. In addition, we examine whether macroprudential policy can improve the resilience of the financial markets and work as buffer against the elections-induced systemic risk.

H.6: Macroprudential policy can mitigate election-related systemic risk.

3. Data and methodology

3.1 Measuring systemic risk

To measure systemic risk, we use one of the most popular metrics in the relevant literature, Conditional Value at Risk (*CoVaR*) by [Adrian and Brunnermeier \(2016\)](#). *CoVaR* is an extension of the traditional Value at Risk (*VaR*) measure and is designed to measure the systemic importance of individual financial institutions. While *VaR* estimates the potential loss in value of a financial asset or portfolio over a specified period for a given confidence interval, *CoVaR* assesses the risk to the entire financial system conditional on a particular institution or sector being under distress. The mathematical representation of *VaR* of a financial institution (*i*) is displayed in Equation (1). Building on the definition of *VaR*, *CoVaR* of the financial system index (*s*) when a financial institutions (*i*) is under distress is presented in Equation (2).

$$P(R_t^i < VaR^i) = q \quad (1)$$

$$P(R_t^s < CoVaR^{s|i} | R_t^i = VaR^i) = q \quad (2)$$

$$\Delta CoVaR^{s|i} = CoVaR_{q=0.05}^{s|i} - CoVaR_{q=0.5}^{s|i} \quad (3)$$

where R_t is the average weekly returns³ and q the examined quantile. The returns of the financial system index, R_t^s , is based on the Thomson Reuters EIKON Datastream (DS) Financials index that includes each country's large financial institutions such as banks, insurance companies, financial services, closed-end funds and other brokers. *CoVaR* is a measure of tail dependency between the financial system and the examined institution. [Adrian and Brunnermeier \(2016\)](#) suggest measuring the systemic importance of a firm as the difference between the *CoVaR* of the financial system index when an

³ We use weekly data series instead of monthly data because the latter may not capture short-lived systemic events that occur within a month. Additionally, using weekly data aligns with the methodology of [Adrian and Brunnermeier \(2016\)](#) and the $\Delta CoVaR$ literature.

institution is at its VaR and its median value as displayed in Equation (3). The difference is defined as $\Delta CoVaR$ and indicates the additional tail risk for the financial system when the examined institution moves from normal to distress times. Following the convention, we use the positive values for all risk metrics. Therefore, higher values of $\Delta CoVaR$ indicate that the examined institution is more systemically important.

The estimation of $\Delta CoVaR$ is based on a set of state variables and the method of quantile regressions. According to [Adrian and Brunnermeier \(2016\)](#), these state variables need to be highly liquid and tractable assets that capture the time variation of systemic risk. The time-varying $CoVaR$ allows for a dynamic assessment of systemic risk by capturing the changing relationships between financial institutions and the financial system over time. This dynamic aspect makes it possible to track how the systemic risk contributions of institutions evolve, providing timely insights for policymakers. The estimation consists of three steps. First, we obtain the dynamic VaR by running a quantile regression of returns of the examined financial institution (R_t^i) and a set of state variables (S_{t-1}) as presented in Equations (4) and (5).

$$R_t^i = a_q + \beta_q S_{t-1} + \varepsilon_{q,t} \quad (4)$$

$$VaR_{q,t}^i = \widehat{a}_q + \widehat{\beta}_q S_{t-1} \quad (5)$$

Second, we repeat the same procedure and we run the quantile regression model with financial market index as the dependent variables on the returns of the examined financial institution (R_t^i) and the set of state variables (S_{t-1}). In Equation (7) we calculate the $CoVaR$ time-series based on the estimates of the coefficients of Equation (6) and we obtain the VaR of the market index conditional on the examined financial institution being at its VaR . The difference between the $CoVaR$ of the financial system when the examined financial institution is under distress ($q=0.05$) and when is at its median returns ($q=0.5$), provides us with $\Delta CoVaR$.

$$R_t^{system} = a_q^{system|i} + \beta_q^{system|i} S_{t-1} + \gamma_q^{system|i} R_t^i + \varepsilon_{q,t} \quad (6)$$

$$CoVaR_{q,t}^{system|i} = \widehat{a}_q^{system|i} + \widehat{\beta}_q^{system|i} S_{t-1} + \widehat{\gamma}_q^{system|i} VaR_t^i \quad (7)$$

$$\Delta CoVaR_{q,t}^{system|i} = CoVaR_{q=0.05,t}^{system|i} - CoVaR_{q=0.5,t}^{system|i} \quad (8)$$

An important factor in the estimation of $\Delta CoVaR$ is the selection of state variables. We select four variables that are available across all countries to ensure consistent estimates across our sample. More specifically, we employ the returns and the volatility of the country's stock market index, the change in

the short-term government bond⁴ and the spread between the 10-year and the short-term government bond.⁵ All the data series are provided by Thomson Reuters EIKON Datastream.

CoVaR provides several advantages compared to other systemic risk metrics in the literature. Firstly, due to the fact that its estimation is based on a quantile regression, *CoVaR* focuses on the tails of the risk distribution, which makes it robust to outliers and extreme events, an important aspect of measuring systemic risk. Secondly, because *CoVaR* is based solely on firms' returns, it can be adapted to various types of financial institutions and markets, making it a versatile tool for systemic risk assessment across different settings and for comparison purposes. Finally, *CoVaR* is not (directly) depending on firm characteristics such as leverage and capital as SRISK and thus it is a valuable tool for understanding and managing systemic risk and also for measuring the impact of macroprudential policies.

[Insert Table 2]

Our sample of financial institutions consists of all firms included in the DS Financials Index, excluding those with less than five years of data. Our final dataset includes 193 banks and 697 other financial institutions from 22 developed countries. Table 2 summarizes the number of financial institutions per country and the percentage of the total sample market capitalization that these institutions represent. USA has the most financial institutions in our sample, accounting for 33.5% of the market capitalization of the banking sample and 42.4% of all financials, followed by the United Kingdom. Table 2 also displays the average $\Delta CoVaR$ for each country, for both banks and all financial institutions in the sample. Ireland and Greece, which account for less than 0.5% of the sample's market capitalization, exhibit the highest values of systemic risk, with 3.743% and 3.456%, respectively.

Figures 1 and 2.A represent the monthly and annual global aggregate systemic risk for the period 2000-2023, respectively. The index is calculated based on the equally weighted average of all financial institutions included in our sample. $\Delta CoVaR$ is based on *VaR* and therefore, it is not additive and its values do not have a particular interpretation. However, the global systemic risk index displays the variation of systemic risk across time. Figure 2.A indicates that there are two main peaks during our sample period; The Global Financial Crisis in 2008 and the start of the pandemic period in 2020. Other crises or major systemic events include the Dot-com crisis (2000-2002), the European Debt crisis (2012-2014), the Brexit referendum (2016) and the most recent Ukraine-Russia war (2023)⁶. They all result in an increase in systemic risk in the affected countries, but our estimates suggest that they did not necessarily have a significant global effect.

⁴ We use the 2-year government bond, which was available for the majority of countries and for the cases that we had missing data, we employ the 1-year government instead.

⁵ Similar state variable selection has been adopted by other studies in the literature that use a global sample (see [Kladakis and Skouralis, 2024b](#)).

⁶ Our estimation is based on the period up until December 2023, so it is likely that the impact of Russia-Ukraine war is not fully quantified in our data.

[Insert Figure 1]

[Insert Figure 2]

Finally, Figure 2.B displays the aggregate systemic risk for banks and non-banks. The latter category includes all other financial institutions, such as insurance and financial services companies and closed-end funds. The sectoral estimates indicate that systemic risk exhibit significant co-movements between the two groups, however, historically, banks have been more systemically important during major financial crises like the GFC and European Debt Crisis, whereas non-banks have seen their systemic importance surge during and after the COVID-19 period. The estimates are in line with our expectations. Banks were in the epicentre of the two major crisis in the period 2008-2014, while in 2020, they received substantial government support (lowering interest rates, purchasing assets, and providing emergency lending facilities) to ensure stability during pandemic. On the other hand, non-banks did not benefit to the same extent and had to navigate the crisis with less direct assistance.

3.2 Elections

For our empirical analysis we construct a global election database for 22 developed countries⁷ in the period 2000-2023. All the countries included in our analysis are presented in Table 2.⁸ We exclude developing countries due to the differences in institutional frameworks, legal and regulatory systems, data quality, political dynamics and the frequent government intervention in the economy and banking sector. In total, we have data on 147 elections, 108 (73.5%) of which were scheduled (end-of-term) elections and the remaining 39 (26.5%) were held before the end of the term period. The country with most elections in the examined time period is Israel with ten, seven of which were snap elections and some of them occurred consecutively in the recent political crisis period (2018-2022). On the other hand, nine countries in our sample had only end-of-term elections. Almost half of the elections result in the incumbent government getting re-elected (49.7%) and the other half of them (50.3%) lead to a new government.

[Insert Figure 3]

3.3 Methodology

To empirically examine the impact of elections on systemic risk, we employ a panel fixed-effect regression model. Systemic risk, measured by $\Delta CoVaR$, is the dependent variable in our panel regression model, with “*ELECTIONS*” as a dummy that takes the value 1 for years when elections occurred:

⁷ We do not take into consideration the European elections since they do not directly affect the domestic economy. In the case of France, we focus on the presidential elections and in Portugal we keep only the legislative elections.

⁸ We include most developed countries, with our only criterion being data availability. For instance, we only include countries with a sufficiently large financial sector and where a DS Financials index has been available for at least ten years within our examined period.

$$\Delta CoVaR_t^{sli} = \beta_0 + \beta_1 ELECTIONS_{i,t} + \beta_2 X_{i,t-1} + \beta_3 M_{c,t-1} + a_t + a_i + \varepsilon_{i,t} \quad (9)$$

The subscripts and superscripts t, i, c and s refer to time (year), firm, financial system (market index) and country, respectively. Following the literature, we control for size with the natural logarithm of total assets (Anginer et al., 2018 ; Brunnermeier et al., 2020), capital adequacy (Davydov et al., 2021 ; Berger et al., 2020) by using the leverage ratio of long-term debt to market value of capital and profitability with ROE (Varotto and Zhao, 2018; Davydov et al., 2021). Moreover, we include country level variables, i.e., GDP growth and inflation, to account for changes in the macroeconomic environment. These two variables capture business cycles and are factors contributing to financial crises (Brunnermeier et al., 2020). Firm data series are provided by Thomson Reuters EIKON Datastream and the macroeconomic data is from the OECD database. All models include firm (a_i) and year (a_t) fixed effects to account for potential omitted variables issues and the standard errors are robust and clustered at firm level.⁹ In addition, Table 3 presents a summary of statistics, including the mean, standard deviation, minimum, and maximum values for each variable, including the election dummies for the banks-only and all financials sample used in our empirical analysis. The reported values correspond only to the years in which the main variable of interest, $\Delta CoVaR$, is available.

[Insert Table 3]

4. Empirical results

4.1 Benchmark Model

The results are reported in Table 4. Our benchmark model specification is initially based on a sample of 193 banks included in the EIKON Datastream Financials country indices.¹⁰ Our results indicate a positive effect of elections on bank systemic risk. In other words, the year elections take place are associated with a 3.74% increase in systemic risk. The results hold with and without the inclusion of control variables. With regards to the latter, our regression estimates, in Model (2) to (7) of Table 4, are in line with the aforementioned literature. We find that bank size is positively related with $\Delta CoVaR$, whereas profitability (ROE) mitigates the level of systemic risk. The results are robust to other indicators of size, such as the number of employees or Market Capitalisation and alternative profitability measures, such as Net Interest Margin and Earnings per Share. Leverage, measured by Debt as a percentage of Capital, presents a positive, but insignificant relationship with $\Delta CoVaR$. GDP growth and inflation are negatively associated with systemic risk, since systemic events is more likely to occur in the downward phase of the business cycle.

⁹ For further clarification, Table A.1 in the Appendix provides a detailed description of all variables included in our analysis.

¹⁰ We do not consider banks with less than five years of observations or those not big enough to be included in the EIKON Datastream sample.

[Insert Table 4]

We then examine if the effect of elections on financial markets varies significantly based on whether the elections are snap or scheduled. As we point out in the previous section, one in four elections occurred before the end of term. Snap elections often lead to higher market uncertainty and volatility due to their unexpected nature, signalling potential political instability and urgent policy shifts, which increases perceived risk for banks. Consequently, investor confidence and economic stability can be adversely affected, leading to capital outflows, currency volatility, increasing funding costs and liquidity risks for banks and thus, higher default probabilities. On the other hand, end-of-term elections are anticipated and allow market participants more time to adjust their strategies, leading to less surprise and lower immediate impact on bank risk. We empirically test the above hypothesis in Table 4, Models (4) and (5), and include two dummy variables (instead of *ELECTIONS*), namely *SNAP* and *END – OF – TERM* that take the value equal to one if the elections occurred are unexpected or scheduled, respectively. Our findings suggest that in both cases there is a significant increase in systemic risk. In the case of snap elections, the estimated coefficient is almost two times larger suggesting that snap elections drive the documented impact on systemic risk. Given that the average value of systemic risk, snap elections increase $\Delta CoVaR$ by 5.24%, compared to a 3.17% increase following end-of-term elections.

Regardless of whether the elections were expected or not, the re-election of the incumbent government could help mitigate the risks associated with elections by reducing uncertainty and providing continuity in policies. To empirically examine if our data support the above, we run the benchmark model with two new dummy variables for when the government (or the leading party in case of a coalition government) wins the elections (*RE – ELECTED*) or not (*NEW GOV*). Our results suggest that the impact of elections on bank systemic risk is significantly higher and almost twice as large in the case of the current government losing the elections. In our elections dataset, there are only few unexpected outcomes since the vast majority of results had been predicted by the polls. Therefore, the increase in systemic risk in the case of a change in government can be attributed to both the uncertainty in the pre-election period and the policy discontinuity after the elections. Moreover, to provide robust evidence on the role of the elections outcomes, we run our benchmark model by including the interactive term *RE – ELECTED* \times *ELECTIONS* and the *ELECTIONS* dummy. In line with our previous findings, the coefficient of the interaction term is negative and statistically significant and therefore indicates that the re-elections of the incumbent government weakens the impact of election cycles on systemic risk.

4.2 Pre- and post-election periods

In addition, we examine the time-varying impact of election by including a dummy variable (*POST*) equal to one in the periods after the elections and a variable (*PRE*) for the year before the elections

occur.¹¹ To investigate the heterogenous across time effect of elections on bank systemic risk, we do not take into consideration pre-and post-election years in the case of consecutive elections. Our results, presented in Table 5, Models (8)-(13), suggest that in the year after the elections, systemic risk is higher, and the effect is at the same level as in the election year. With regards to the pre-election period, our results are suggest that $\Delta CoVaR$ values are lower in the period before the elections. Moreover, we include the two variables, *SNAP* and *RE – ELECTED*, as described in the previous section and we obtain some very interesting findings. Unexpected (snap) elections increase systemic risk both before (Model 10) and after (Model 13) the election period. Alternatively, the re-election of the incumbent government in a snap election alters the direction of the effect and reduces systemic risk in the post-election period, whereas it has an insignificant effect in the pre-election period.

[Insert Table 5]

4.3 The role of bank characteristics

In addition, we examine whether firm characteristics of the examined financial institutions can act as a buffer against election-related uncertainty. Our empirical findings and the literature suggest that profitability is negatively associated with systemic risk, whereas firm size and *VaR* exhibit a positive association with systemic risk metrics. We empirically examine whether financially healthier institutions are more resilient to election cycles. The results are displayed in Table 6 with and without firm and country-level controls. *VaR* is positively associated with a financial institution's systemic risk, and the coefficient of interaction term between *ELECTIONS* \times *VaR* is also positive and statistically significant. This suggests that the impact of election cycles on systemic risk is greater for firms with higher idiosyncratic risk. Conversely, the interaction terms with ROE and size are negative and statistically significant for banking institutions. Profitable banks with larger portfolios appear in the election year better equipped to navigate the uncertainties of election periods, likely due to their stronger financial positions and operational resilience.

[Insert Table 6]

4.4 Other financial institutions

Our analysis so far has focused only on banks, however other financial institutions, such as insurance companies and investment firms are also expected to experience an increase in their stock price volatility and systemic risk during election periods. For that purpose, we extend our sample to include a wide range of financial institutions, the choice of which is based on the constituents of the EIKON Datastream Financials country indices. Our new sample consists of 697 financial institutions. Banks still dominate the portfolio in terms of Market capitalisation, since the 193 banking institutions in our

¹¹ A similar approach has been presented by [Li et al. \(2018\)](#) that examine the impact of national elections on stock tail risk.

sample account for 47.28% across all firms and through the entire sample period. The extended sample includes 120 insurance companies and 380 investment trusts, financial services companies, support financial services and closed-end funds, which account for 22.01% and 30.71% of the sample Market capitalization.

To examine whether other types of financial institutions are affected by election cycles, we run our benchmark model with the extended sample. Our results are presented in Table 7. In line with our previous findings, systemic risk is increased in the election years. The effect is, however, not as great as on the banking sector alone. This is in line with our expectations since banks operate in a highly regulated environment, and changes in government can lead to shifts in regulatory frameworks that directly influence their operations, such as lending practices and capital requirements. Moreover, banks are highly sensitive to market sentiment and consumer confidence, both of which can fluctuate during election periods, whereas insurance companies and investment trusts, have more diversified portfolios and longer investment horizons, that buffer them against the immediate impacts of election outcomes.

Similar to the bank systemic risk analysis, snap elections have a stronger impact on systemic risk which increases in the pre and post-election years. In contrast, the re-election of the incumbent government mitigates the effect, which is primarily driven by the election of a new government. Finally, the time-varying pattern is consistent with our previous findings as a high level of systemic risk is observed in the post-election period, while $\Delta CoVaR$ values are lower in the pre-election year.

[Insert Table 7]

4.5 Mitigating factors & transmission channels

In this section, we examine the driving factors behind the relationship between election cycles and systemic risk. Specifically, we focus on government expenditures, stock price informativeness, financial stress, and trust in government. These variables are well-documented in the literature as influential in the effect of elections and political uncertainty on financial markets. Table 8 presents the average values of these four variables for the year before and on the election year. Additionally, the table shows the average values for the post-election period based on the election outcome.

The first variable is government expenditures, measured as a percentage of GDP. We use year-on-year changes for cross-country comparisons. The data suggests that fiscal expansion is typically adopted in the period before elections, while expenditure levels decrease following elections. This aligns with our expectations that fiscal policy is used by the incumbent government as a strategy to stimulate the economy and create a perception of prosperity, thereby directly benefiting the electorate and increasing the chances of re-election. In addition to Table 8's statistics, our data confirm the latter re-election probability hypothesis since it suggests that the probability of the incumbent government to win the elections increases from 49.6% (sample average) to 53.6% if the previous year the government

expenditures had increased. If the increase is above 5%, the probability then reaches 60%. The data is influenced by end-of-term elections rather than unexpected or snap elections. The latter are often characterized by a lack of preparation time for significant fiscal changes or are called during political crises, which may limit the opportunity for a fiscal expansion. Overall, 74.4% of all elections were held within the last six months of the term. However, if we consider only years that were preceded by a fiscal expansion, then 78.6% of the elections were scheduled during this period.

Secondly, we examine how stock price informativeness varies across the election cycle. We use the change in the spread between ask and bid prices (Bhattacharya et al., 2020) for all financial institutions in our sample per country. A higher value indicates lower informativeness in the examined market. Consistent with our hypotheses, we observe a low degree of informativeness in the pre-election period, which declines after elections, particularly if the incumbent government is re-elected. Next, we examine in which phase of the election cycle financial markets react more strongly. We use the annual average of the weekly stock market volatility based on each country's general stock market index. The data suggests that volatility increases in the post-election period, particularly in the case of snap elections and when a new government is elected. This increase in volatility is expected, as these situations are associated with greater uncertainty about future policies. Finally, Table 8 presents the average year-on-year change in the percentage of people who trust their government. The data suggest that trust declines before elections and increases after the election period ends. These results are particularly influenced by snap elections, where the pre-election decline in trust is significant. This decline likely contributes to the observed increases in systemic risk during the campaign period of snap elections. Additionally, trust levels also decline if the incumbent government wins a snap election, a situation in which systemic risk also rises.¹²

[Insert Table 8]

We then incorporate the aforementioned driving factors into our model to empirically examine whether they affect the relationship between election cycles and systemic risk. Table 9 presents the results.¹³ Model (26) shows that stock price volatility during the election year is positively associated with systemic risk. The interaction term $VIX * ELECTIONS$ is positive and statistically significant, whereas the estimated coefficient for $ELECTIONS$ is negative indicating that the impact of elections is primarily driven by periods of high volatility. Results from Model (27) suggest that stock price informativeness is positively associated with systemic risk. Stock price informativeness refers to the degree to which stock prices reflect the underlying economic and financial conditions of a company. High informativeness means that stock prices accurately represent a company's value based on available

¹² The summary statistics of all the variables are presented in the Appendix, Table A.2.

¹³ Table 9 presents the results for all financial institutions. Similar findings are obtained for the banking sector alone.

information, which can lead to more efficient markets.¹⁴ However, in line with our hypotheses, a lower degree of informativeness mitigates the impact of election cycles on systemic risk. The latter can be attributed to the fact that stock prices are less responsive to new information or changes in economic conditions when stock price informativeness is lower.¹⁵ In such cases, the market's reaction to election cycles is less pronounced and stock prices do not adjust as quickly or as accurately to political events, which can dampen the impact of election cycles on systemic risk. If the market is not fully reflecting the political uncertainties due to low informativeness, the changes in systemic risk due to election cycles will be less significant.

[Insert Table 9]

The next factors we examine are fiscal policy and economic growth. Model (28) indicates that economic growth in the election year substantially mitigates the adverse impact on systemic risk. This suggests that robust economic performance in the election year can buffer against the uncertainties and volatilities typically associated with electoral processes. The results also hold when we use government expenditures as percentage of GDP as the fiscal expansion variable in Model (29). The relationship between fiscal policy and systemic risk is indirect and therefore ambiguous. While fiscal expansion can boost economic growth and reduce systemic risk, financial markets might react negatively to expansionary policies, especially in countries with high debt or if such policies are perceived as cynical attempts to buy votes before elections. However, our empirical findings confirm our hypothesis that increased government spending, observed in Table 7, before elections can weaken election-related systemic risk.¹⁶

In addition, our empirical results reveal that the dynamics between electoral cycles and systemic risk can be moderated by social factors. More specifically, the results in Table 8, Model (30) highlight the significant role of societal trust in government. The interaction coefficient is negative and statistically significant, suggesting that in countries with a high degree of trust in governmental institutions, the adverse effect of elections on systemic risk is considerably diminished. This implies that confidence in the government's stability and efficacy can act as a stabilizing force during politically turbulent times. It is important to note that trust in government fluctuates during different phases of the election cycle, as shown in Table 8, however, our findings are primarily driven by significant cross-country variations. For example, Switzerland exhibits an average trust level of 77.09% with a standard deviation of 8.42%, followed by Norway (67.22%) and Finland (60.87%). In contrast, countries such as Greece and Italy show average trust levels below 27.33% and 28.26%, respectively. Consequently, regardless of the

¹⁴ Our results are in line with [Kladakis and Skouralis \(2024b\)](#) who find that press freedom is associated with lower systemic risk.

¹⁵ [Chen et al. \(2007\)](#) find a negative relationship between stock price information and the sensitivity of corporate investment.

¹⁶ The results hold for the year-on-year change in Government Expenses.

election cycle phase, the countries in our sample exhibit distinct differences in government trust, which is reflected in our results shown in Table 9, Model (30).

4.5 The role of macroprudential policy

In this section we empirically examine the role of macroprudential policies as a mitigating factor against election uncertainty. To account for changes in the macroprudential policy regime, we use the iMaPP dataset by the IMF and [Alam et al. \(2019\)](#). The dataset includes dummy-type indicators of tightening and loosening macroprudential instruments. More specifically, it includes, among others, data on macroprudential tools such as Countercyclical Capital Buffer (CCyB), capital requirements, Limits to leverage, Loan-to-Value (LTV), Loans-to-Deposit (LTD) and Debt-service-to-income (DSTI) ratios, stress testing and a series of measures focused on systemically important institutions. The original database is of monthly frequency and we use the aggregate average annual value in our model.

Based on the stance of macroprudential policy, we define two dummy variables, “MP TIGHTENING” and “MP EXPANSION” that take the value one if the aggregate country index is positive and negative, respectively. Despite the fact that macroprudential tools vary in terms of purpose and effectiveness, we adopt [Alam et al. \(2019\)](#)’s approach that puts equal weights to all different tools. That is because we are interested in the direction of the policy and not explicitly in quantifying its effect on systemic risk. The average value of our dummy variable is 0.79 and its standard deviation 0.95. For more than half (57.6%) of the examined years and countries, no macroprudential policies were adopted. On the remaining observations, tightening of the macroprudential policies occurred in almost 86% of them (36.5% overall). Only in the remaining 6% of observations we observe the implementation of expansionary macroprudential policies. Finally, our sample period ends at 2021, since the iMaPP does not include data for later years.

[Insert Table 10]

Table 10 displays our results. Initially, in Model (31), we confirm that macroprudential policies have a significant effect on financial stability, with tightening resulting in a decline of bank systemic risk. On the other hand, our empirical results suggest that expansionary macroprudential policy does not result in an increase in systemic risk. In Model (32), we include the interaction term between macroprudential policy and our main variable of interest, ELECTIONS. The estimated coefficient for the macroprudential policy tightening is negative and statistically significant across all model specifications. Our findings suggest that in years following a macroprudential policy tightening, the banking sector is more resilient and the effect of elections is mitigated. In order to test the robustness of our findings, in Models (33) and (34), we show that the results hold for both the extended sample that includes both banking and non-banking institutions.

5. Robustness

5.1 Alternative measures of systemic risk

In this section, we present the results of the previous analysis, but by using alternative systemic risk metrics. We employ two popular measures in the systemic risk literature, namely Marginal Expected Shortfall (MES) by [Acharya et al. \(2017\)](#) and SRISK by [Brownlees and Engle \(2016\)](#). These two measures capture a different aspect of systemic risk and provide us with an important robustness test.

5.1.1 Marginal Expected Shortfall (MES)

MES is a measure used to estimate the systemic risk contribution of a financial institution based on the expected loss that an institution would suffer in the tail of the overall market loss distribution, specifically when the market is in distress. $\Delta CoVaR$ and MES are likely to be correlated, but they capture a different aspect of risk ([Brunnermeier et al., 2020](#)). $\Delta CoVaR$ measures the systemic risk of a financial institution, whereas MES estimates how exposed a financial institution is to the market. More specifically, the MES of a financial institution i at time t is defined as the expected equity loss of institution i given that the market (or a reference portfolio) is experiencing an extreme loss. The mathematical definition of MES is as follows:

$$MES_{i,t} = E[R_t^i | R_t^M \leq C = VaR^M] \quad (10)$$

R_t^i and R_t^M is the return of institution i and of the market index, M , respectively, at time t and C is a threshold that indicates the market is in distress, which we define as the 5th percentile of the market return distribution. For the estimation of MES, we use the weekly returns of our sample of financial institutions and the Kernel Density Estimation (KDE). The estimation consists of three steps. First, we obtain the standardised returns based on the standard deviation of the returns and the correlation coefficient between the returns of firm i and the market index returns. In the next step, the values of the cumulative distribution function (CDF) of the normal distribution are computed. Similarly to the estimation of $\Delta CoVaR$, we use the DS Financials index returns as the market index. At this point, we select the bandwidth parameter which influences the smoothness of the resulting density function. Its estimation is computed using the minimum of the standard deviation and the interquartile range (IQR) adjusted by a factor of 1.349 (the normal distribution range between the 75th and 25th percentiles). In the last step, we compute MES for an asset by estimating how changes in the asset's weight in the market index affect the market ES. Based on Equation (10), MES is defined as the partial derivative of the system ES with respect to the weight of firm i :

$$ES_{i,t}(C) = \frac{dES_{m,q}(C)}{dw_{i,t}} = E_{t-1}(R_{i,t} | R_{m,t} \leq C) \quad (11)$$

5.1.2 SRISK

SRISK is a measure of systemic risk that estimates the expected capital shortfall of a financial institution during periods of financial distress. It quantifies how much additional capital an institution would need to function properly if there was a severe market downturn. *SRISK* was introduced by [Brownlees and Engle \(2016\)](#) and combines information about the firm's leverage, size, and market risk exposure to assess its vulnerability and systemic importance. The calculation of *SRISK* relies on the Marginal Expected Shortfall (*MES*), but also on the institution's capital structure. As we mentioned before, *MES* measures the expected loss for a financial institution in the event of market/system distress. *SRISK* is derived by estimating how this potential loss impacts the firm's capital buffer relative to its liabilities. In other words, *SRISK* identifies institutions that are likely to require significant capital injections to maintain solvency and support financial stability during crises. To provide the mathematical definition of *SRISK*, we need to define capital shortfall of the firm i at time t :

$$\text{Capital Shortfall}_{i,t} = k A_{i,t} - MCap_{i,t} \quad (12)$$

where $A_{i,t}$ is the value of assets defined as the sum of the market value of capital and the book value of debt ($D_{i,t}$), $MCap_{i,t}$ is the market value of capital and k is the prudential capital fraction, which is set at 8%. *SRISK* is defined as the expected capital shortfall conditional on a systemic event. We use a horizon h of one month and the threshold (T) is set at -10% in line with [Brownlees and Engle \(2016\)](#).

$$SRISK_{i,t} = E_t(\text{Capital Shortfall}_{i,t} | R_{t+1:t+h} < T) \quad (13)$$

$$SRISK_{i,t} = k E_t(D_{i,t+h} | R_{t+1:t+h} < T) - (1 - k) E_t(W_{i,t+h} | R_{t+1:t+h} < T) \quad (14)$$

$$SRISK_{i,t} = k \times DEBT_{i,t} - (1 - k) \times W_{i,t} \times (1 - LRMES_{i,t}) \quad (15)$$

The estimation of $LRMES_{i,t}$ is based on the Kernel Density Estimation in line with *MES* as described in the previous section. All data series is provided by Thomson Reuters EIKON Datastream and all values are expressed in billions of US dollars, except from *MES* and *LRMES* that are expressed as percentages.

[Insert Table 11]

5.1.3 Results from *MES* and *SRISK*

The results of the analysis using *MES* and *SRISK* are presented in Table 11. Our analysis consistently demonstrates that the observed relationship holds robustly across different measures of systemic risk. This consistency is evidently irrespective of the inclusion of control variables. These findings affirm the robustness of our results, suggesting that the effect of electoral cycles on systemic risk is consistent to various modelling approaches.

5.2 Time fixed effects

Our benchmark model specification includes both firm and year fixed effects. In this section, we present our main findings with the exclusion of the year fixed effects since these could absorb part of the variation that we are interested in. A similar approach was adopted by [Brunnermeier et al. \(2020\)](#), who study the impact of asset bubbles on systemic risk. They argue that if two countries exhibit a bubble simultaneously, then banks will experience the same increase in systemic risk and in this case, their bubble dummy variable that captures the change in systemic risk relative to the average of the two countries, will be statistically insignificant. Following their approach, we present our main findings in Table 11, Models (39-40) without the inclusion of year fixed effects, but by including macroeconomic variables such as GDP growth and inflation. Our results suggest that the relationship between election cycles and systemic risk holds with or without the inclusion of the year fixed effects. Finally, to account for the recent crisis, we include a dummy variable for the 2019-2020 COVID-19 pandemic. The results are reported in Table 11, Models (41)-(42) and confirm our previous findings.

5.3 Endogeneity issues

5.3.1 2SLS

To mitigate endogeneity concerns, we implement a two-stage instrumental variable (2SLS) approach. Following [Jens \(2017\)](#) we use term limits as an instrumental variable that is pre-determined and thus does not have any impact on systemic risk metrics, but it is the main factor based on which the incumbent government proceeds to elections. Term limits is an appropriate instrument for election cycles since it isolates the effect of political uncertainty rather than economic uncertainty ([Jens, 2017](#)). This would be an issue if we use [Baker et al. \(2016\)](#)'s Economic Policy Uncertainty Index that considers a series of macroeconomic variables to account for economic uncertainty and they are highly correlated with systemic risk ([Fang et al., 2023](#) ; [Matousek et al., 2020](#)). The results of the 2SLS regression model are presented in Table 12. Models (43) and (45) displays the first stage where we regress our main variable of interest ELECTIONS with TERM LIMITS, with and without control variables, and we find a strong positive relationship between the two variables. Models (44) and (46) present the second stage of the regression model. Our analysis provides further evidence to support our initial findings.

[Insert Table 12]

Moreover, we construct a new political uncertainty index using Google trends. Although Google trends as a research tool provides some limitations, it is ideal for the purposes of our analysis, that is to measure people's expectations regarding when the next election will take place. A similar approach was adopted by [Fungáčová et al. \(2024\)](#) who use Google search data to construct a political uncertainty index (dummy variable) and analyse the impact on bank lending. For our instrument, we use five terms, "elections", "parliamentary elections" (or the type of elections for each country), "election news",

“elections results” and “exit polls”. Except from the latter term, we use the equivalent translated terms for each country.¹⁷ The political uncertainty index for each country is presented in Figure 4. Based on the indices, we construct a dummy variable that takes the value equal to one if the political uncertainty index is above the upper quartile of each country and zero, otherwise. We then employ this dummy variable in the 2SLS model together with TERM LIMIT and the findings are presented in Table 12, Models (47)-(50). Our data suggest that our results hold and are robust to endogeneity concerns.

[Insert Figure 4]

5.3.2 Banking crises

According to our results, elections are associated with higher systemic risk, however, periods of increased financial distressed could put pressure on the government to call an election. To strengthen our analysis and address potential endogeneity, we re-estimate the model excluding periods of banking crises.¹⁸ For the purpose of our analysis, we use two distinct and comprehensive datasets. First, we employ the Global Crises Data from Harvard Business School, which tracks crises globally up to 2016 and secondly, we use the dataset by [Metrick and Schmelzing \(2021\)](#), which covers banking interventions from historical periods up to 2019. The use of these two datasets allows us to exclude crisis periods, providing more robust findings. The results are presented in Table 13 with and without firm and macroeconomic controls. Our empirical findings suggest that systemic risk increases during election periods independently of banking crises. As expected, the coefficient is slightly smaller when periods of banking crises are excluded, since we have removed the years with the highest systemic risk. Nonetheless, our findings remain consistent and reinforce the robustness of our conclusions.

[Insert Table 13]

5.4 Evidence from the monthly data series

For robustness purposes, we also run our benchmark model using the monthly systemic risk estimates. The main drawback of the monthly dataset is the limited number of firm controls that we can use to control for changes in firm’s balance sheet. In this case, we use the Value-at-Risk (VaR) to measure firms’ idiosyncratic risk and Market Capitalisation to account for changes in firm size. Moreover, we include the OECD Industrial Production index to control for changes in the macroeconomic environment. In total, we have 162,684 observations, which decreases to 147,380 when we include all the control variables.

¹⁷ For countries with more than one official language, we use all languages with equal weights in the country indicator.

¹⁸ A similar approach has been presented by [Brunnermeier et al. \(2020\)](#) who study the impact of asset price bubbles on systemic risk. They did not include time fixed effects to their benchmark model specification, but a set of macroeconomic variables and a dummy for banking crises.

[Insert Table 14]

These results are presented in Table 14. Our empirical evidence confirms our previous findings. The estimated coefficient of *ELECTIONS* is positive and statistically significant. The results hold with and without the inclusion of the control variables and the year and month fixed effects. The high frequency data is also useful for examining the time dynamics in the relationship between elections and systemic risk. For that purpose, we extend our benchmark model specification, but by including further lags between the dependent and independent variables. A similar approach has been adopted by [Gulen and Ion \(2016\)](#) and [Matousek et al. \(2020\)](#) that run 24 regressions, corresponding to lags 1 through 24 for a two-year horizon. In Table 14 and Figure 5 we present the findings for one and up to eight quarters before and after the election month. Our results indicate that in all the pre-elections periods, systemic risk is lower than the peak presented in the election month. In post-election period, the response of systemic risk exhibits a hump shape with a peak value in the six month after the election period. The effect declines, but it does not disappear in a period of 12 months after the elections.

[Insert Figure 5]

6. Conclusions

This paper examines how election cycles affect systemic risk. The findings indicate that systemic risk increases during election and post-election periods, while it decreases in the pre-election period, which can be attributed to the suppression of negative information and expansionary fiscal policies. The impact of elections on systemic risk varies with outcomes, being mitigated by re-elections or strong majorities but heightened by unexpected (snap) elections. The robustness of our findings is confirmed through the use of instrumental variables in a 2SLS model, which supports the validity of our conclusions. Our findings carry significant policy implications for both policymakers and financial regulators. Given the documented variation of systemic risk during election cycles, it is crucial for policymakers to implement strategies that mitigate these risks. According to our findings, tightening macroprudential policies can mitigate the impact on systemic risk during election years. Additionally, fostering strong economic growth and maintaining high public trust in government can help buffer the financial system against election-induced uncertainties. Finally, for financial regulators, monitoring bank-specific characteristics such as profitability and idiosyncratic risk is essential, as these factors can influence the impact of elections and political instability on systemic risk.

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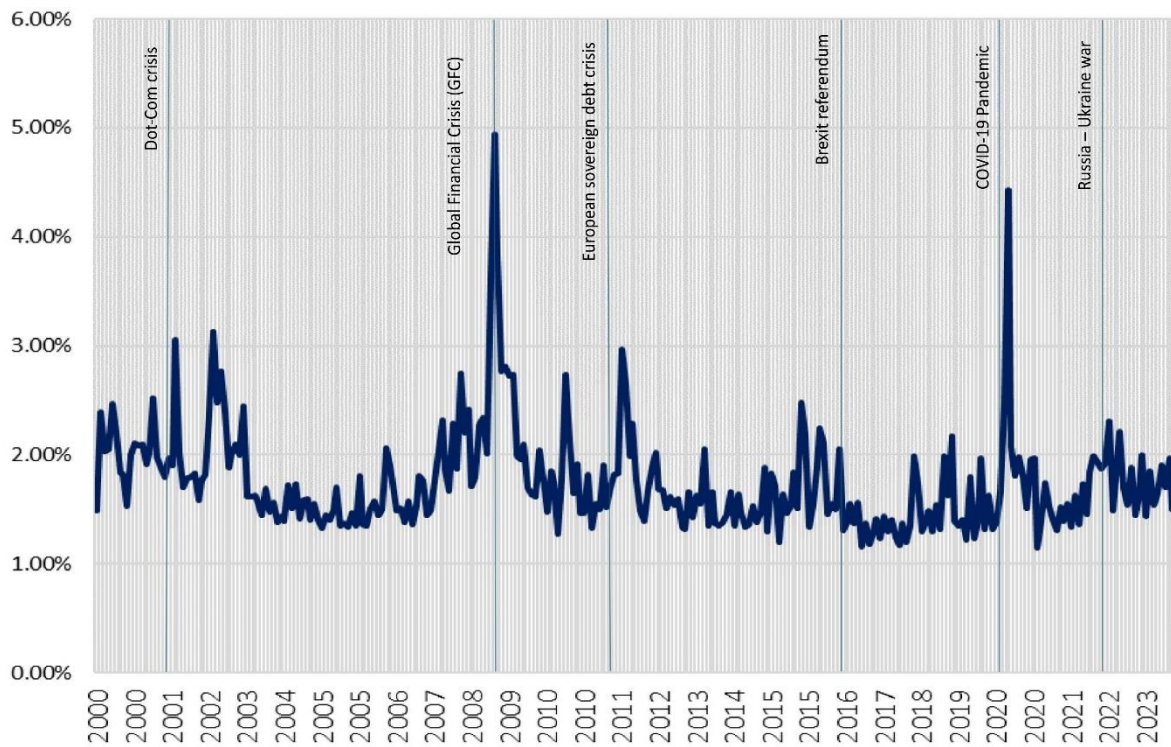
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Tables & Figures

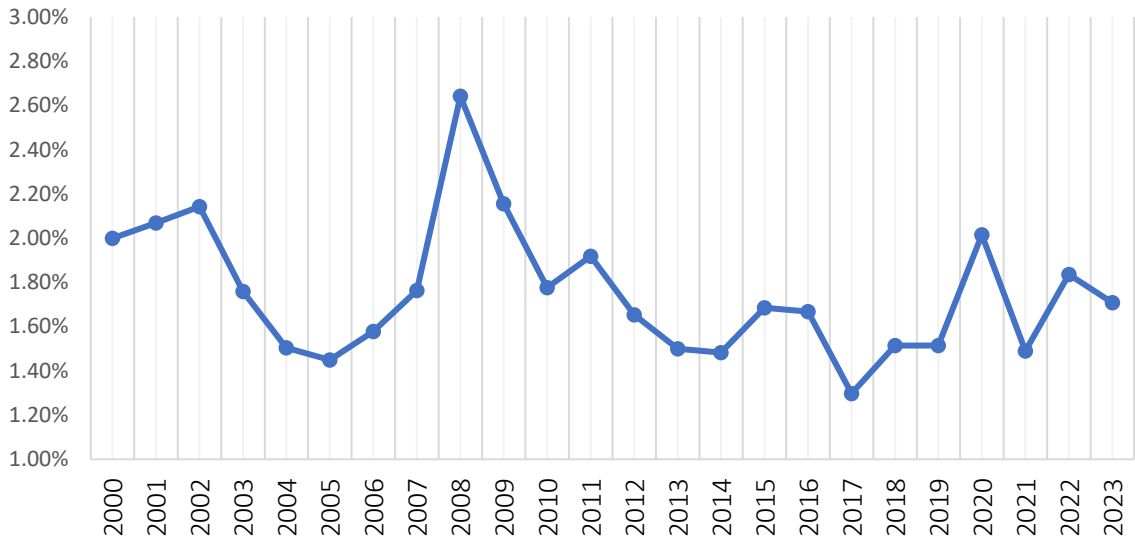
Figure 1: Aggregate systemic risk



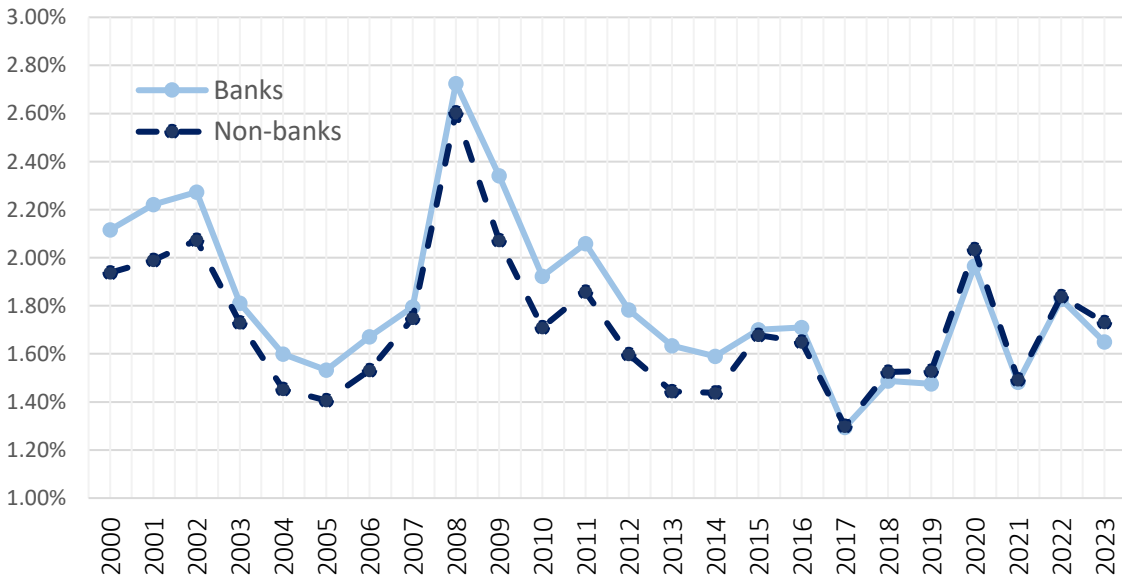
Notes: The Figure presents the monthly global average $\Delta CoVaR$ (systemic risk) based on a sample of 697 financial institutions (banks, insurance companies, financial services companies, investment trusts, closed-end funds) from 22 developed countries, namely Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, South Korea, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the UK and the US. The $\Delta CoVaR$ estimation is based on the state variables approach and weekly returns for the period 2000-2023.

Figure 2: Annual Aggregate Systemic Risk

A. All Financials



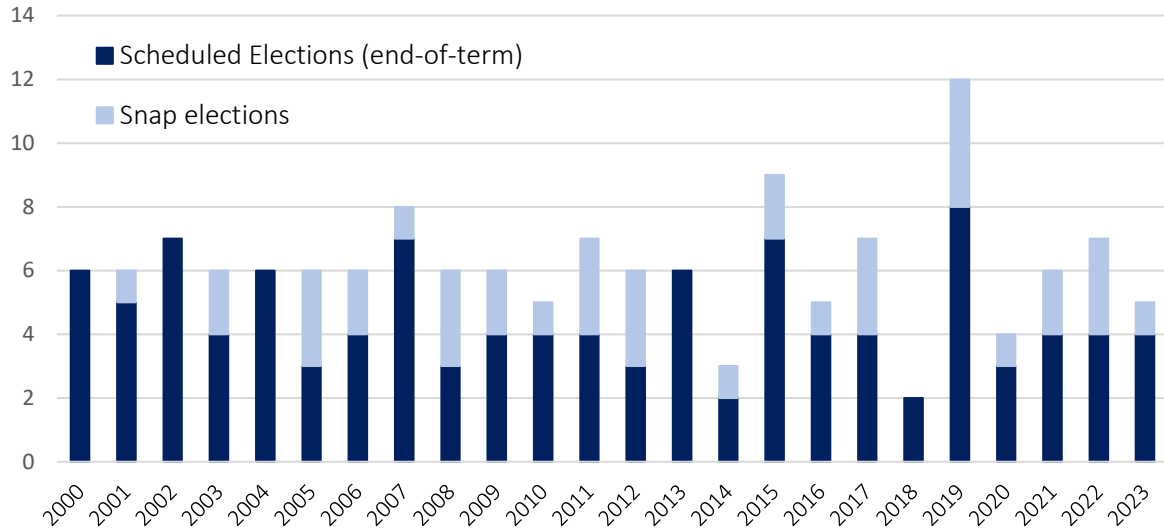
B. Banks vs. Non-banks



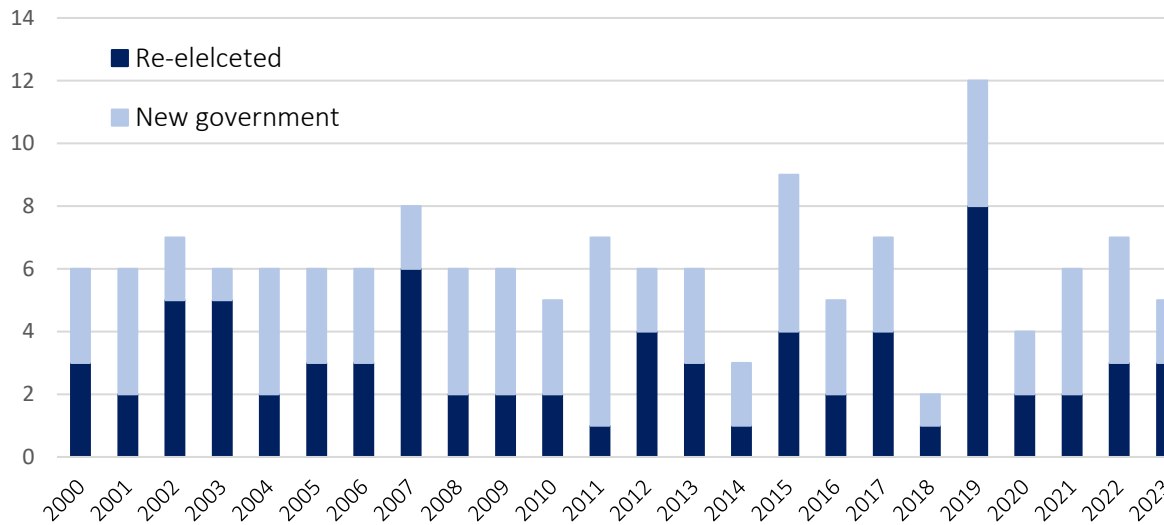
Notes: Figure A presents the annual global average $\Delta CoVaR$ (systemic risk) based on a sample of 697 financial institutions (banks, insurance companies, financial services companies, investment trusts, closed-end funds) from 22 developed countries, namely Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, South Korea, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the UK and the US. For comparison purposes, Figure B splits the sample into two groups: banks and non-banks, and presents the respective average value for both. The $\Delta CoVaR$ estimation is based on the state variables approach and weekly returns for the period 2000-2023.

Figure 3: Elections per year

A. Scheduled and Snap Elections

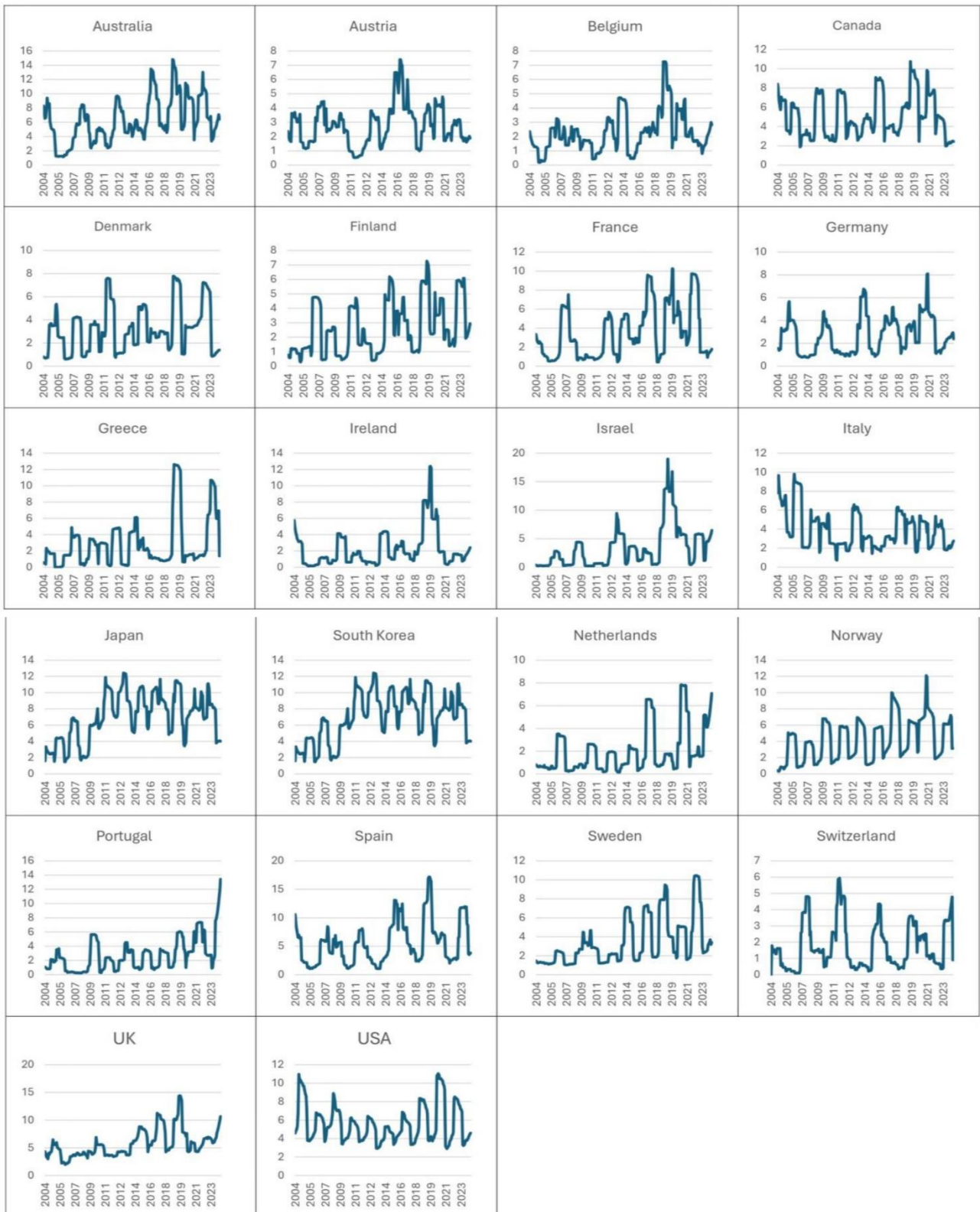


B. Re-elected and New government



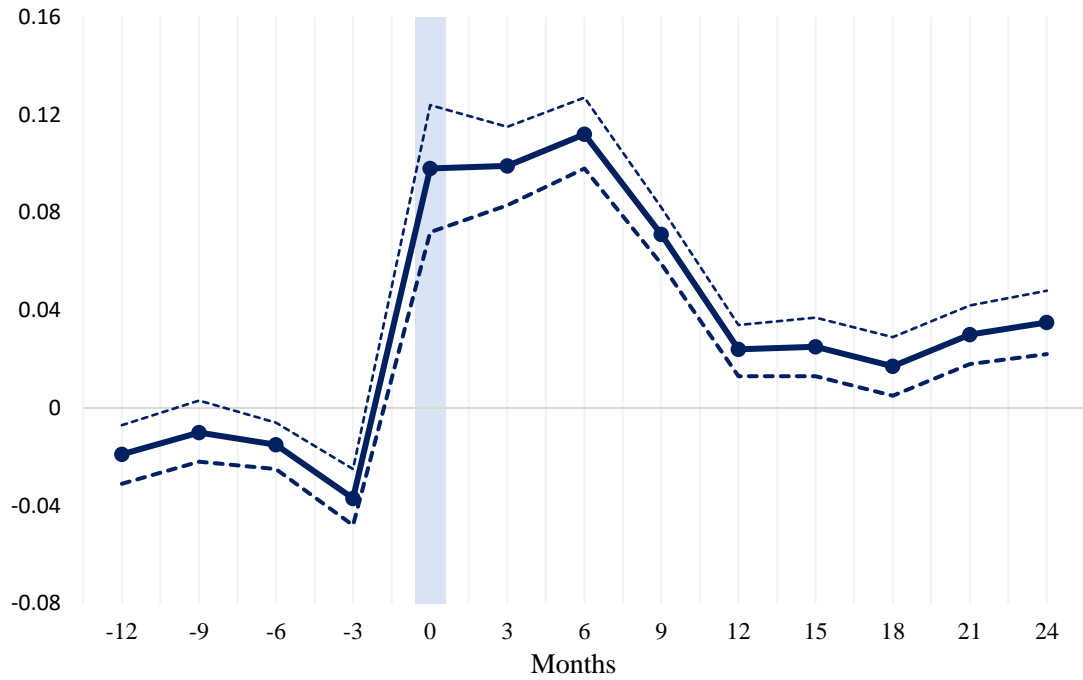
Notes: The Figure displays the number of national elections occurred in our sample of 22 countries, namely Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, South Korea, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the UK and the US. In Figure A, the sample is divided into two groups; Snap and scheduled elections, based on whether they occur before or in the end-of-term. Figure B divides the sample into re-elected or new governments. Some countries in the sample have historically coalition governments, so we assume that the incumbent is re-elected if the leading party of the coalition participates in the new government.

Figure 4: Google Trends Political Uncertainty Index



Notes: The Figure displays the election uncertainty index based on Google Trends. For its construction we use five terms, “elections”, “parliamentary elections” (or the type of elections for each country), “election news”, “elections results” and “exit polls”, which, except from the latter, are translated into each country official language(s). The equally-weighted sum of each term constructs the above Google Trend index. The estimation period is 2004-2023.

Figure 5: Pre- and Post-Elections Estimated Coefficients



Notes: The figure displays the dynamic effect of elections on systemic risk, measured by $\Delta CoVaR$. $\Delta CoVaR$ is estimated based on weekly returns and the state variables approach. The variable ELECTIONS is a dummy variable that takes the value of one in years when elections occurred and zero otherwise. For the period after the election month, the dummy variable takes the value of one for the period from t to $t + h$, where h is the examined month. Respectively, for the pre-election period, the dummy variable takes the value of one between $t - h$ to $t - 1$. The sample includes 22 developed countries and 636 financial institutions. The model includes firm characteristics (VaR, Market Capitalization) and macroeconomic controls (year-on-year monthly growth of the industrial production index). Year, month, and firm fixed effects are included in all model specifications. The dotted line represents the 95% confidence interval based on robust standard errors, clustered at the firm level.

Table 1: Hypotheses summary

	Elections	Snap Elections	Re-elected
PRE (t-1)	-	?	?
ELECTION YEAR (t)	+	+	+
POST (t+1)	+	+	?

Notes: The Table summarises our hypotheses with regards to the relationship between elections and systemic risk. We define three time periods, pre-elections (t-1), election year (t) and post-elections (t+1). In addition, we examine all elections, those called before the end-of-term (snap elections) and the elections where the incumbent government was re-elected.

Table 2: Summary Statistics per country

Country	No of Banks	MCap (%)	$\Delta CoVaR$	No of Financial Institutions	MCap (%)	$\Delta CoVaR$
Australia	6	7.36%	0.963	27	5.03%	1.211
Austria	6	0.94%	2.231	9	0.55%	2.173
Belgium	3	0.89%	1.470	11	1.03%	1.899
Canada	8	8.83%	1.055	34	7.37%	1.193
Denmark	6	0.85%	1.584	9	0.58%	1.617
Finland	3	1.17%	1.531	5	0.83%	1.461
France	7	4.53%	1.997	26	3.76%	2.400
Germany	4	1.68%	1.362	24	3.41%	1.836
Greece	5	0.68%	3.456	6	0.34%	3.455
Ireland	3	0.95%	3.743	4	0.46%	3.958
Israel	6	0.68%	1.334	11	0.41%	1.491
Italy	11	3.44%	2.093	29	2.88%	2.109
Japan	43	10.12%	1.822	75	8.43%	1.824
South Korea	5	1.66%	1.346	13	1.48%	1.523
Netherlands	3	2.22%	1.482	18	2.14%	1.959
Norway	5	0.76%	1.932	9	0.60%	1.864
Portugal	1	0.18%	1.654	2	0.08%	2.300
Spain	6	5.21%	1.453	11	2.72%	1.756
Sweden	4	1.77%	1.636	10	1.50%	1.598
Switzerland	16	0.87%	2.156	29	3.30%	1.974
UK	10	11.75%	1.522	207	10.66%	1.573
United States	33	33.48%	1.790	128	42.43%	1.736
Total	194	100%	1.802	697	100%	1.737

Notes: The table presents the decomposition of our sample across countries. It shows the number of firms and the percentage of the sample's market capitalization per country. Additionally, the table reports the average annual $\Delta CoVaR$ for each country's sub-sample. $\Delta CoVaR$ is expressed as a percentage, and its estimation is based on weekly returns and the state variables approach.

Table 3: Summary statistics

	Obs	Mean	St.dev	Min	Max
Banks (N = 193)					
Elections	4,081	0.283	0.451	0	1
Snap Elections	4,081	0.088	0.283	0	1
End-of-Term Elections	4,081	0.196	0.400	0	1
Re-elected GVT	4,081	0.155	0.362	0	1
New GVT	4,081	0.128	0.335	0	1
ΔCoVaR	4,081	1.802	0.871	0.048	9.584
VaR	4,081	0.691	1.575	-6.610	12.438
Log Assets	4,047	18.112	1.710	11.032	22.078
ROE	4,017	0.070	0.735	-42.985	1.353
Leverage	4,081	2.710	6.490	0	147.264
GDP growth	4,081	1.620	2.682	-11.175	22.175
Inflation	4,081	1.779	1.920	-4.500	10.616
All financials (N = 697)					
Elections	13,439	0.269	0.444	0	1
Snap Elections	13,439	0.080	0.272	0	1
End-of-Term Elections	13,439	0.189	0.391	0	1
Re-elected GVT	13,439	0.156	0.363	0	1
New GVT	13,439	0.113	0.317	0	1
ΔCoVaR	13,439	1.737	0.758	-0.711	9.584
VaR	13,439	0.815	1.515	-8.258	16.511
Log Assets	13,292	16.145	2.616	5.781	22.078
ROE	13,108	0.099	0.593	-42.985	19.812
Leverage	13,439	1.331	8.862	-0.221	598.378
GDP growth	13,439	1.689	2.880	-11.175	22.175
Inflation	13,439	2.157	1.982	-4.500	10.616

Notes: The Table displays the summary statistics for the main variables used in our empirical analysis. The Table is split into parts with the first one to refer to the banks-only sample and the second part to include the summary statistics for other types financial institutions, such as insurance companies, financial services companies and investment trusts. More specifically it presents the mean value, standard deviation, minimum and maximum value for the election-related dummy variables, the systemic risk metric, ΔCoVaR , firm and macroeconomic characteristics. The reported values are calculated for the period 2000-2023 and they refer only to years that ΔCoVaR is available.

Table 4: Elections and bank systemic risk

Models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Systemic risk:	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
ELECTIONS	0.051*** (0.011)	0.060*** (0.012)	0.065*** (0.013)		0.055*** (0.015)		0.088 (0.017)
SNAP				0.091*** (0.022)	0.036 (0.025)		
END-OF-TERM				0.055*** (0.015)			
RE-ELECTED						0.046*** (0.018)	-0.043* (0.023)
NEW GOV						0.088*** (0.017)	
L.Log ASSETS		0.115*** (0.040)	0.101*** (0.038)	0.099*** (0.038)	0.099*** (0.038)	0.100*** (0.038)	0.100*** (0.038)
L.VaR		0.138*** (0.031)	0.133*** (0.028)	0.133*** (0.028)	0.133*** (0.028)	0.133*** (0.028)	0.133*** (0.028)
L.LEVERAGE		0.005 (0.006)	0.004 (0.005)	0.004 (0.005)	0.004 (0.005)	0.004 (0.005)	0.004 (0.005)
L.ROE		-0.036* (0.021)	-0.028 (0.019)	-0.027 (0.018)	-0.027 (0.018)	-0.028 (0.018)	-0.028 (0.018)
L.GDP growth			-0.029*** (0.008)	-0.029*** (0.008)	-0.029*** (0.008)	-0.028*** (0.008)	-0.028*** (0.008)
L.INFLATION			-0.051*** (0.010)	-0.051*** (0.010)	-0.051*** (0.010)	-0.050*** (0.010)	-0.050*** (0.010)
CONSTANT	2.118*** (0.039)	0.158 (0.698)	0.617 (0.667)	0.649 (0.667)	0.649 (0.667)	0.625 (0.666)	0.625 (0.666)
FIRM FE	YES	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES
No of OBS	4,081	3,827	3,827	3,827	3,827	3,827	3,827
No of FIRMS	193	193	193	193	193	193	193
R ² (within)	0.389	0.444	0.459	0.459	0.459	0.459	0.459

Notes: The Table presents the results of fixed-effects panel regressions. The dependent variable is ΔCoVaR , expressed as a percentage, and its estimation is based on weekly returns and the state variables approach. The sample consists of 193 banking institutions from 22 developed countries. ELECTIONS is a dummy variable that takes the value of one in years when elections occurred and zero otherwise. ELECTIONS is then split into SNAP and END-OF-TERM based on whether the elections occurred prematurely or at the end of the term, respectively, and into RE-ELECTED or NEW GVT based on the outcome for the incumbent government. Log ASSETS is the natural logarithm of Total Assets, LEVERAGE is defined as the ratio of Total Debt to Capital, and ROE is the Return on Equity ratio. All data are provided by Thomson Reuters EIKON Datastream. GDP growth and Inflation are the year-on-year growth rates as provided by the OECD. Year and firm fixed effects are included in all model specifications. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Pre- and Post-election periods and bank systemic risk

Models:	(8)	(9)	(10)	(11)	(12)	(13)
Systemic risk:	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
POST	0.037*** (0.010)	0.030*** (0.011)	0.039*** (0.014)			
PRE				-0.032*** (0.009)	-0.034*** (0.010)	-0.098*** (0.022)
SNAP \times POST			0.189*** (0.029)			
RE-ELECTED \times POST			-0.116*** (0.019)			
SNAP \times PRE						0.190*** (0.036)
RE-ELECTED \times PRE						0.017 (0.022)
L.Log ASSETS		0.101*** (0.038)	0.097*** (0.038)		0.093*** (0.043)	0.088*** (0.042)
L.VaR		0.131*** (0.028)	0.130*** (0.027)		0.137*** (0.029)	0.136*** (0.029)
L.LEVERAGE		0.004 (0.005)	0.004 (0.005)		0.004 (0.005)	0.004 (0.005)
L.ROE		-0.029* (0.018)	-0.028 (0.018)		-0.028 (0.018)	-0.028 (0.018)
L.GDP growth		-0.027*** (0.008)	-0.029*** (0.008)		-0.029*** (0.008)	-0.030*** (0.008)
L.INFLATION		-0.052*** (0.010)	-0.058*** (0.010)		-0.062*** (0.011)	-0.064*** (0.011)
CONSTANT	2.182*** (0.039)	0.602 (0.672)	0.716 (0.662)	2.155*** (0.038)	0.786 (0.747)	0.889 (0.738)
FIRM FE	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES
No of OBS	4,022	3,827	3,827	3,921	3,668	3,668
No of FIRMS	193	193	193	193	193	193
R ² (within)	0.391	0.456	0.465	0.394	0.468	0.475

Notes: The Table presents the results of fixed-effects panel regressions. The dependent variable is ΔCoVaR , expressed as a percentage, and its estimation is based on weekly returns and the state variables approach. The sample consists of 193 banking institutions from 22 developed countries. POST and PRE are election dummy variables that takes the value of one in years when elections occurred the year before or after the current year and zero otherwise. Elections variables are then split into SNAP and END-OF-TERM based on whether the elections occurred prematurely or at the end of the term, respectively, and into RE-ELECTED or NEW GVT based on the outcome for the incumbent government. Log ASSETS is the natural logarithm of Total Assets, LEVERAGE is defined as the ratio of Total Debt to Capital, and ROE is the Return on Equity ratio. All data are provided by Thomson Reuters EIKON Datastream. GDP growth and Inflation are the year-on-year growth rates as provided by the OECD. Year and firm fixed effects are included in all model specifications. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Firm characteristics as mitigating factors

Models:	(14)	(15)	(16)	(17)	(18)	(19)
Systemic risk:	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
ELECTIONS	0.027*** (0.011)	0.056*** (0.012)	0.198* (0.102)	0.029*** (0.012)	0.069*** (0.013)	0.313*** (0.109)
VaR	0.192*** (0.040)			0.187*** (0.034)		
VaR \times ELECTIONS	0.018** (0.009)			0.020* (0.012)		
ROE		-0.012 (0.018)			-0.001 (0.012)	
ROE \times ELECTIONS		-0.092*** (0.033)			-0.065*** (0.024)	
SIZE			0.108*** (0.047)			0.097*** (0.039)
SIZE \times ELECTIONS			-0.008 (0.006)			-0.014** (0.006)
FIRM CONTROLS	NO	NO	NO	YES	YES	YES
MACRO CONTROLS	NO	NO	NO	YES	YES	YES
FIRM FE	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES
No of OBS	4,081	4,017	4,047	3,885	3,837	3,825
No of FIRMS	193	193	193	193	193	193
R ² (within)	0.461	0.394	0.393	0.490	0.458	0.458

Notes: The Table presents the results of fixed-effects panel regressions. The dependent variable is ΔCoVaR , expressed as a percentage, and its estimation is based on weekly returns and the state variables approach. ELECTIONS is a dummy variable that takes the value of one in years when elections occurred and zero otherwise. Firm controls include SIZE (natural logarithm of Total Assets), Value-at-Risk (VaR), leverage (Total Debt to Capital), and the Return on Equity (ROE) ratio. All data are provided by Thomson Reuters EIKON Datastream. Macro controls include GDP growth and Inflation are the year-on-year growth rates as provided by the OECD. Year and firm fixed effects are included in all model specifications. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Elections and systemic risk: All Financials

Models:	(20)	(21)	(22)	(23)	(24)	(25)
Systemic risk:	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
ELECTIONS	0.044*** (0.006)	0.047*** (0.007)				
SNAP ELECTIONS			0.060*** (0.014)			
END-OF-TERM ELECTIONS			0.043*** (0.008)			
RE-ELECTED				0.002 (0.008)		
NEW GOVT				0.103*** (0.011)		
POST					0.052*** (0.007)	
PRE						-0.052*** (0.012)
SNAP \times POST or PRE					0.072*** (0.017)	0.131*** (0.020)
RE-ELECTED \times POST or PRE					-0.116*** (0.011)	-0.002 (0.014)
L.Log ASSETS		0.022* (0.012)	0.022* (0.012)	0.023* (0.012)	0.022* (0.012)	0.022* (0.013)
L.VaR		0.052*** (0.015)	0.052*** (0.015)	0.052*** (0.015)	0.052*** (0.015)	0.053*** (0.016)
L.LEVERAGE		-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)
L.ROE		-0.016* (0.009)	-0.017* (0.009)	-0.018** (0.009)	-0.016* (0.009)	-0.015* (0.009)
L.GDP growth		-0.017*** (0.006)	-0.017*** (0.006)	-0.016** (0.007)	-0.017*** (0.006)	-0.019*** (0.006)
L.INFLATION		-0.013* (0.007)	-0.013* (0.006)	-0.013** (0.006)	-0.013* (0.007)	-0.024* (0.008)
CONSTANT	2.032*** (0.020)	1.774*** (0.190)	1.777*** (0.190)	1.774*** (0.189)	1.774*** (0.190)	1.833*** (0.200)
FIRM FE	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES
No of OBS	13,439	12,431	12,431	12,431	12,431	11,748
No of FIRMS	693	691	691	691	691	691
R ² (within)	0.404	0.418	0.418	0.420	0.420	0.441

Notes: The table presents the results of fixed-effects panel regressions. The dependent variable is ΔCoVaR , expressed as a percentage, and its estimation is based on weekly returns and the state variables approach. The sample consists of 693 financial institutions from 22 developed countries. ELECTIONS is a dummy variable that takes the value of one in years when elections occurred and zero otherwise. POST and PRE are election dummy variables that takes the value of one in years when elections occurred the year before or after the current year and zero otherwise. ELECTIONS is then split into SNAP and END-OF-TERM based on whether the elections occurred prematurely or at the end of the term, respectively, and into RE-ELECTED or NEW GVT based on the outcome for the incumbent government. Log ASSETS is the natural logarithm of Total Assets, LEVERAGE is defined as the ratio of Total Debt to Capital, and ROE is the Return on Equity ratio. All data are provided by Thomson Reuters EIKON Datastream. GDP growth and Inflation are the year-on-year growth rates as provided by the OECD. Year and firm fixed effects are included in all model specifications. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Transmission channels summary statistics

Period:	All Elections	Snap Elections	End-of-Term Elections
Δ Government Expenditure			
Pre-Elections (t-1)	0.133%	-0.662%	0.424%
Election year (t)	0.067%	-0.420%	0.235%
Post (t+1) & Re-elected	-0.201%	-0.396%	-0.146%
Post (t+1) & New government	-0.064%	1.326%	0.080%
Δ Price Informativeness			
Pre-Elections (t-1)	0.309%	-0.122%	0.476%
Election year (t)	0.477%	0.040%	0.127%
Post (t+1) & Re-elected	-0.122%	-0.117%	-0.124%
Post (t+1) & New government	0.083%	0.166%	0.271%
Financial stress (VIX %)			
Pre-Elections (t-1)	1.122%	1.129%	1.120%
Election year (t)	1.161%	1.227%	1.135%
Post (t+1) & Re-elected	1.160%	1.209%	1.146%
Post (t+1) & New government	1.272%	1.369%	1.164%
Δ Trust in Government			
Pre-Elections (t-1)	-2.804%	-5.017%	-1.821%
Election year (t)	4.760%	7.003%	3.716%
Post (t+1) & Re-elected	1.492%	-3.606%	3.370%
Post (t+1) & New government	13.115%	23.519%	2.768%

Notes: The Table displays the summary statistics for different time periods in the election cycle. All the statistics, except from VIX, refer to the year-on-year change in the country-level variables for cross-country comparison purposes. ΔGovernment Expenditure is defined as the year-on-year change in the percentage of GDP in Government Expenditures as measured by the IMF. Price Informativeness is measured as the spread between country average ask and bid price spread for all financial institutions in our sample. Financial market sentiment is captured by the standard deviation of weekly returns per annum for each country's stock market index. Trust in Government is provided by OECD and it measures the share of people who report having confidence in the national government. The statistics reported are based on the period 2000-2019, except from the Trust in Government data that start in 2007.

Table 9: Regression analysis with transmission channels

Models:	(26)	(27)	(28)	(29)	(30)
Systemic risk:	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
ELECTIONS	-0.040* (0.024)	0.057*** (0.007)	0.114*** (0.012)	0.140*** (0.053)	0.188*** (0.030)
VIX	0.764*** (0.037)				
VIX \times ELECTIONS	0.076*** (0.023)				
PRICE_INFO		0.003*** (0.001)			
PRICE_INFO \times ELECTIONS		-0.001*** (0.000)			
GDP growth			-0.021*** (0.005)		
GDP growth \times ELECTIONS			-0.039*** (0.005)		
GOV. EXP.				0.018*** (0.005)	
GOV.EXP \times ELECTIONS				-0.002* (0.001)	
TRUST					-0.415*** (0.075)
TRUST \times ELECTIONS					-0.288*** (0.063)
FIRM CONTROLS	YES	YES	YES	YES	YES
MACRO CONTROLS	YES	YES	YES	NO	YES
FIRM FE	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES
No of OBS	11,748	12,295	12,431	11,748	9,498
No of FIRMS	691	691	691	691	691
R ² (within)	0.505	0.424	0.428	0.442	0.451

Notes: The Table presents the results of fixed-effects panel regressions. The dependent variable is ΔCoVaR , expressed as a percentage, and its estimation is based on weekly returns and the state variables approach. ELECTIONS is a dummy variable that takes the value of one in years when elections occurred and zero otherwise. GOV EXP is defined as the year-on-year change in the percentage of GDP in Government Expenditures as measured by the IMF. PRICE_INFO is defined as the stock price informativeness measured as the spread between country average ask and bid price spread for all financial institutions in our sample. The statistics refer to the year-on-year change in the spread for cross-country comparison purposes. VIX (Volatility Index) measures financial market sentiment and it is calculated as the standard deviation of weekly returns per annum for each country's stock market index. TRUST stands for Trust in Government as provided by OECD and measures the share of people who report having confidence in the national government. Firm controls include the natural logarithm of Value-at-Risk (VaR) Total Assets, leverage (Total Debt to Capital), and the Return on Equity (ROE) ratio. All data are provided by Thomson Reuters EIKON Datastream. Macro controls include GDP growth and Inflation are the year-on-year growth rates as provided by the OECD. Year and firm fixed effects are included in all model specifications. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Elections, systemic risk and the role of Macroprudential policies

Models:	(31)	(32)	(33)	(34)
Sample:	BANKS	BANKS	ALL FINANCIALS	ALL FINANCIALS
Systemic risk:	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
ELECTIONS		0.096*** (0.019)		0.113*** (0.011)
L.MP EXPANSION	0.023 (0.058)	0.063 (0.067)	0.013 (0.032)	0.062* (0.036)
L.MP TIGHTENING	-0.154*** (0.027)	-0.111*** (0.030)	-0.080*** (0.013)	-0.036** (0.014)
L.MP EXPANSION \times ELECTIONS		-0.085 (0.065)		-0.124*** (0.035)
L.MP TIGHTENING \times ELECTIONS		-0.101*** (0.027)		-0.133*** (0.015)
FIRM CONTROLS	YES	YES	YES	YES
MACRO CONTROLS	YES	YES	YES	YES
FIRM FE	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES
No of OBS	3,636	3,636	11,748	11,748
No of FIRMS	193	193	691	691
R ² (within)	0.477	0.480	0.440	0.445

Notes: The Table presents the results of fixed-effects panel regressions. The dependent variable is ΔCoVaR , expressed as a percentage and its estimation is based on weekly returns and the state variables approach. ELECTIONS is a dummy variable that takes the value of one in years when elections occurred and zero otherwise. The macroprudential policy indicator (MP) is based on the dataset by [Alam et al. \(2019\)](#). Firm controls include the natural logarithm of Value-at-Risk (VaR) Total Assets, leverage (Total Debt to Capital), and the Return on Equity (ROE) ratio. All data are provided by Thomson Reuters EIKON Datastream. Macro controls include GDP growth and Inflation are the year-on-year growth rates as provided by the OECD. Year and firm fixed effects are included in all model specifications. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Robustness Analysis

Models:	(35)	(36)	(37)	(38)	(39)	(40)	(41)	(42)
	Alternative SR metrics				No Year FE			
Sample:	BANKS	ALL FIN	BANKS	ALL FIN	BANKS	ALL FIN	BANKS	ALL FIN
Systemic risk:	MES	MES	SRISK	SRISK	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
ELECTIONS	0.075**	0.052***	0.014***	0.010*	0.043***	0.016*	0.043***	0.019***
	(0.031)	(0.015)	(0.013)	(0.005)	(0.017)	(0.009)	(0.017)	(0.009)
COVID-19 dummy							-0.018	0.166***
							(0.044)	(0.024)
FIRM CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES
MACRO CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES
FIRM FE	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	NO	NO	NO	NO
No of OBS	3,827	12,431	3,717	9,743	3,827	12,431	3,827	3,827
No of FIRMS	193	691	192	621	193	691	193	193
R ² (within)	0.413	0.370	0.338	0.254	0.099	0.079	0.99	0.99

Notes: The Table presents the results of fixed-effects panel regressions. Systemic risk is measured by three alternative measures, namely Marginal Expected Shortfall (*MES*), ΔCoVaR , both expressed as percentages and based on weekly returns, and, *SRISK*, measured in billions of USD. ELECTIONS is a dummy variable that takes the value of one in years when elections occurred and zero otherwise. COVID-19 dummy variable takes the value equal to 1 for the period 2019-2020. Firm controls include the natural logarithm of Value-at-Risk (VaR) Total Assets, leverage (Total Debt to Capital), and the Return on Equity (ROE) ratio. All data are provided by Thomson Reuters EIKON Datastream. Macro controls include GDP growth and Inflation are the year-on-year growth rates as provided by the OECD. Year and firm fixed effects are included in all model specifications. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12: 2SLS model results

Models:	(43)	(44)	(45)	(46)	(47)	(48)	(49)	(50)
Systemic risk:	ELECTIONS	ΔCoVaR	ELECTIONS	ΔCoVaR	ELECTIONS	ΔCoVaR	ELECTIONS	ΔCoVaR
ELECTIONS		0.045*** (0.011)		0.051*** (0.012)		0.063*** (0.011)		0.073*** (0.012)
TERM LIMITS	0.685*** (0.007)		0.660*** (0.008)		0.533*** (0.007)		0.527*** (0.008)	
GT Political Uncertainty dummy					0.356*** (0.008)		0.356*** (0.008)	
FIRM CONTROLS	NO	NO	YES	YES	NO	NO	YES	YES
MACRO CONTROLS	NO	NO	YES	YES	NO	NO	YES	YES
FIRM FE	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
No of OBS	13,349	13,349	11,709	12,547	11,850	11,850	10,615	11,385
No of FIRMS	693	693	691	691	693	693	691	691
R ² (within)	0.496	0.404	0.466	0.408	0.551	0.392	0.546	0.397

Notes: The Table presents the results of two-stage least squares (2SLS) regressions. The dependent variables is systemic risk (ΔCoVaR), expressed as a percentage and the two instruments, for ELECTIONS, are TERM LIMITS and GT (Google Trends) Political Uncertainty Dummy. To capture uncertainty we use the following five terms, “elections”, “parliamentary elections” (or the type of elections for each country), “election news”, “elections results” and “exit polls”, which, except from the latter, are translated into each country official language(s). The dummy takes the value equal to one if the equally-weighted sum of each term is greater or equal to its upper quartile. Firm controls include the natural logarithm of Value-at-Risk (VaR) Total Assets, leverage (Total Debt to Capital), and the Return on Equity (ROE) ratio. All data are provided by Thomson Reuters EIKON Datastream. Macro controls include GDP growth and Inflation are the year-on-year growth rates as provided by the OECD. Year and firm fixed effects are included in all model specifications. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 13: Results excluding banking crises

Models:	(51)	(52)	(53)	(54)
Exclude banking crises data:	Harvard Global Crisis Data	Harvard Global Crisis Data	MS (2021)	MS (2021)
Systemic risk:	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
ELECTIONS	0.038*** (0.006)	0.015** (0.007)	0.025*** (0.006)	0.015** (0.006)
CONSTANT	1.999*** (0.018)	2.297*** (0.216)	2.030*** (0.020)	2.030*** (0.020)
Firm Controls	NO	YES	NO	YES
Macro Controls	NO	YES	NO	YES
FIRM FE	YES	YES	YES	YES
TIME FE	YES	YES	YES	YES
No of OBS	6,452	5,742	9,621	8,711
No of FIRMS	693	613	692	667
R ² (within)	0.423	0.454	0.458	0.485

Notes: The Table presents the results of fixed-effects panel regressions. The dependent variable is ΔCoVaR , expressed as a percentage, and its estimation is based on weekly returns and the state variables approach. The sample consists of 693 banking institutions from 22 developed countries. ELECTIONS is a dummy variable that takes the value of one in years when elections occurred and zero otherwise. Firm controls include Log ASSETS, the natural logarithm of Total Assets, LEVERAGE, defined as the ratio of Total Debt to Capital, and ROE, the Return on Equity ratio. All data are provided by Thomson Reuters EIKON Datastream. Macro controls include GDP growth and Inflation are the year-on-year growth rates as provided by the OECD. Year and firm fixed effects are included in all model specifications. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 14: Elections and systemic risk: Evidence from monthly data

Models:	(55)	(56)	(57)	(58)	(59)	(60)
Systemic risk:	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
ELECTIONS	0.088*** (0.016)	0.081*** (0.016)	0.099*** (0.012)	0.098*** (0.013)	0.107*** (0.013)	0.106*** (0.014)
PRE (3 Months)					-0.026*** (0.006)	-0.023*** (0.006)
POST (3 Months)					0.097*** (0.009)	0.101*** (0.008)
L.VaR		18.873*** (0.998)		12.299*** (1.022)		12.379*** (1.027)
L.MCAP (\$bn)		-0.002** (0.001)		0.0001 (0.0005)		0.0001 (0.0005)
L.IP growth		-0.758*** (0.059)		-0.0569 (0.048)		-0.0136** (0.064)
CONSTANT	1.736*** (0.000)	1.610*** (0.010)	1.939*** (0.022)	1.837*** (0.027)	1.937*** (0.022)	1.789*** (0.029)
FIRM FE	YES	YES	YES	YES	YES	YES
TIME FE	NO	NO	YES	YES	YES	YES
No of OBS	162,684	147,380	162,684	147,380	159,480	145,604
No of FIRMS	692	636	692	636	692	636
R ² (within)	0.0003	0.108	0.182	0.219	0.184	0.221

Notes: The Table presents the results of fixed-effects panel regressions. The dependent variable is ΔCoVaR , expressed as a percentage and its estimation is based on weekly returns. The sample consists of financial institutions from 22 developed countries. ELECTIONS is a dummy variable that takes the value of one in years when elections occurred and zero otherwise. The model includes firm characteristics (VaR, Market Capitalisation) and macroeconomic controls (year-on-year monthly growth of the industrial production index). Year, month (time) and firm fixed effects are included in all model specifications. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Table A.1: Benchmark model variables definition

VARIABLE	Definition
ELECTIONS	The dummy variable is equal to one for years that elections occurred and zero otherwise.
SNAP	The dummy variable is equal to one for years that elections occurred before the end of term and zero otherwise.
END-OF-TERM	The dummy variable is equal to one for years that scheduled elections occurred (within six months from the term limit) and zero otherwise.
RE-ELECTED	The dummy variable is equal to one for years that elections occurred and the incumbent government was reelected. In cases of countries with coalition governments, we assume that reelection is when the leading party of the coalition participates in the new government. For all other years, the variable is equal to zero.
NEW GOV	The dummy variable is equal to one for years that elections occurred and the incumbent government was not reelected or the leading party on a coalition government did not participate in the next government. For all other years, the variable is equal to zero.
ΔCoVaR	Introduced by Adrian and Brunnermeier (2016) and it is defined as the difference between the Conditional Value-at-Risk of the DS Financials index when the examined institution shifts from its median returns to its Value-at-risk.
VaR	Value-at-Risk (VaR) is estimated in line with Adrian and Brunnermeier (2016) and a set of state variables.
Log ASSETS	The natural logarithm of the firm's total Assets. The variables captures firm's size.
ROE	Return on Equity. The ratio captures firm's ability to generate profits.
LEVERAGE	Calculated as the ratio of Total Debt divided by Market Capitalization. Leverage shows how much of a company's capital structure is financed by debt compared to equity.
GDP growth	Year-on-year GDP growth.
Inflation	Year-on-year growth of the Consumer Price Index (CPI).

Notes: The Table describes the variables used in our empirical analysis. The elections data are collected by national sources for each country in our sample. Stock price returns, Log Assets, ROE and LEVERAGE are provided by Thomson Reuters EIKON Datastream. Based on the stock price returns and a set of state variables, we calculated VaR and ΔCoVaR . GDP growth and Inflation are provided by OECD database.

Table A.2: Extended summary statistics

	Obs	Mean	St.dev	Min	Max
Banks (N = 193)					
Elections	4,081	0.283	0.451	0	1
Snap Elections	4,081	0.088	0.283	0	1
End-of-Term Elections	4,081	0.196	0.400	0	1
Re-elected GVT	4,081	0.155	0.362	0	1
New GVT	4,081	0.128	0.335	0	1
Δ CoVaR	4,081	1.802	0.871	0.048	9.584
VaR	4,081	0.691	1.575	-6.610	12.438
Log Assets	4,047	18.112	1.710	11.032	22.078
ROE	4,017	0.070	0.735	-42.985	1.353
Leverage	4,081	2.710	6.490	0	147.264
GDP growth	4,081	1.620	2.682	-11.175	22.175
Inflation	4,081	1.779	1.920	-4.500	10.616
Government Expenditure	3,888	41.096	7.971	18.520	55.820
Price Informativeness	3,973	9.375	27.226	-70.650	188.451
Trust in Government	2,878	42.664	15.226	12.600	85.000
Stock Market Weekly Volatility	3,888	1.147	0.429	0.408	2.822
MES	4,101	2.789	1.967	-0.043	24.207
SRISK	4,042	10.243	0.852	6.821	12.374
Term Limits	4,081	0.272	0.445	0	1
Google Trend Uncertainty Dummy	3,535	0.257	0.437	0	1
All financials (N = 697)					
Elections	13,439	0.269	0.444	0	1
Snap Elections	13,439	0.080	0.272	0	1
End-of-Term Elections	13,439	0.189	0.391	0	1
Re-elected GVT	13,439	0.156	0.363	0	1
New GVT	13,439	0.113	0.317	0	1
Δ CoVaR	13,439	1.737	0.758	-0.711	9.584
VaR	13,439	0.815	1.515	-8.258	16.511
Log Assets	13,292	16.145	2.616	5.781	22.078
ROE	13,108	0.099	0.593	-42.985	19.812
Leverage	13,439	1.331	8.862	-0.221	598.378
GDP growth	13,439	1.689	2.880	-11.175	22.175
Inflation	13,439	2.157	1.982	-4.500	10.616
Government Expenditure	12,746	41.686	7.094	18.520	66.820
Price Informativeness	13,190	8.315	25.039	-70.649	188.452
Trust in Government	9,900	42.809	12.551	12.600	85.000
Stock Market Weekly Volatility	12,746	1.087	0.419	0.408	2.822
MES	13,478	2.318	1.538	-1.438	24.207
SRISK	10,588	9.822	1.046	2.884	12.374
Term Limits	13,349	0.249	0.432	0	1
Google Trend Uncertainty Dummy	11,850	0.267	0.442	0	1

Notes: The Table displays the extended summary statistics for the all the variables used in our empirical analysis. The Table is split into parts with the first one to refer to the banks-only sample and the second part to include the summary statistics for other types financial institutions, such as insurance companies, financial services companies and investment trusts. More specifically it presents the mean value, standard deviation, minimum and maximum value for the election-related dummy variables, the systemic risk metric Δ CoVaR, firm and macroeconomic characteristics. The reported values are calculated for the period 2000-2023 and they refer only to years that Δ CoVaR is available.