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Political Fragility

Coups d'État and Their Drivers

Aliona Cebotari, Enrique Chueca-Montuenga, Yoro Diallo, Yunsheng Ma, Rima Turk, Weining Xin and Harold Zavarce

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ABSTRACT: The paper explores the drivers of political fragility by focusing on coups d’état as symptomatic of such fragility. It uses event studies to identify factors that exhibit significantly different dynamics in the runup to coups, and machine learning to identify these stressors and more structural determinants of fragility—as well as their nonlinear interactions—that create an environment propitious to coups. The paper finds that the destabilization of a country’s economic, political or security environment—such as low growth, high inflation, weak external positions, political instability and conflict—set the stage for a higher likelihood of coups, with overlapping stressors amplifying each other. These stressors are more likely to lead to breakdowns in political systems when demographic pressures and underlying structural weaknesses (especially poverty, exclusion, and weak governance) are present or when policies are weaker, through complex interactions. Conversely, strengthened fundamentals and macropolicies have higher returns in structurally fragile environments in terms of staving off political breakdowns, suggesting that continued engagement by multilateral institutions and donors in fragile situations is likely to yield particularly high dividends. The model performs well in predicting coups out of sample, having predicted a high probability of most 2020-23 coups, including in the Sahel region.

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WORKING PAPERS

Political Fragility

Coups d’État and Their Drivers

Prepared by Aliona Cebotari, Enrique Chueca-Montuenga, Yoro Diallo, Yunsheng Ma, Rima Turk, Weining Xin and Harold Zavarce[1]

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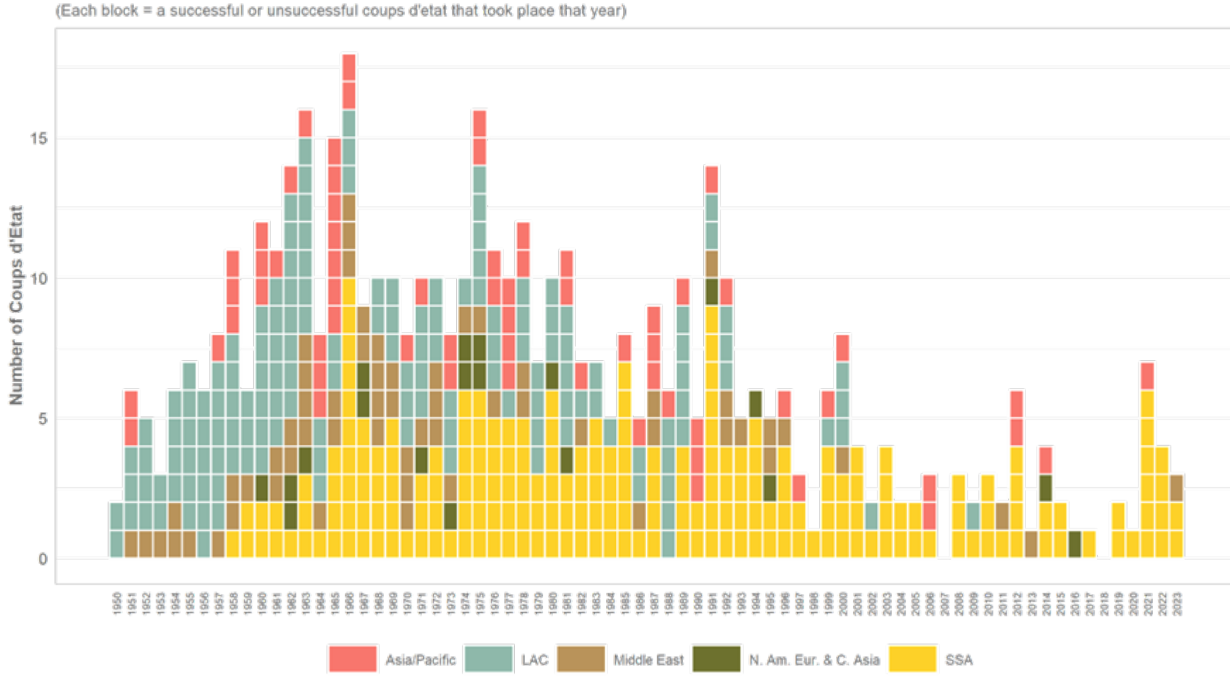
1. Introduction

Against the secular decline in coups d'état, the surge in coups in 2020–23 stands out in terms of sheer number and concentration in sub-Saharan Africa, reminding us of the fragility of many political systems. The string of military takeovers or takeover attempts in and around the Sahel region (Chad, Central African Republic, Mali, Burkina Faso, Niger, Guinea, Sudan) interrupted the marked downward trend in coups since the 1960s (Figure 1). They took place amid heightened pressures in the aftermath of the global pandemic, deteriorating security situation, domestic socio-political instability, and rising geo-political tensions. They also took place against the backdrop of heightened attention in much of the international community to issues of fragility. During this period, several international bodies adopted strategies or frameworks for fragile states (the OECD, the World Bank, and IMF, among others), by way of raising awareness about the drivers of fragility and drawing lessons on how best to mitigate them.

Figure 1: Number of Coup Attempts by Region (1950-2023)

(Each block = a successful or unsuccessful coups d'etat that took place that year)



Source: Powell and Thyne (database on coups) and authors' calculation.

As part of the efforts to better understand fragility in its various manifestations, this paper focuses on coups d'état as symptomatic of political fragility.[1] If one views fragility as breakdowns in the economic or political systems due to a disproportionate adverse response to shocks, in the political realm such breakdowns happen through irregular power transfers (coups d'état) or internal conflicts due to inability to resolve sociopolitical grievances otherwise. The paper focuses on coups as a manifestation of such fragility and aims to identify their drivers and the potentially complex interactions between them through

[1] This paper is part of a broader work towards developing an analytical framework for state fragility in Cebotari et al (2023). This framework is built on the concept of fragility developed by Taleb (2014)—where fragility is defined mathematically as a supra-linear response to large negative shocks or to time (as a stressor)–and extends it to the positive realm as a sub-linear response to positive shocks (or to time). In other words, the framework defines fragility as breakdowns in the economic or political systems due to a disproportionate adverse response to negative shocks ("stress-induced fragility") or as inability to generate/sustain growth over time ("chronic fragility").

use of machine learning techniques. We are interested in exploring both the conjunctural factors that may stress economic and political systems to the point where the sociopolitical environment becomes propitious to coups, i.e., the stressors, but also in the more structural factors that could explain why—when faced with such stressors—some countries experience coups and others do not, i.e., the sources of fragility. At the same time, we do not seek to explore the immediate triggers for the coup that tend to be quite random and unpredictable—such as Mohamed Bouazizi setting himself on fire in Tunisia's Sidi Bouzid in 2010 that sparked the Arab Spring or the firing of the head of the Presidential Guard in Niger in July 2023 that is said to have been the proximate cause of the coup.

The paper first uses the event study methodology to study the dynamics of variables in a ten-year window around coups to identify pre-coup stressors, which we define as fast-moving variables that exhibit significantly different dynamics in the years leading up to coups. It then employs machine learning models, which are able to accommodate nonlinearities and a wide range of predictors, to study not only the stressors, but also the sources of political fragility—the more structural characteristics that make countries prone to coups in the presence of stressors. More importantly, the flexible nonparametric nature of machine learning methods allows us to examine the interactions between stressors and sources of fragility (as well as among stressors and sources themselves), given that coups are often the outcome of a complex interplay of political, economic, social, and historical factors. While the event study exercise helps us understand the dynamics of variables around coup events and machine learning exercise allows us to find drivers that have high predictive power for coups, it may be worth noting upfront that neither of these would point to causal relationships between the variables in consideration and coups events.

The literature on conflict—of which coups are usually a subset—is quite well-developed. Many authors identify **low income levels** and **growth rates** as robust correlates of coups and more generally of civil wars (Alesina et al., 1996; Blattman and Miguel, 2010; Bazzi and Blattman, 2014; Muchlinski et al., 2016, Redl and Hlatshwayo, 2021). Indeed, **poor economic conditions**—namely high unemployment, high inflation, or economic downturns—can contribute to a sense of discontent, create grievances, erode public support, and increase the likelihood of coups. Collier and Hoeffler (2004, 2005, 2007 and 2009)—surveyed in Collier (2007, chapter 2)—study the links between poverty, stagnation, and conflict, and argue that countries in a state of fragility could be trapped in conflict patterns with events that are either persistent (civil wars) or swift (coup d'état). Their research shows that risks of civil war and of coups are affected by **low growth** (hopelessness), **low income** (poverty), **low state capacity** and **past conflict or coup events.** Also, they show that a civil war is socially costly with persistent economic, political and health losses, while the private cost for rebels is low when **state capacity is limited** and expected benefits could be substantial specially in countries with **dependence on primary commodity exports**. Unlike for civil wars, Collier and Hoeffler (2005, 2007b) find that risk of coups d'état is not affected by export commodity dependance and that risk of coup leads to increased military spending related to coup proofing strategies. Acemoglu et al. (2011) also finds that countries exposed to coups are characterized by **weak institutions and low levels of economic development**, which can lead to permanent internal instability. Indeed, one of the most cited factors that can lead to coups is **political instability**, including factors such as **weak or ineffective government**, **corruption**, or **political polarization** (Hunter et al, 2020). The **potential of military intervention in politics** is also found to be an important driving factor of coups—even more important than economic influences—when the ability of the party in power to control the miliary group is weak (Feaver, 2003 and Powell, 2016). Several military factors can contribute to military intervention, such as low morale, a lack of trust in civilian leadership, or institutional weaknesses in the military. Tilly's (1975) case study of European states argues that the ability to monopolize violence is a key characteristic of state power, which can lead to coups and other forms of political violence when challenged. Social factors, such as **ethnic or religious tensions**, can also contribute to coup attempts, particularly if they are associated with political or economic inequality (Hiroi and Omori, 2015).

Despite of the rich literature on drivers of conflicts and more generally of civil wars, few papers have focused on coups specifically and examined their drivers empirically. To the best of our knowledge, this paper is not only the first one to examine empirically the predictive power of a wide range of macroeconomic and sociopolitical variables for coups and to provide global evidence from more than 190 countries and more than 50 years, but also the first one to apply machine learning to predicting coups.[2]

The paper finds that (i) the main stressors that increase coup probabilities are a destabilized economic situation (weaker growth or external position, high overall and food inflation) and a destabilized political and security situation, in line with the literature; (ii) the main sources of political fragility are usually demographic pressures (a younger population) and weak structural fundamentals that point to poverty, lower economic, social or political inclusion (higher inequality, lower literacy rates, higher ethnic fractionalization, weaker democratization), weak governance, and a more recent and higher incidence of coups; (iii) these structural sources of fragility act as double-sided amplifiers of stressors: they increase the probability of coups when stressors are present but also reduce the probability of coups faster when the stressors recede, pointing to the increased benefits of maintaining macroeconomic and socio-political stability in countries where structural fundamentals are generally weak; (iv) policy improvements also yield stronger dividends in fragile states: even moderate improvements in the policy environment (fiscal position and governance) help reduce coup probabilities, especially when structural fundamentals are weaker; (v) a corollary of the previous two findings is that in countries where structural fundamentals are strong, coup probabilities are not very responsive to economic, political or policy shocks or, put differently, improving structural fundamentals on macroeconomic, institutional, political, and social fronts can enhance resilience to stressors or shocks; (vi) weaknesses on multiple structural fundamentals, which usually characterize fragile countries, compound each other and make countries more prone to coups; and finally (vii) stressors can also compound each other, with the overlapping crises facing most countries in 2020–23 likely prone to fragilizing political systems, especially in countries with weaker fundamentals. Overall, the results suggest that political and economic instability are easier to exploit (e.g., to stage a coup) if the structural sources of fragility are present, but that strengthened policies and macroeconomic outcomes similarly have higher returns in such environments. These results strengthen the case for international financial institutions to remain engaged in difficult fragile situations by both providing financial assistance and supporting stronger policies.

The rest of this paper is structured as follows. The next section presents some stylized facts about coups. Section 3 discusses the results from the event study, focusing on the identified stressors of coups but also discussing the dynamics of various indicators during and after the year of the coup. Section 4 presents the results from the machine learning model in terms of identifying the main drivers of coups (be they structural or conjunctural), examining how these drivers affect the probability of coups (which is oftentimes nonlinear and reflects interacting effects between drivers), and discussing how these drivers differ across regions and times. Section 5 uses the machine learning results to understand the likelihood of coups during 2020-2022, comparing the predictions to actual outcomes. Section 6 concludes.

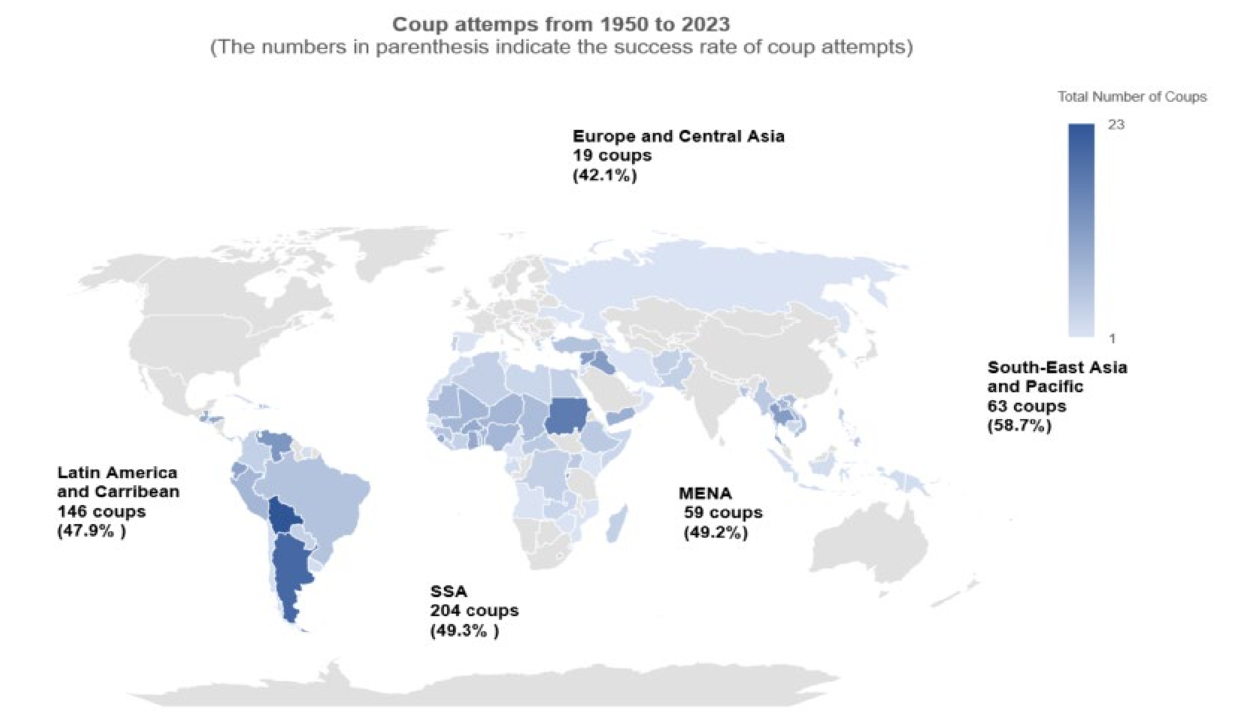
[2] A few papers on conflict analysis have used a machine learning approach (for example, Barrett et al. (2022) on measuring social unrest and Redl and Hlatshwayo (2021) on forecasting social unrest, and Mueller et al. (2022) on predicting conflict).

2. Some Stylized Facts about Coups

In the paper, we follow the definition of coups d'état from Powell and Thyne (2011), who describe coups as "overt attempts by the military or other elites within the state to unseat the sitting head of state using unconstitutional means". If the coup perpetrators hold power for at least seven days, the coup is considered successful, otherwise it remains a coup attempt.[3] We refer to both successful coups and coup attempts as "coups" and focus on both in the empirical analysis, unless otherwise noted.

About half of the countries in the world have experienced at least one (attempted) coup d'état (Figure 2). Based on the database by Powell and Thyne (2011) that covers all countries for the period 1950–September 8, 2023, a total of 491 coups occurred in 97 countries since 1950. While a fifth of the countries that experienced coups only had one coup, around 80 percent have a repeated incidence of coups. Bolivia and Argentina have had the highest numbers of coups, at 23 and 20 respectively, followed by Sudan (17), Venezuela (13), Haiti (13), and Burundi (11). This in part explains why a history of conflicts or coups is often a significant predictor of future conflict or coup (Londregan and Poole, 1990). Of all 491 coups since 1950, about half (49.8 percent) were successful in changing the regime in power and half unsuccessful, i.e., coup attempts.

Figure 2. Coups d'État in Historical Perspective

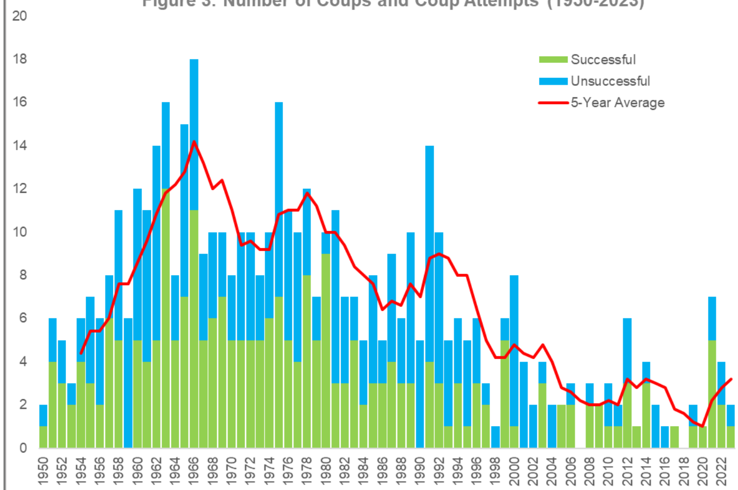


Source: Powell and Thyne (2011) database on coups.

[3] In other databases, such as the one from the Cline Center, coup attempts are not restricted to those undertaken by the military or existing elites and could be undertaken by outsiders.

The number of coups has consistently decreased over the past seven decades but resurged since the pandemic (Figure 3). The number of coups peaked at 18 in 1966 and fell from an average of 12 per year during the 1960s—when coups in Latin America were prevalent and the newly independent African states were going through political turbulence—to 3 during the 2010–19 decade, the lowest in history. The pandemic and post-pandemic period of 2020-2023 saw a significant resurgence in coup incidence, with 15 coups and coup attempts in these few years, all but one in sub-Saharan Africa (Figure 1). Overall, sub-Saharan Africa has had the largest share of coups (46½ percent), followed by Latin America and the Caribbean (24.1 percent) and the Middle Eastern region (11.2 percent). The relative incidence of coups shifted even stronger towards sub-Saharan Africa over the last two decades (2000-2023), with 70.7 percent of the coups occurring in this region, followed by East Asia and the Pacific (10.7 percent) and Latin America and the Caribbean (8 percent).

Figure 3: Number of Coups and Coup Attempts (1950-2023)

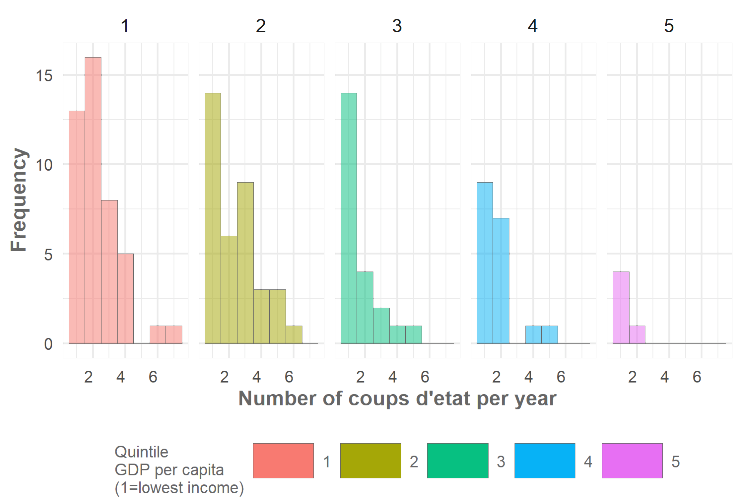


Source: Powell and Thyne (database on coups), and authors' calculations

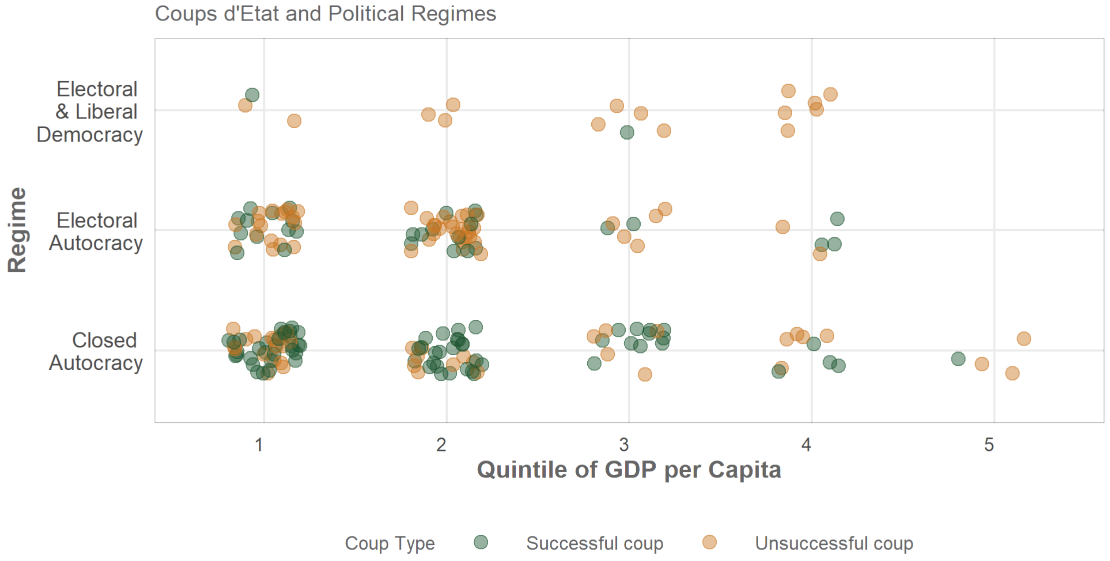
The frequency of coups decreases with the level of development and degree of democratization. The probability of experiencing at least one coup is on average 28 percent for the countries in the first (poorest) income quintile, but less than 5 percent for those in the fifth (wealthiest) income quintile (Figure 4, top). Coups d'état take place most often under autocratic regimes, where they are also more likely to succeed (Figure 4, bottom). Close to 92 percent of the coups occurred in either closed or electoral autocracies, and of these 53 percent succeeded.

Figure 4. Frequency of Coups d'État by Income Level and Type of Political Regime

Distribution of Annual Number of Coups per Quintile of GDP per Capita



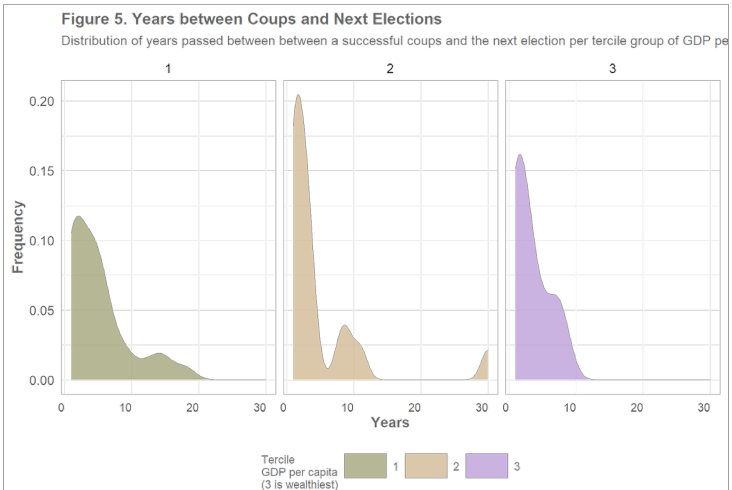
Source: authors' estimates based on Powell and Thyne (database on coups).
Note: The number of country-years with no coups is not shown to maintain a readable scale.



Source: authors' estimates based on Powell and Thyne (database on coups) for the period 1975-2020 and Polity V database on political regime classification.
Note: political regime classification was taken from the Polity V database methodology that examines concomitant qualities of democratic and autocratic authority in governing institutions.

The transition governments installed in the aftermath of coups are relatively slow to organize democratic elections. Based on the election dates recorded in the Database of Political Institutions, the restoration of electoral powers happens faster in high income countries (after two years, on average), whereas in low-income countries a transition government stays on relatively longer (4 years on average) (Figure 5). In low-income countries, approximately 50 percent of cases experience a transition duration of around 2 years between the coup year and the subsequent election, although about a quarter of the countries have transitions that last five years or more. In contrast, in the higher income group, the median country has a corresponding duration of transition of about 1 year, although in a quarter of the countries the transitions last three years or more.

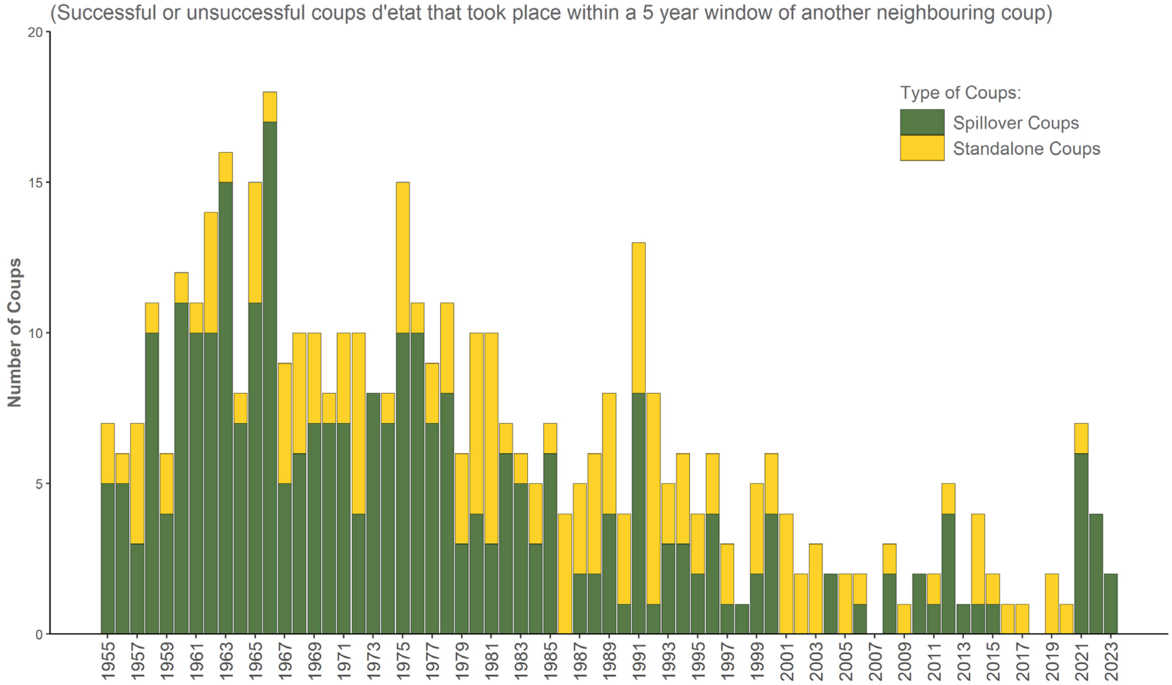
Figure 5. Years between Coups and Next Elections



Source: authors' estimates based on Powell and Thyne (database on coups) and the Database of Political Institutions (2020) database and WEO.

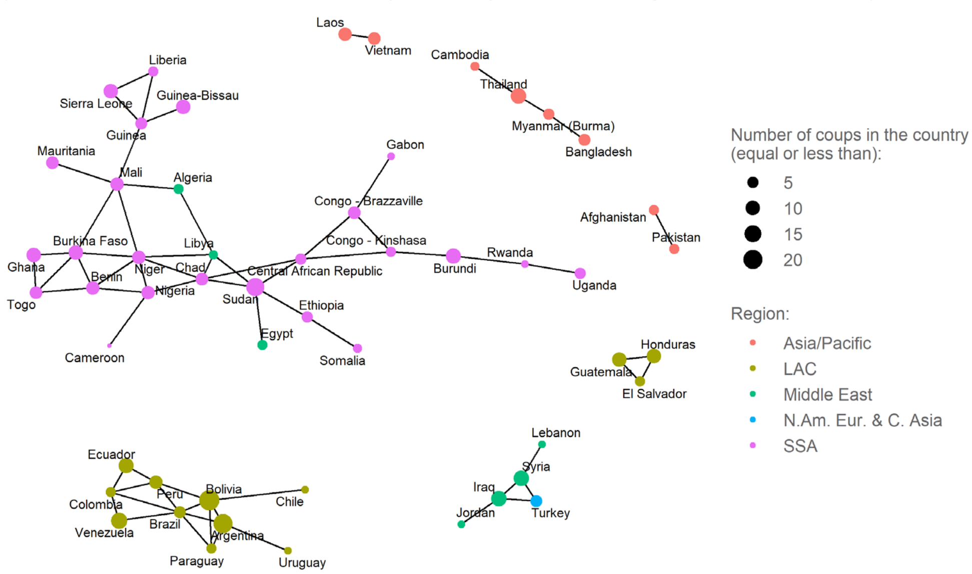
Coups often tend to spread to neighboring countries. Of the 491 coups we use from the Powell and Thyne database, 65.4 percent of coups occurred against the backdrop of other coups in the adjacent countries within the previous five years (Figure 6) and 45.7 percent of coups within 2 years of other coups in the adjacent countries (Figure 7). This relationship could be driven either by “spillover” effects from one country to another or could be due to common challenges faced by the countries in the region, or both. An example of such spillovers is the wave of coups during 2020–23 in the Sahel countries, which faced common challenges such as an escalation in terrorist incidents, social discontent fueled by the confluence of a weak economic environment and geopolitical dynamics vis-à-vis a former colonial power, as well as a strong influence of social media that fueled such discontent. Remarkably, all countries within the Sahel (narrowly defined), except for Mauritania, have had at least one instance of a coup since 2020.

Figure 6: Coups in the context of neighbouring coups (1955-2023)
(Successful or unsuccessful coups d'etat that took place within a 5 year window of another neighbouring coup)



Source: Powell and Thyne (database on coups), and authors' calculation

Figure 7: Spatial Correlation of Coups
(Countries that had successful or unsuccessful coups within a 2-year window of its neighbours between 1950-2023)



Source: authors' estimates based on Powell and Thyne (database on coups)

3. Dynamics Around Coups d'État: Event Study

To identify the drivers of coups, we use two methodologies: an event study and machine learning models. The event study, discussed in this section, is used to understand the dynamics of variables around the coup events and identify those that exhibit significantly different dynamics before coups, i.e., stressors of political systems. The machine learning model, discussed in the next section, is used to identify both stressors (conjunctural drivers that contribute to coup probabilities)—as a complementary and validation exercise to the event study—but also the sources of political fragility (the structural drivers or characteristics of the environment in which coups occur), which do not change much over time. The machine learning exercise will also help us explore how conjunctural and structural drivers interact.

For the event study methodology, we use the specification that follows Gourinchas & Maurice (2012) and Catão and Milesi-Ferretti (2014) and we report the results in terms of the regression coefficients that measure the value of the predictors in the ten-year window around the coup year relative to the tranquil period outside this window (see Annex I for a description of data and methodology). In other words, the coefficients we report measure how proximity to a coup affects the dynamics of the variables of interest.[4] For the coup drivers, we rely on 86 variables that capture demographic, development, inclusion, governance, macro stability, and sociopolitical stability characteristics of 192 countries during the period 1970–2019 that are associated with interpretable channels described in the literature discussed above.[5] However, in what follows we discuss the results only for those variables that show statistically significant dynamics relative to tranquil periods either in the full sample or in the regional, time, or income subsamples.

Table 1. Example of variables by category

Category	Variables
Development and Demagraphics	Income per capita Share of Elder Population Literacy Rate …
Inclusion and Governance	Degree of Democratization Gini Inequality Voice and Accountability …
Macro Stability	Real GDP Growth Inflation CA Balance …
Sociopolitical Stability	Political Stability and Absence of Terrorism Weighted Conflict Index …
Policy	Fiscal Balance Public Debt Military Spending …

Pre-coup dynamics: stressors

The main indicators that showed a statistically significant deterioration prior to coups are *growth collapses* and *heightened political instability, including government crises, major cabinet changes and social unrest* (Figure 8).[6] Specifically, growth is on average more than 1 percentage point lower one year before coups than in tranquil times. Political instability and the security situation deteriorate significantly prior to coups–

[4] In overlapping coup windows, these coefficients are additive, capturing the combined effects of relevant coups.

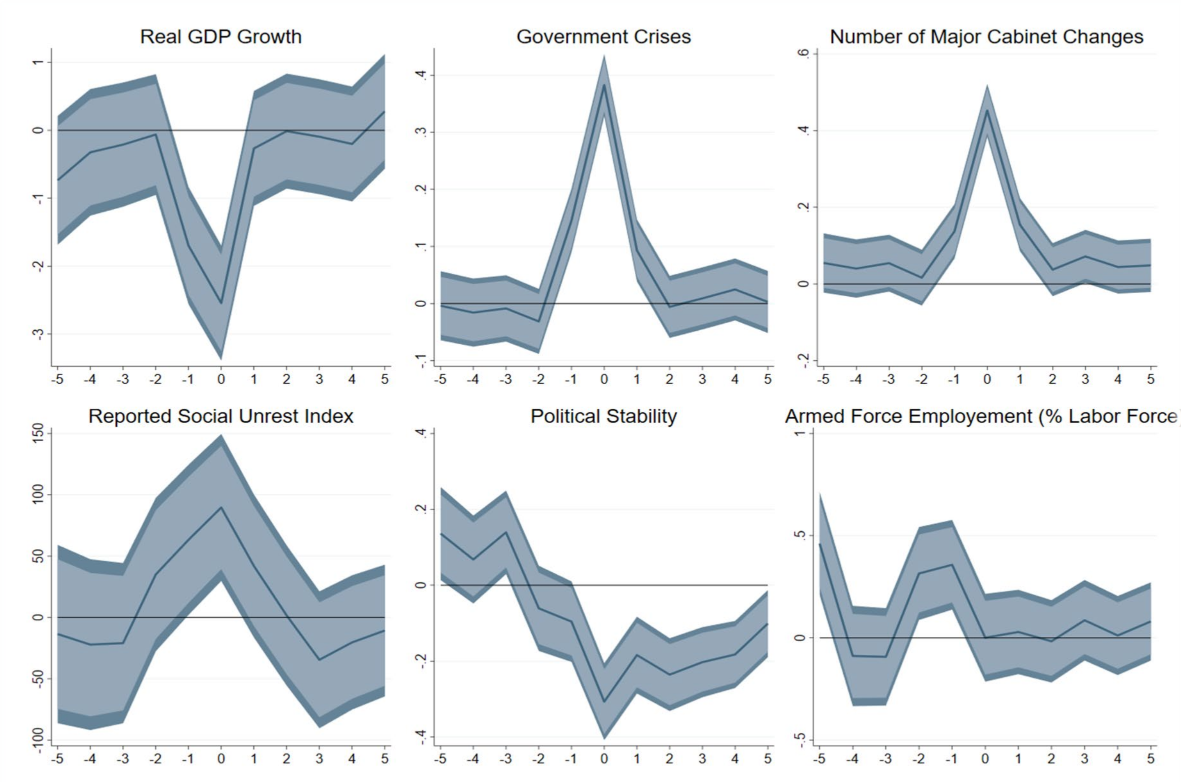
[5] We limit the sample to 2019, because data on the predictors are scarcer in more recent years and because the dynamics of many predictors during the pandemic years of 2020–22 may be very different from history and therefore could introduce noise.

[6] Political instability and security are proxied in our exercise by World Governance Indicators' "political stability and absence of violence/terrorism" variable, which measures perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism. The results are similar if we use other political stability variables, such as the political risk rating from the International Country Risk Guide (ICRG) database.

a result that is driven particularly by the last twenty years, during which political stability seems to have gained in importance. There is also an increased incidence of government crises, major cabinet changes, and social unrest in the year prior to coups, although these intensify even further in the year of the coup. Additionally, army recruitment increases significantly at least two years prior coup events, possibly as a result of intensified internal conflict or of coup-proofing.

While these variables show significance in the full sample, their magnitudes could differ across the regional, time and income subsamples we consider for robustness checks (see Annex II for a fuller set of results of the event studies, including by subsamples). For example, economic growth is on average 2 percentage points lower one year before coups in low-income countries (LICs) and in sub-Saharan African countries. Additionally, energy and food inflation increase significantly a year before coups in LICs and Middle East and Central Asia (ME&CA) countries, respectively.

Figure 8. Dynamics of Selected Variables Before Coups
(full sample)

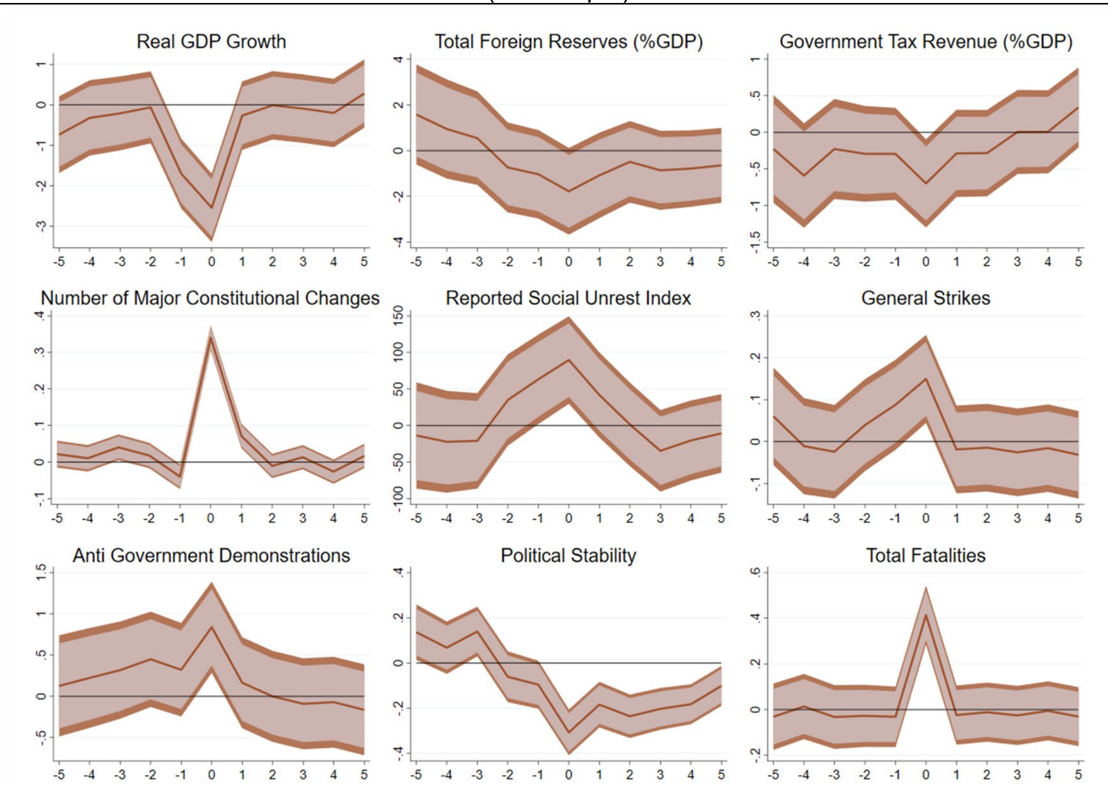


Source: authors' calculations.
Note: The graphs show the value of the estimated regression coefficients (and their 90 and 95 percent confidence intervals) for the reported predictors during the 10–year window around the coup relative to tranquil times outside this window (these are the coefficients β_p as described in Annex 1). The x-axis shows years around the coup event (coup year = 0).

Concurrent dynamics: co-movements with coups

Some variables show movements that are significantly different from tranquil times during coup years, but the frequency of the available data does not allow us to determine whether these movements precede or follow coups (Figure 9). For instance, the deterioration of the macroeconomic situation in the year of the coup—such as the deepening decline in *growth*, *foreign reserves*, and the drop in *tax revenue* —can be both a precursor of coups and a consequence of coup events. Similarly, *major constitutional changes* often happen in the year of the coup—it is plausible that these changes are implemented following a coup by way of consolidating power or they may happen before coups, triggering a negative response and subsequently a coup.[7] Heightened *social unrest*, *strikes* or *anti-government demonstrations* in the year of the coup could also be either preceding the coups (as in the case of 2020 coup in Mali) or could follow the coups as unrest against the putschists and the transition government, demanding restoration of a democratically elected government (as in the case of Sudan, 2021–22). There is also a spike in *fatalities*, associated either with the bloodier coups in the earlier period and/or with the overall background of heightened insecurity against which some of the coups happen (e.g., the coups in the Sahel in 2020-22). More generally, *political instability and violence* show a significant deterioration during the coup years. Finally, in our subsamples, the increase in *energy inflation* is statistically significant during the coup year in LICs and over the period 1970-1999 (see Annex II). Further work could be done to leverage higher-frequency data to examine whether these movements precede or follow coups within the same year.

Figure 9. Dynamics of Selected Variables around Coups
(full sample)



[7] For example, in 2014, the attempt by the President of Burkina Faso to amend the constitution for another presidential term led to a coup attempt. On the other hand, several transition governments led by the military suspended or amended the constitution after a coup to bolster and stabilize the new power dynamics (e.g., Egypt 2013, Cote d'Ivoire 1999, and Central African Republic 2003).

Source: authors' calculations.

Note: The graphs show the value of the estimated regression coefficients (and their 90 and 95 percent confidence intervals) for the reported predictors during the 10–year window around the coup relative to tranquil times outside this window (these are the coefficients β_p as described in Annex 1). The x axis shows years around the coup event (coup year = 0).

Post-coup dynamics: implications of political fragility

The pre-coup dynamics are relevant for identifying the drivers of fragility, which is the focus of the paper. Nevertheless, the event study also provides a useful glimpse into the dynamics of economic, political and governance indicators after coups. These post-coup dynamics can help understand consequences of coups, although as cautioned earlier they are not causal implications of coups. Here we report the results for successful coups only—where irregular transitions actually happen and therefore are likely to have a notable impact—but the results for the full sample (coup and coup attempts) are also reported in Annex II for a broadly similar qualitative effect.[8] Finally, a formal examination of the impact of the coups on these indicators (such as using the local projections model) is left for future research, but we report here on significant deviations in post-coup dynamics relative to tranquil times.

- The *quality of policymaking and governance* deteriorates significantly after coups: regulatory quality, control of corruption, rule of law, government and legislative effectiveness, voice and accountability and other indicators of governance see a long-term decline (Figure 10). Some of these variables broadly revert to normality 4–5 years after the coup, possibly coinciding with the return to democratic elections, consistent with results shown in Figure 5, but many remain depressed over the medium-term.

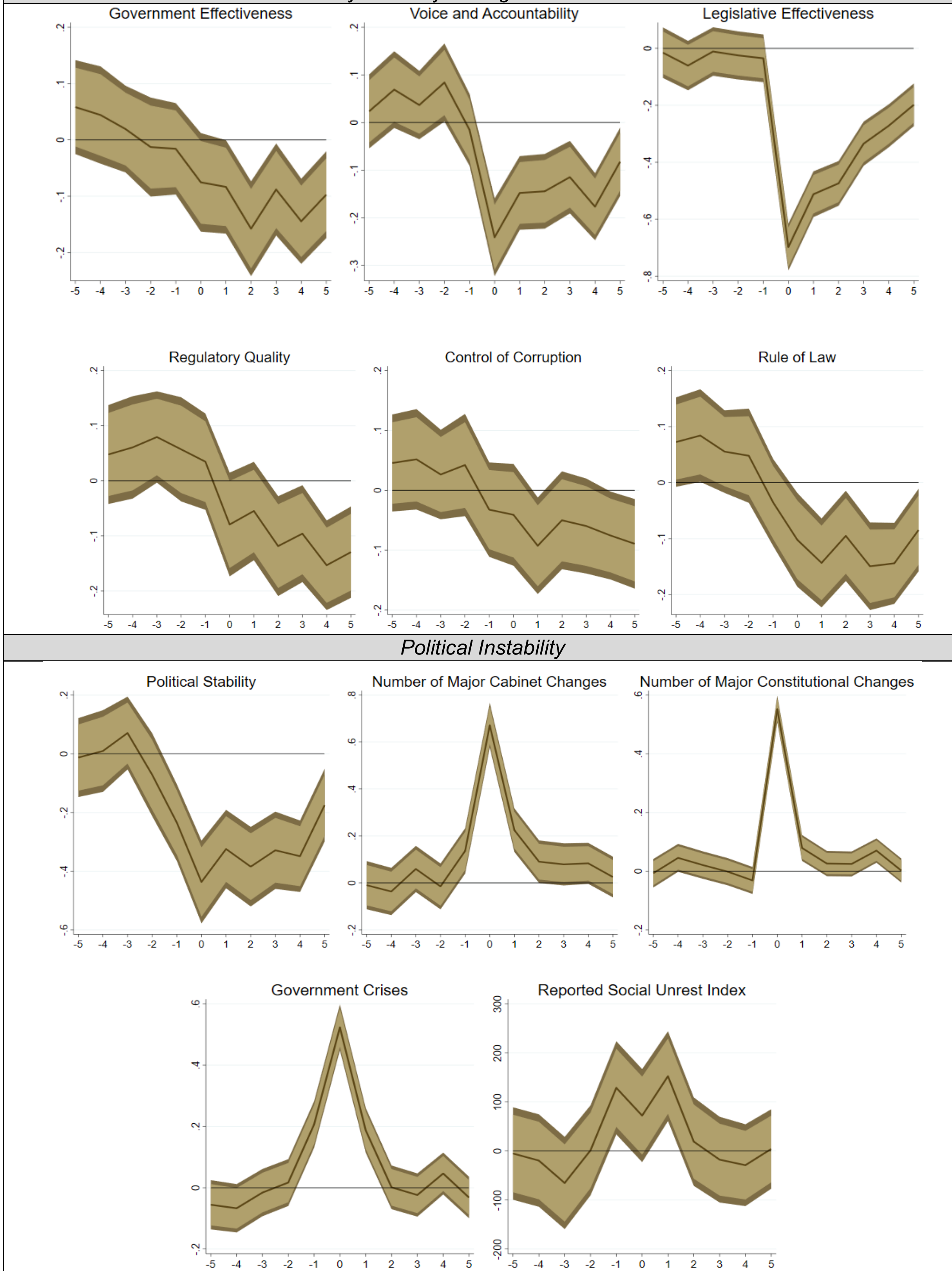
- *Political instability and violence/terrorism*—which flare up a few years before coups—also seem to persist into the medium-term. It is most pronounced, however, the year after the coup, when social unrest, government crises and constitutional changes flare up with almost equal force as pre-coup. In the case of social unrest these could reflect either anti-government demonstrations or built-up social demands that come to the fore under the new regimes. In the case of government crises these normally reflect fragmentation within the transition governments along reform lines that lead to frequent changes in government compositions following the coups.

- On the *macroeconomic* front, weaknesses in economic activity and in the external and fiscal positions linger post-coup but to a different extent. As we have seen in Figures 8-9, growth declines a year prior to coups and dips further during the coup year, it however seems to recover to its "tranquil" time levels very soon following the coup. In the case of successful coups, however, growth underperformance persists one more year after the coup. Official development assistance clearly declines in the first three years after a coup, recovering to normal levels only afterward. Finally, the fiscal position seems to weaken in the first three years after successful coups: the fiscal deficits widen—though only statistically significant in the year following the coup—in part as a result of a decline in revenues, and public debt increases. It strengthens only afterward, possibly when an elected government comes to power or when the financing constraints bind.

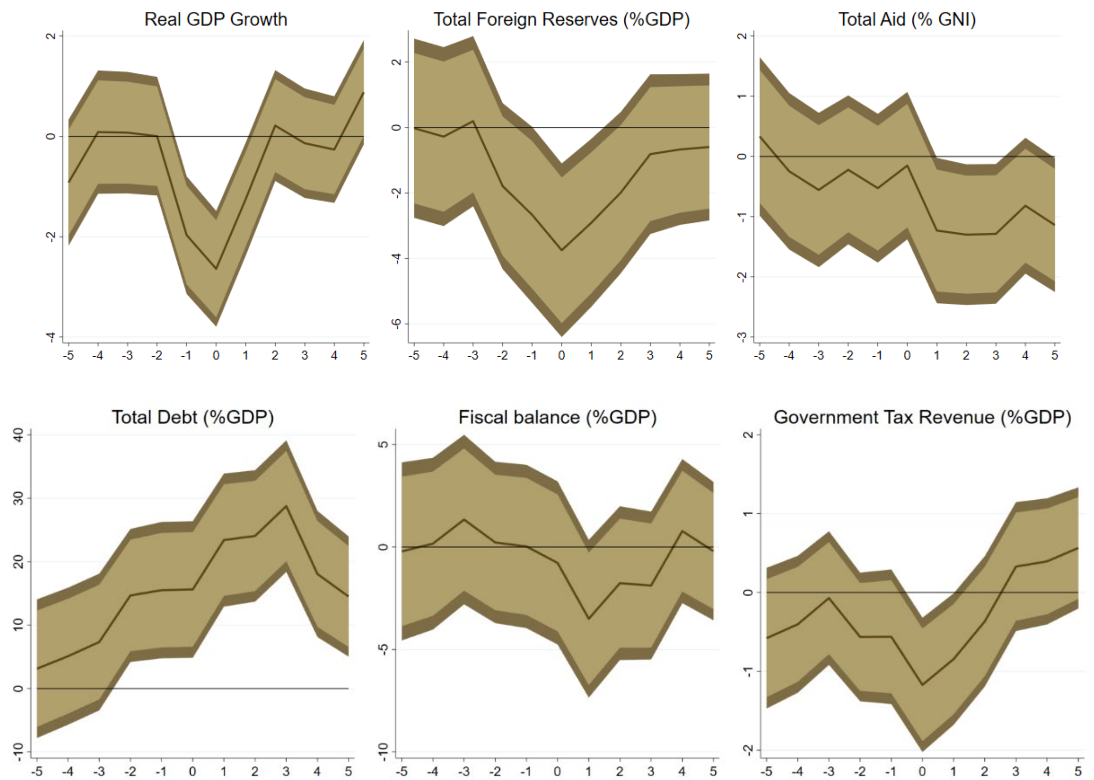
[8] Quantitatively, the "impact" of successful coups on governance, political stability and macroeconomic variables is more significant in terms of magnitude and persistence than in the case of the full sample, which includes both successful and unsuccessful coups.

Figure 10. Post-Coup Dynamics
(Sample of successful coups only)

Quality of Policymaking and Governance



Macroeconomic effects



Source: authors' calculations.

Note: The graphs show the value of the estimated regression coefficients (and their 90 and 95 percent confidence intervals) for the reported predictors during the 10–year window around the coup relative to tranquil times outside this window (these are the coefficients β_p as described in Annex 1). The x axis shows years around the coup event (coup year = 0).

4. Understanding the Drivers of Coups: Machine Learning

In this section, we report the results of the machine learning exercise by presenting the top predictors of coups from the best-performing machine learning model (random forest), based on the dataset and model specifications discussed in Annex I. The machine learning exercise uses broadly the same variables as the event study but includes first difference transformations—to capture within country dynamics—and excludes some variables that capture similar channels by consolidating them so that only one variable for each channel is included to improve interpretability, for a total set of 55 predictors. The training sample for the exercise consists of 192 countries during the period 1970–2019, whereas the period 2020-2022—which has seen a resurgence in coups—is kept for out-of-sample testing. The prediction framework uses year t-1 data to predict coup in year t. We discuss the results in terms of (i) their individual importance to predicting coups (through their relative ranking and how these have evolved over time); (ii) how each predictor affects coup probabilities, including any nonlinearities in their contributions; and (iii) interaction effects between predictors, which include both conjunctural stressors and structural sources of fragility. We report the results for the full sample from 1970 to 2019 and for selected subsamples, such as the sub-Saharan Africa and the Middle East and Central Asia (ME&CA) subsamples and the subsample for the most recent two decades (2000-2019). Bearing in mind that machine learning models only tell us about predictive power of the variable rather than causal relationships, many of the results we found are consistent with the empirical and theoretical literature which points to causal interpretation.

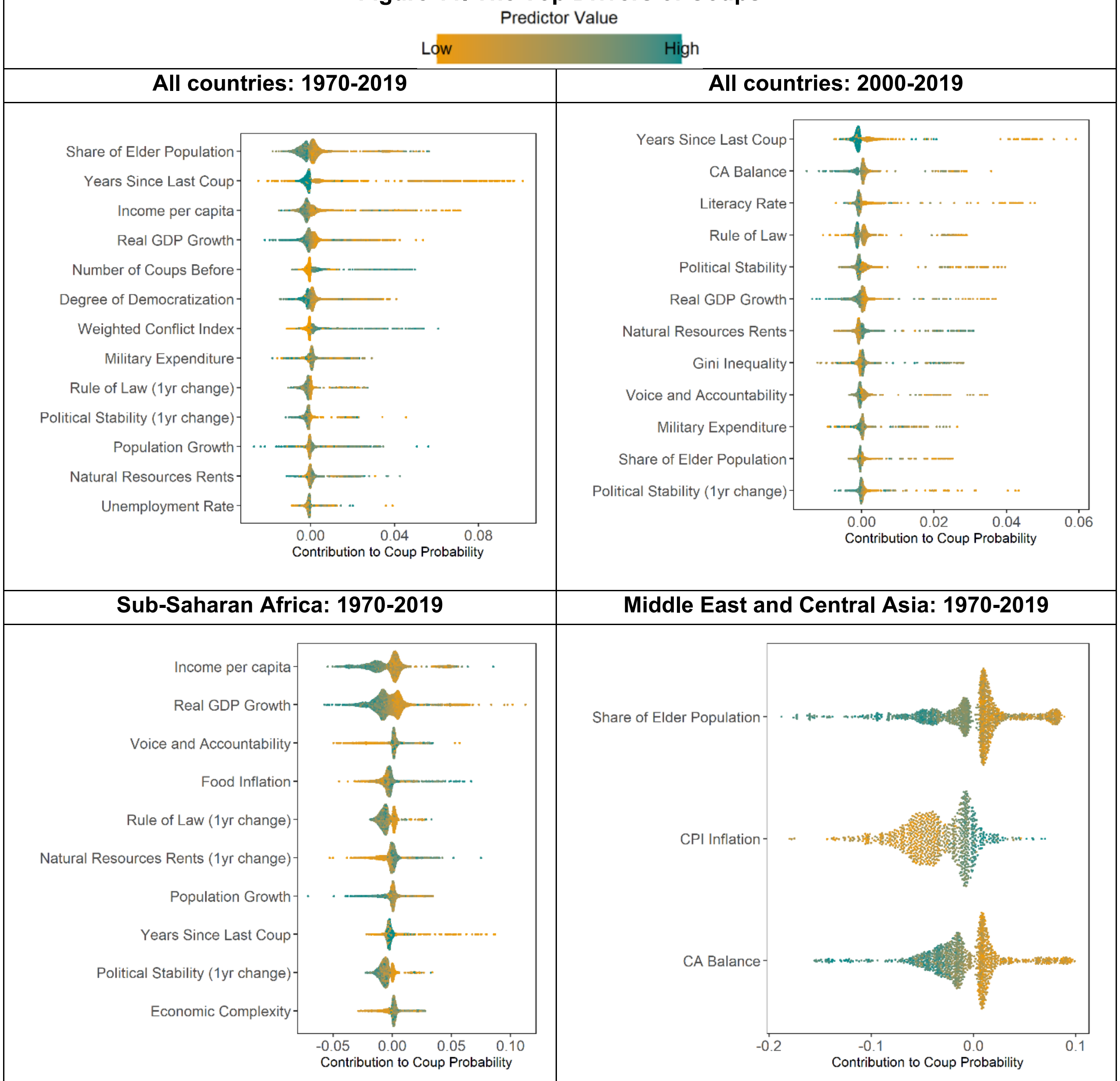
Top predictors and their evolution through time

In terms of their relative importance in predicting coups, the top drivers of coups over the past fifty years were younger demographics, a more recent coup history, followed by a lower level of development, economic and political instability, conflict, and a weaker degree of democratization. In Figure 11, we report the top drivers of coups that account for 50 percent of the contributions to the estimated coup probability for the respective sample, while Annex III reports the top 20 drivers for all samples. Across most samples, *a more recent history of coups* and *poor growth performance* are common important predictors, in line with the findings of the literature on conflict.

- For the full sample, the conjunctural factors that increase the probability of coups include *weaker growth, increased conflict, higher political instability* (which is found to be particularly important in recent years, as shown by its higher rank in the 2000-19 sample), and *a deterioration in governance*. On the side of the more structural factors, countries that have a *higher share of young population*, a *more recent and higher incidence of coups, a lower income per capita*, and a *lower degree of democratization* are more likely to be vulnerable to coups.
- For the regional subsamples, it is worth noting that the drivers of coups are found to be more homogenous, as there are much fewer drivers accounting for half of the coup probabilities in both sub-Saharan Africa and Middle East and Central Asia subsamples. For example, in Middle East and Central Asia only three predictors—a younger population, a higher inflation, and a lower current account balance—have an oversized importance in explaining coup probabilities. In these subsamples, in addition to the drivers from the full sample, *inflation* (including food inflation) appears to be a common important predictor for sub-Saharan Africa and Middle East and Central

Asia. *Higher natural resource rents* are found to be one of the important drivers of coups in sub-Saharan Africa, while a *deterioration of the current account balances* is one of the top-three important drivers in Middle East and Central Asia.

Figure 11. The Top Drivers of Coups



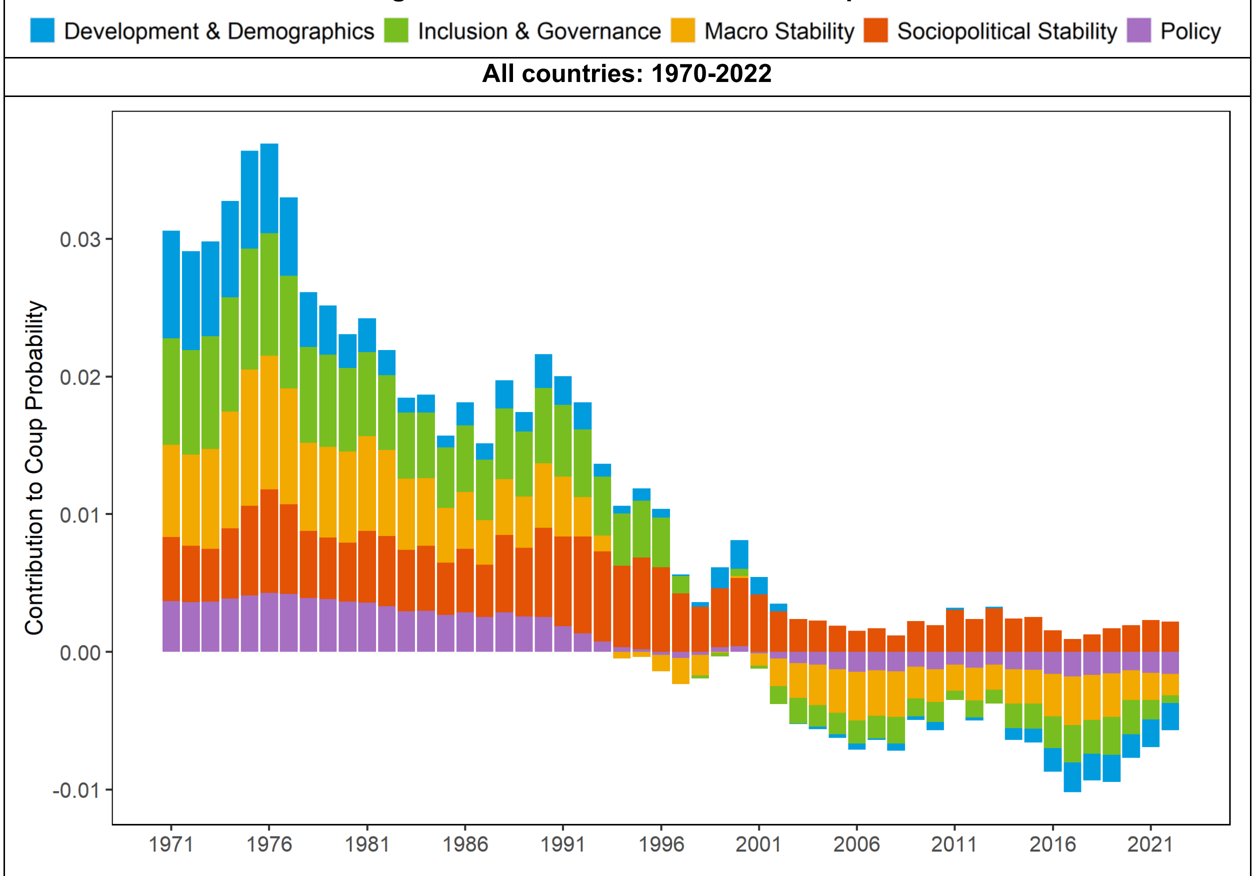
Source: authors' calculations.
Notes: Each chart shows the contribution to coup probability (as measured by the Shapley value) for those drivers that together account for 50 percent of the contributions to the coup probability for the sample. Each dot represents one observation (one country-year pair), and its color indicates the predictor value, with orange being low and green high. Therefore, the value of the contribution (and its negative or positive sign) and color together illustrate how the predictor value affects the coup probability. For example, for the share of elder population, the top predictor in the full sample, most green dots (observations with higher share of elder population) are to the left (i.e., reduce coup probability, relative to the sample average) and orange dots (observations with lower share of elder population) to the right (i.e., increase coup probabilities, relative to the sample average).

The relative importance of coup predictors also varies over time, with a notable shift towards *social and political instability* in the most recent period. Figure 12 reports the contribution of various coup drivers—grouped into five broader categories as reported in Annex I—to the probability of coups relative to the average coup probability for the entire sample.[9] We note that in early years (1970s-1990s), an unstable macroeconomic environment, weak policies, weak inclusion and governance, poverty and demographic headwinds were the main drivers of coups, a large share of them in Latin America. In the more recent period, when coup incidence declined significantly relative to early years, improved economic policies, macroeconomic stability and governance have not only receded as contributors to coups but have reduced coup probabilities (relative to the sample average) throughout most of the last two decades. On the other hand, political instability has remained a steady driver of coups, its *relative* contribution significantly increased—consistent with the earlier results on predictor importance.

A few results stand out in the regional subsamples. For example, in sub-Saharan Africa, younger demographics and lower development levels are significantly more important as coup drivers relative to the full sample, while sociopolitical stability is also one of the main drivers of coups and increasing over time (Figure 12, bottom left chart). In Middle East and Central Asia, macroeconomic instability was the most important driver for earlier coups until early 1990s but has since fully receded, with sociopolitical instability emerging as a strong—and almost only—driver of coups in the lead-up to the Arab Spring.

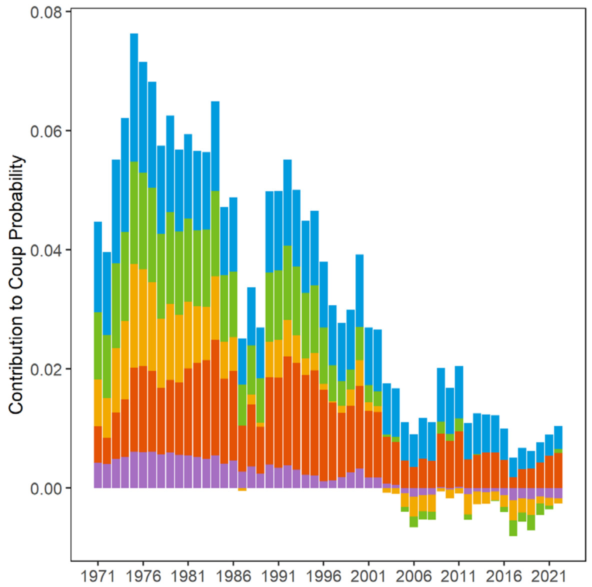
Figure 12. Evolution of Drivers of Coups*

All countries: 1970-2022

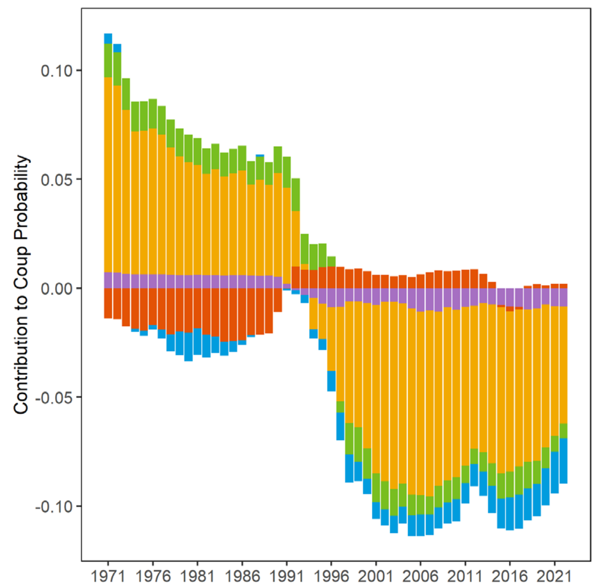


[9] Because the number of coups was relatively high in the 1970s, the Shapley values in early years are positive (adding to the sample-average probability) and in the recent years are negative (subtracting from the sample average probability).

Sub-Saharan Africa: 1970-2022



Middle East and Central Asia: 1970-2022



Source: authors' calculations.
Notes: The figures show the contribution of various categories to year-average coup probabilities relative to the average coup probability of the entire 1970–2019 sample. Contribution to coup probability relative to sample-average coup probability is measured by the Shapley value. Annex I shows how predictors are grouped into the five categories including development and demographics, inclusion and governance, macro stability, sociopolitical stability, and policy.

How predictors affect probability of coups

Most predictors do not affect coup probabilities in a linear way, with such nonlinearities captured by machine learning techniques. As Figures 13 illustrates below, the likelihood of coups increases or decreases with the value of the predictors only over a certain range and does not affect it over the remaining ranges. For example, although a coup is less likely to happen in a country with older demographics, a higher level of development, or when a country experiences higher growth, the probability of coups does not decrease further once the share of elderly population reaches 5-6 percent, the GDP per capita exceeds approximately 2,500 PPP dollars, or when growth is above 5-6 percent. Similarly, although a deterioration in political stability increases the likelihood of coups, an improvement does not always achieve the reduction in the likelihood to the same extent. Such nonlinear effects are present in almost all relevant variables as we will see below.

The probability of a coup incidence is affected by structural fundamentals of a country, conjunctural stressors, and government policies. Figures 13 a-c discuss how the top predictors in these groups affect coup probabilities, covering the full sample (1970-2019) and three other subsamples (most recent 2000-19 period, countries in the SSA and ME&CA region). Predictors often overlap across the samples and their dynamics are largely similar, hence we give priority to showing the drivers in the full sample or for the sample for which the driver is the most prominent.[10] In these figures, each dot represents a country-year pair in the sample where the Shapley value of a predictor (its contribution to the probability of a coup

[10] The full set of the results for the four samples can be found in the online appendix.

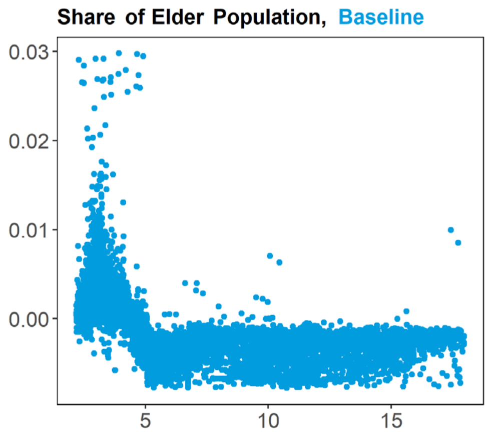
for the specific country-year pair vis-à-vis the sample-average coup probability) is plotted on the y-axis against the predictor value for the country-year pair on x-axis.

(i) For **structural predictors**, the probability of a coup is higher when a country has *younger demographics*, a *more recent and higher incidences of coups*, a *lower level of development*, a *lower level of economic, social or political inclusion* (higher inequality, lower literacy rate, more autocratic regimes, and less decentralized power), *weaker governance* (weaker rule of law), and a *higher reliance on natural resources*. Figure 13a discusses in more detail the nonlinearities associated with these effects. We also refer to younger demographics and these weaker structural fundamentals (like less developed economies and institutions, weaker inclusion and governance) as ***sources of political fragility*** as they are slow moving variables which make countries prone to coups.

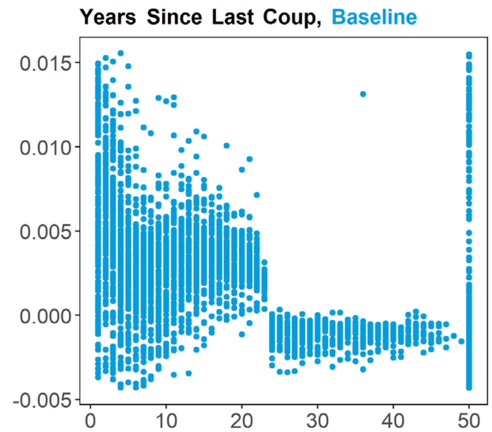
Figure 13a. Structural Predictors of Coups d’État

(in order of predictor importance for the full sample, i.e., all countries during 1970-2019, then subsamples)

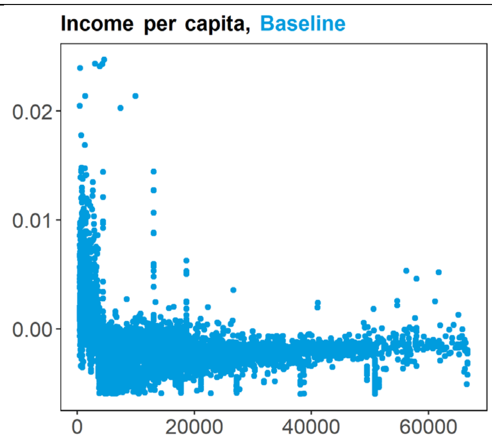
Countries with a high share of younger population (younger than 65 years of age)—above 95 percent or so—are more prone to coups. In 2020-23, countries with such high populations included Chad, Mali, Niger, and Burkina Faso.



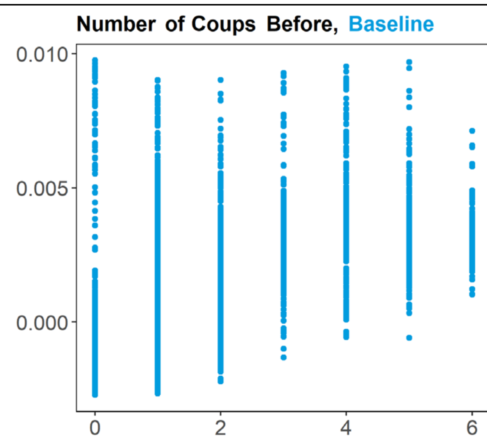
Countries with a recent history of coups have a higher likelihood of having a new coup. The probability of coup drops significantly only after some 23 years without coups.



Most coup incidence is associated with low income levels—below some 2,500 PPP dollars per capita—which corresponds to lower and some lower-middle income countries.



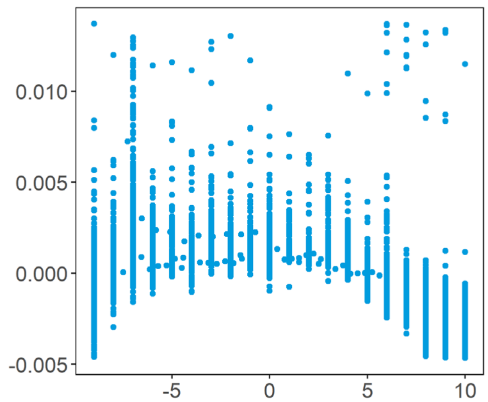
Having no coup in its history helps reduce probability of a coup incidence, while having 3 or more coups significantly increases the probability of another coup.



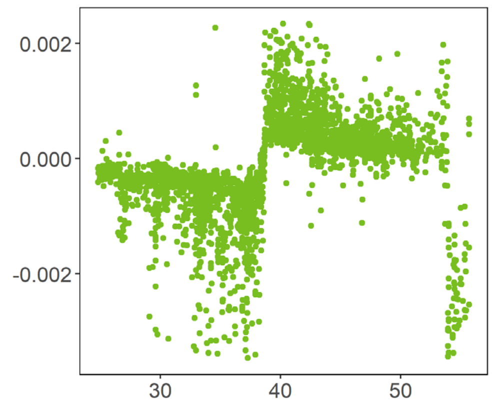
Countries with low political inclusion—as proxied by a high autocracy index—face a higher coup probability. In the full sample, the exception are highly autocratic or highly liberal governments, which have low coup probabilities. In the sub-Saharan African subsample coups, on the other hand, have generally occurred under the most autocratic governments (not shown).

In the most recent 2000-19 period, countries with large income disparities (with a Gini above some 40 out of 100) have a much higher probability of coup incidence.

Degree of Democratization, Baseline

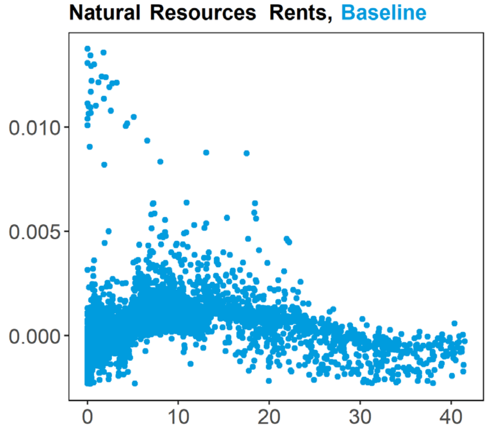


Gini Inequality, 2000-19

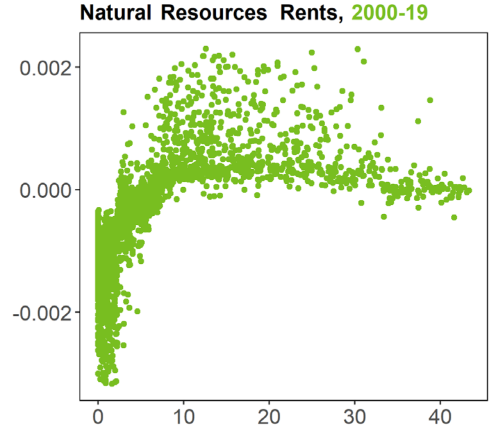


Countries that have higher natural resources rents as share of GDP are more prone to coups. In the full sample, the coup probability is particularly high when rents range from 5-25 percent of GDP (left chart below) but in the most recent 20 years, rents above 10 percent of GDP are associated with high propensity for coups (right chart below).

Natural Resources Rents, Baseline



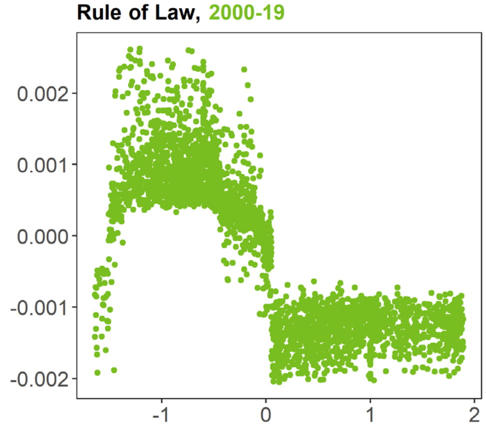
Natural Resources Rents, 2000-19



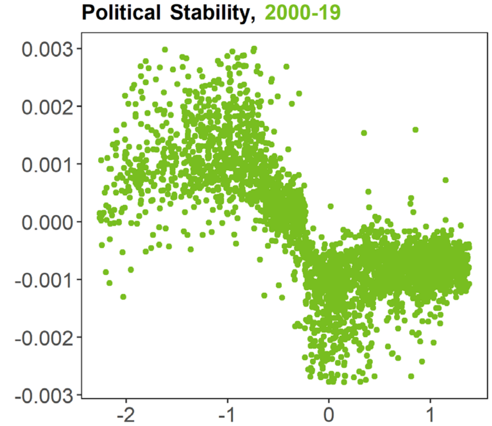
Similarly, in the most recent twenty years, drivers related to weak governance become more important. For example, countries with weak rule of law face a higher coup probability….

… as do countries with low political stability…

Rule of Law, 2000-19

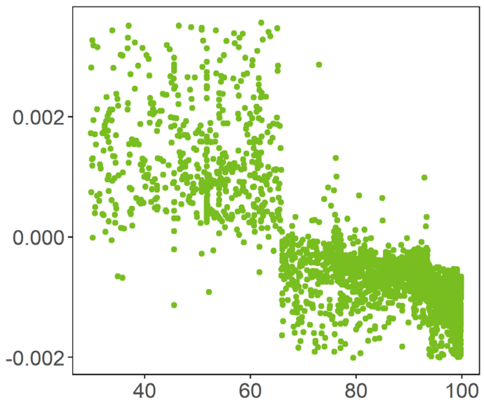


Political Stability, 2000-19



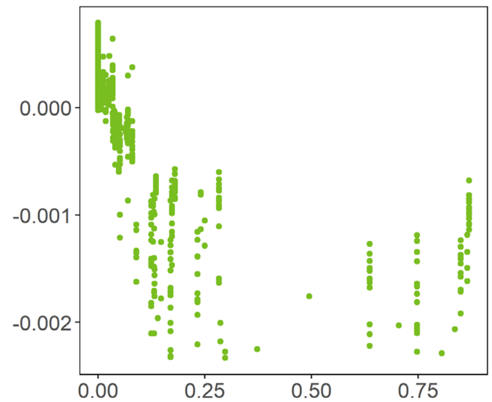
Lower literacy rates also become a more important driver in the recent period in increasing probability of coups, especially when literacy rates below 60-70 percent of population. In the SSA subsample, literacy rates below some 40 percent increase coup probabilities.

Literacy Rate, 2000-19



Finally, higher degree of centralization—as measured by lower share of population with regional autonomy—is associated with higher coup probability in recent years (2000-2019 sample shown below).

Degree of Regional Autonomy, 2000-19



Source: authors’ calculations.
Notes: The y-axis shows the contribution to estimated coup probability as measured by the Shapley value, and the x-axis shows the value of the predictor. To better illustrate the trend, outliers (observations with predictor value or Shapley value below the 2.5th percentile or above the 97.5th percentile of the respective sample) are not shown.

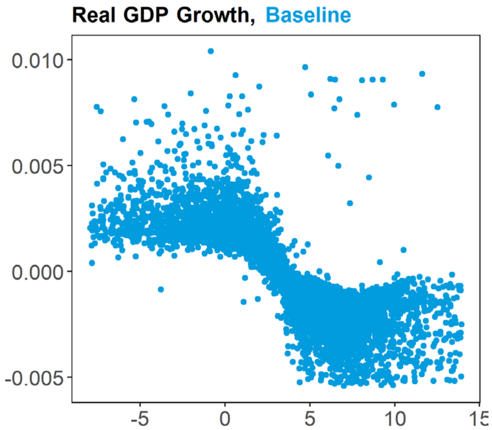
(ii) In addition to the variables capturing more structural fundamentals, there are a number of **conjunctural developments** that increase the probability of coups—we will also refer to these as ***stressors of political systems*** as they are fast moving variables that are not always present, but often stress political systems and increase the probability of coups when present (Figure 13b). First, *a destabilized economic situation*—as reflected in low or negative growth, high inflation (food or overall CPI, depending on the sample) or weak external position (a weaker current account balance and lower FX reserves)—increases the probability of a coup, in line with the findings of the event study. Second, *a destabilized political and security situation*—as reflected in a deteriorated political stability or an increase in violence or terrorism and conflicts—is another determinant factor, which became more dominant over the last two decades. An increase in *natural resources rents* (as a share of GDP) appears to be an important predictor for coups in sub-Saharan Africa, consistent with the findings in the literature that higher natural resources rents could lead to rent-seeking behaviors and often political violence, given that access to oil wealth can be obtained largely by being in power.

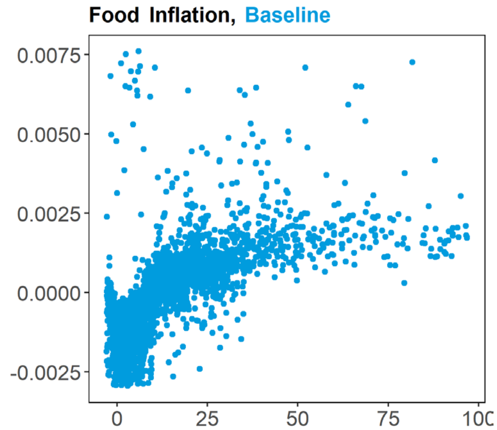
Figure 13b. Conjunctural Predictors of Coups d'État

(in order of predictor importance for the full sample, i.e., all countries during 1970-2019, then subsamples)

*Lower **growth** rates (especially below 2-4 percent, depending on the sample) increase coup probabilities, while strengthening growth rates reduces these probabilities.*

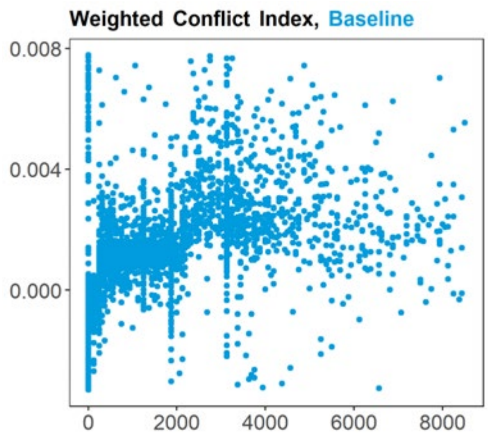
*Higher **food inflation** (especially above 10-15 percent) increases coup probabilities.*

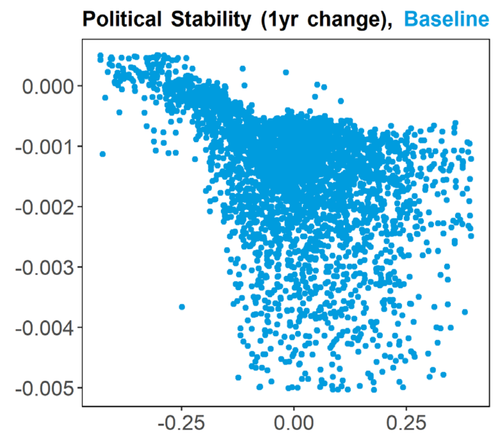




*More **conflicts**, proxied by higher weighted conflict index (shown) or an increase in weighted conflict index, increase coup probabilities.*

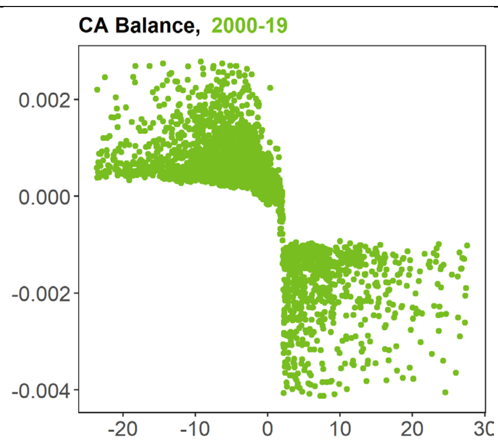
*A significant **deterioration in political instability** or an increase in **violence/terrorism** is associated with a higher coup incidence, evident in most samples.*

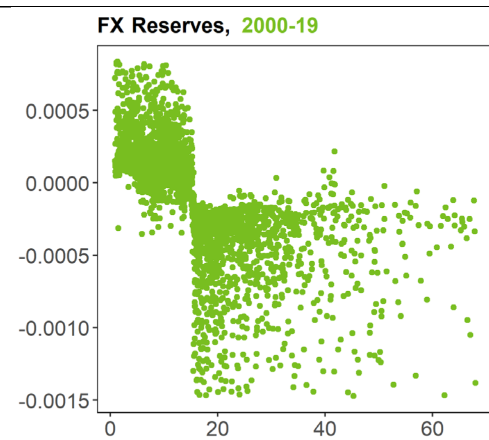




*In most subsamples—e.g., the 2000-19 period, and countries of ME&CA regions—a **weak external position** is a significant driver of coup probability. For example, **a higher current account deficit**…*

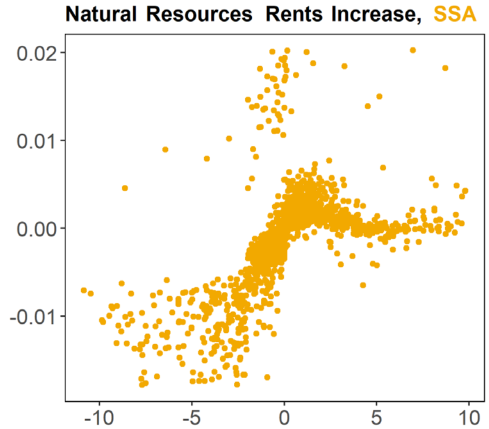
*…as well as **lower FX reserves** increase coup probabilities (2000-19 period shown).*

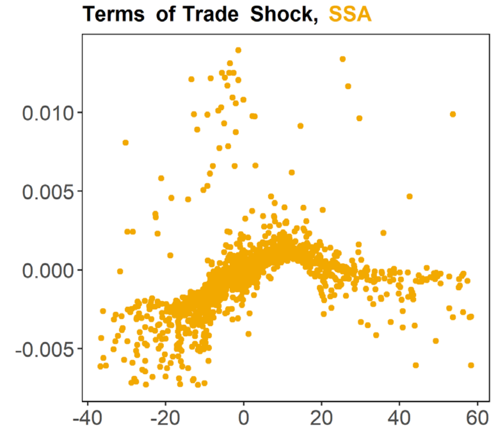




*However, in the SSA sample the opposite is true—higher current account balances (usually higher than about -6 percent of GDP) increase coup probabilities. This is because many SSA countries rely on oil wealth, hence an increase in **rents from natural resources…***

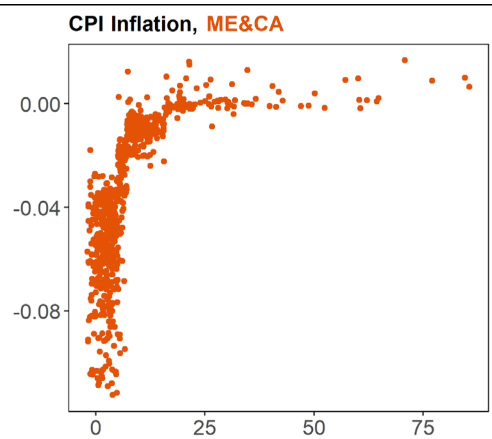
*…associated with positive **terms of trade shocks** increases coup probabilities, likely due to higher incentives to seize power (SSA sample shown) …*

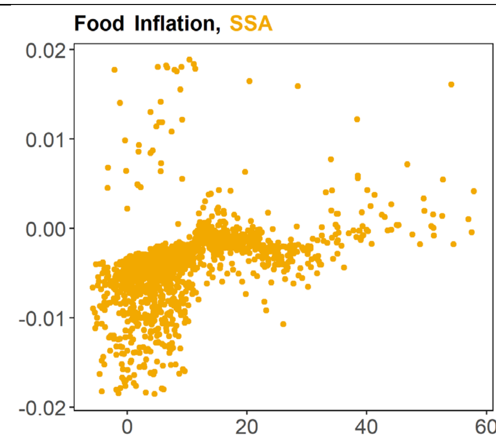




*Higher **inflation** is associated with higher likelihood of coups in most samples (except outliers that are beyond normal inflation range) including ME&CA samples (shown).*

***Food inflation** above some 10 percent is another coup driver, most significant in the SSA sample (shown).*





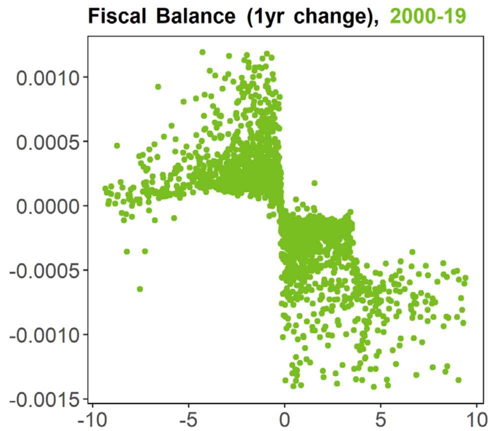
Source: authors' calculations.
Notes: The y-axis shows the contribution to estimated coup probability, and the x-axis shows the value of the predictor. To better illustrate the trend, outliers (observations with predictor value or Shapley value below the 2.5th percentile or above the 97.5th percentile of the respective sample) are not shown.

(iii) Even moderate improvements in **the policy environment** (fiscal position and governance) help reduce the probability of coups (Figure 13c). Policy variables are most significant in the recent 2000-19 period and in the sub-Saharan African countries, where fiscal position, governance, military spending and armed forces are the variables that seem to affect most the coup probabilities. For example, an improvement in the fiscal position or in governance indicators can reduce coup probabilities relative to the average in the sample. Similarly, countries with weaker overall fiscal positions (a lower revenue intake or higher debt) face a higher coup probability, possibly related to a lower state capacity and a narrower fiscal space to address social and developmental needs. Additionally, an increase in military expenditure is associated with lower probability of coups—either as a result of coup-proofing through setting up special military forces around the head of state or through the creation of more and more fragmented parts of the military, or simply because higher spending on the miliary reduces their grievances. A cut in military expenditure is consequently associated with higher probability of coups.

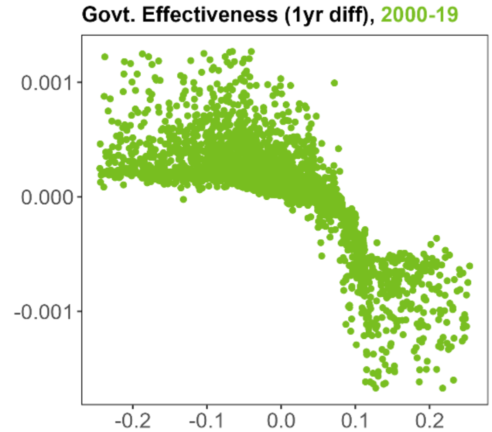
Figure 13c. Policy Predictors of Coups d'État

(in order of predictor importance for the full sample, i.e., all countries during 1970-2019, then subsamples)

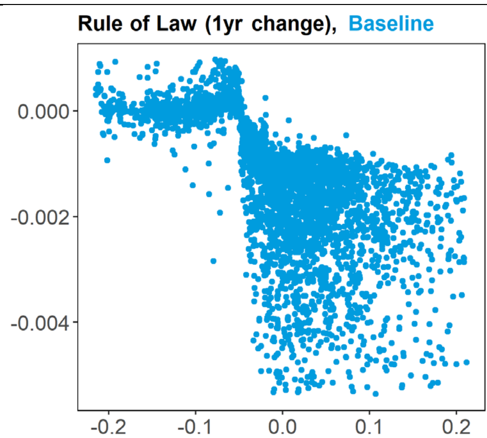
Improvements/deteriorations in the ***fiscal balance*** *reduces (increases) coup probabilities, possibly due to a signaling effect of policy competence (2000-19 sample shown).*



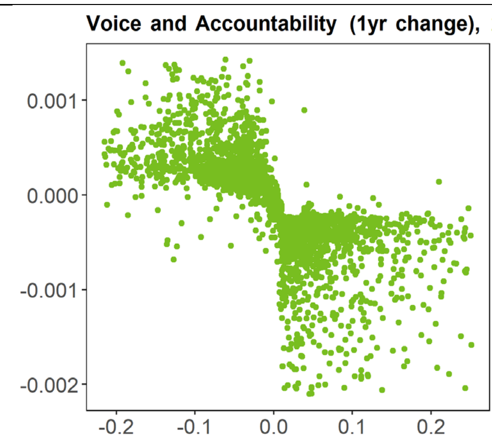
Improvements in governance *contribute to lowering coup probabilities. These include improvements in the* ***government effectiveness*** *(2000-19 sample shown),*



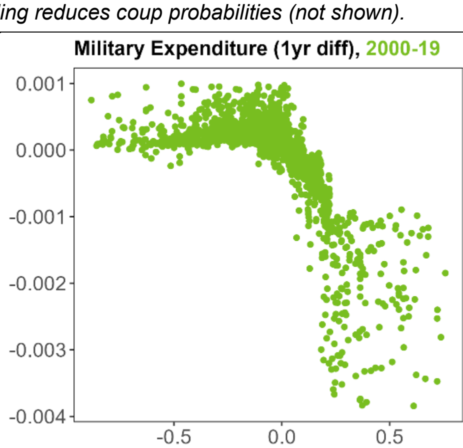
… in the ***rule of law*** *(full sample shown),*



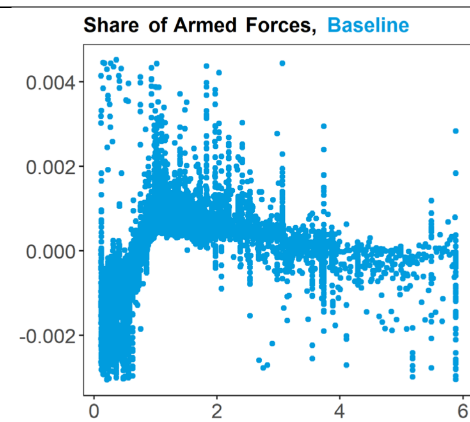
…and in ***voice and accountability*** *(2000-19 sample shown).*



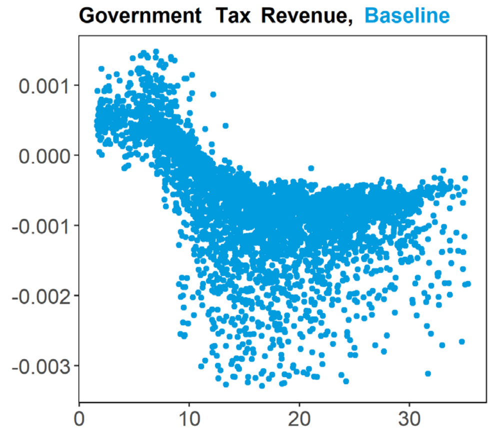
An ***increase in military spending*** *(as share of GDP) is associated with lower coup probability, especially in the recent 2000-19 period (shown below) and in SSA. The* ***level of military spending*** *is also significant in these two subsamples but has a u-shaped effect: only very low (less than 1 percent of GDP) or very high (above 2-5 percent of GDP) levels of spending reduces coup probabilities (not shown).*

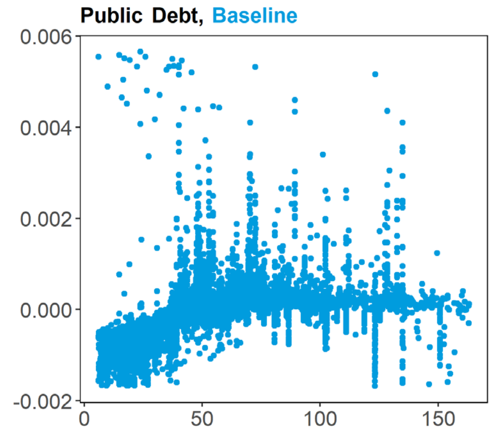


A higher ***share of armed forces*** *increases probability of coups in the full sample (shown) and in recent years when they exceed about 1 percent of the labor force.*



Government revenues as a share of GDP is not a significant contributor to coup probabilities (ranked 21st in terms of average contribution to coup probability), but it may be worth highlighting that when revenues fall below 10 percent of GDP for the full sample and below 18 percent for the last twenty years, coup probability increases, likely due to weaker state capacity.	*While not significant, when **public debt** is below about 50 percent of GDP, the higher it is, the higher coup probability.*





Source: authors' calculations.
Notes: The y-axis shows the contribution to estimated coup probability, and the x-axis shows the value of the predictor. To better illustrate the trend, outliers (observations with predictor value or Shapley value below the 2.5th percentile or above the 97.5th percentile of the respective sample) are not shown.

Interactions between Conjunctural and Structural Predictors of Coups

The tree structure of the machine learning models allows us to uncover interaction effects between sources and stressors of political fragility. These interactions can have important policy implications if structural features of the economy or government policies amplify or moderate the effects of stressors. We parse out the following effects from the interaction charts (see embedded box on how to read these charts):

(i) **In countries with stronger structural fundamentals, shocks do not affect the probability of coups significantly**. **However, weaker structural fundamentals act as double-sided amplifiers of stressors on the probability of coups**: they increase the probability of coups more when stressors are present, and they also reduce the probability of coups faster when the stressors recede. In other words, they amplify they negative effect of the negative shocks and the positive effects of the positive shocks. For example, *negative growth*

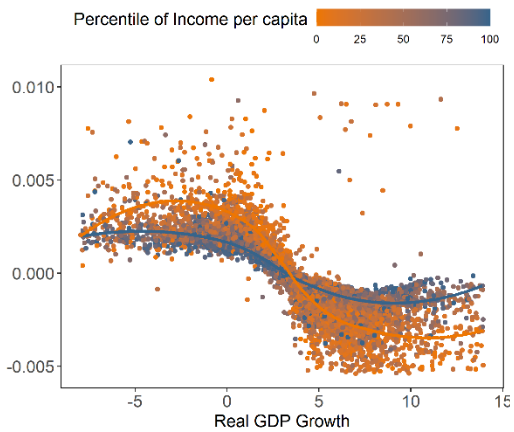
> **How to read the interaction charts**? In the interaction charts below, each dot represents a country-year pair in the sample. The x axis shows the value of the main predictor, e.g., GDP growth. The y axis shows the Shapley value of this predictor which measures its contribution to the estimated probability of a coup for this country-year pair vis-à-vis the predictor's average Shapley value across the sample. The color of the dots corresponds to the value of the second predictor in consideration which could be for example the sources of political fragility (e.g., demographics, strength of institutions, etc.). The blue color indicates larger values of this second predictor, and the orange color smaller values. The blue and orange lines in the plot are fitted estimates based on local regression for the subsamples of the highest quartile of the second predictor (blue line) and its lowest quartile (orange line). Comparing the slopes of the two fitted lines illustrates whether the relationship between the contribution of growth to coup probability and the actual growth depends on the value of the source of political fragility.

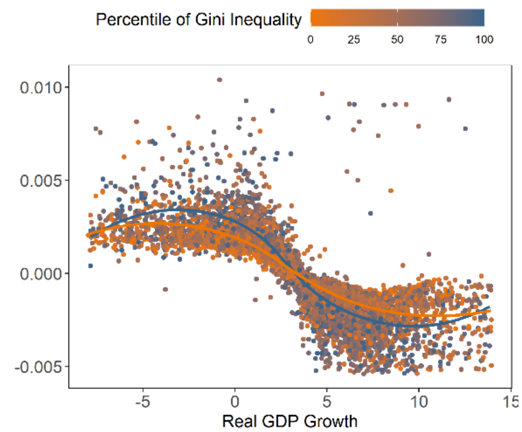
shocks (or other stressors such as high inflation) increase more the probability of coups in countries with weaker fundamentals (lower income, higher inequality, weaker inclusion, and weaker governance), but positive shocks also reduce the probability more in such countries (Figure 14a). Similarly, *political instability* is easier to exploit (to stage a coup) if the sources of fragility are present. These effects point to increased benefits from improving structural fundamentals on macroeconomic, institutional, political, and social fronts, which does not only help reduce sources of political fragility, i.e., making countries less prone to coups, but also improve resilience to stressors or shocks, i.e., making countries' probabilities of coups less sensitive to stressors.

Figure 14a. Interaction Effects Between Stressors and Sources of Fragility

In low-income countries, weak growth has a larger impact on increasing the probability of coups, while strong growth is more effective in reducing the coup probability.

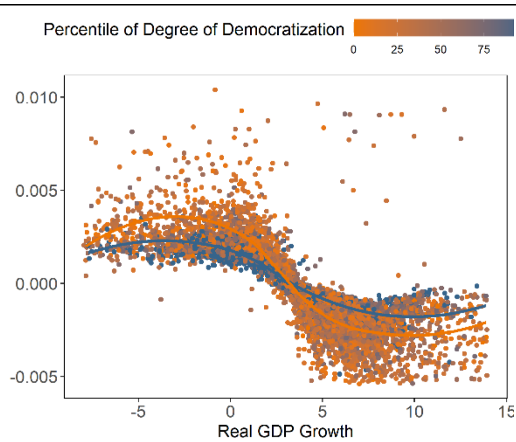
Other weak structural fundamentals have a similar amplifying effect on political or economic shocks, such as income inequality, …

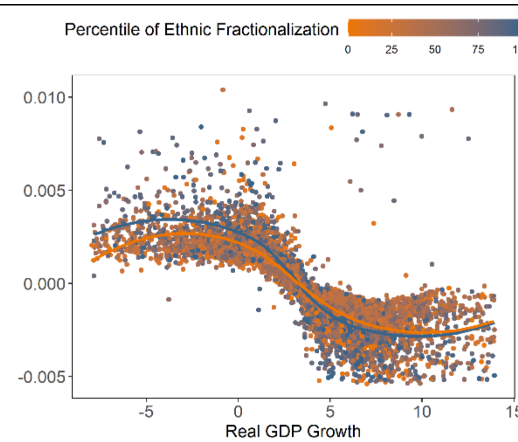




… weaker inclusion, especially on the political front (measured by the degree of democratization) …

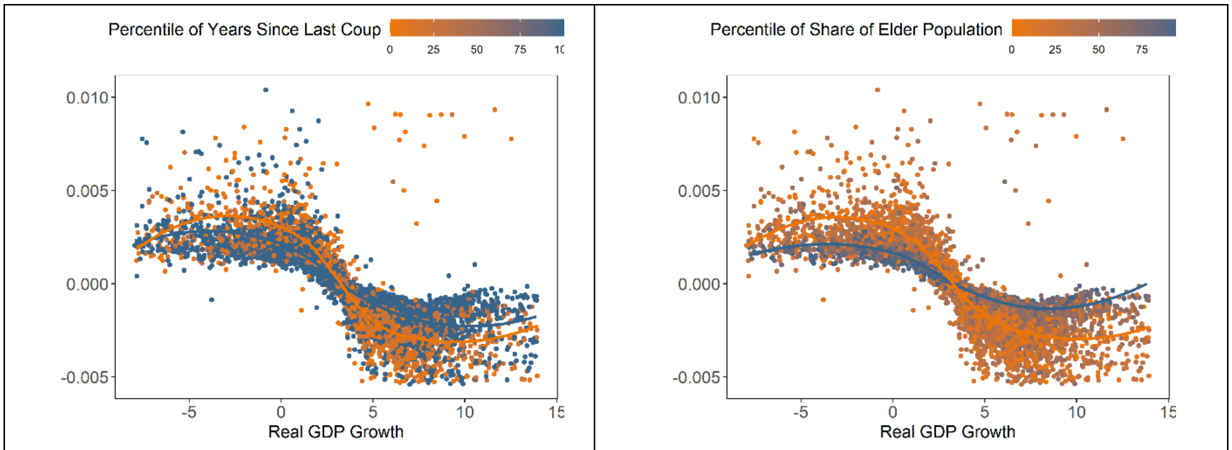
… and ethnical front, …



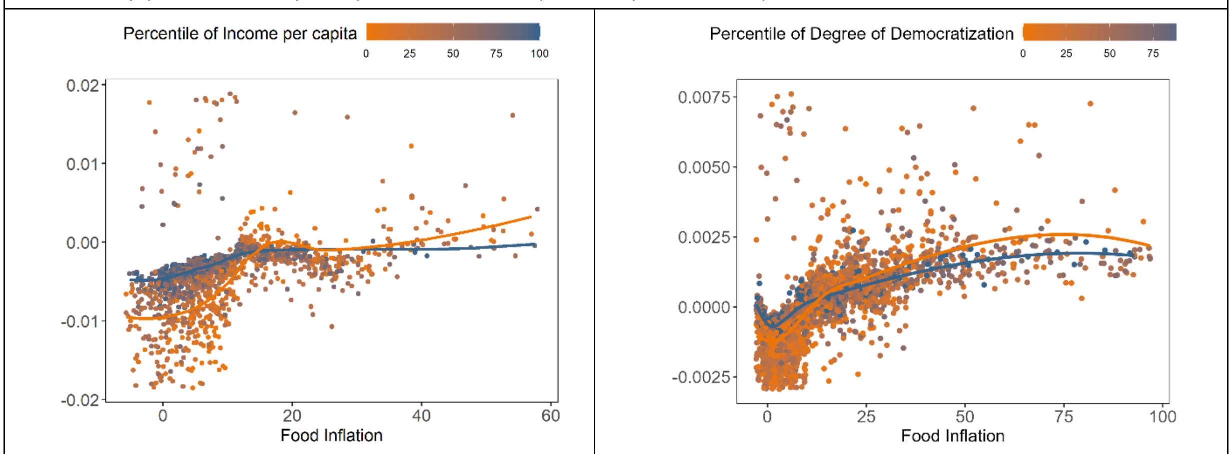


…, and weaker political stability, proxied by a recent incidence of coups.

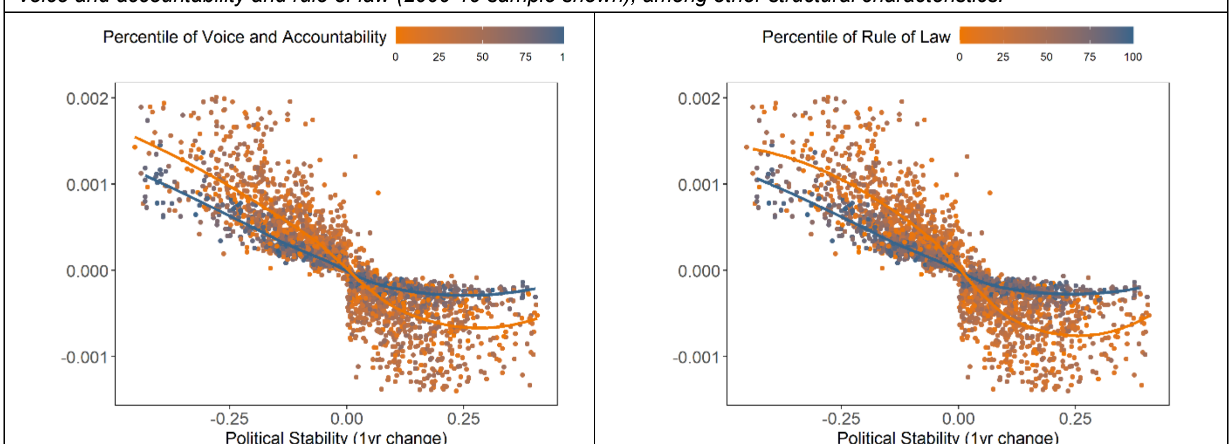
Weak growth would also make coup more likely in countries with a younger population.



Countries with a lower income per capita or a lower degree of democratization would see a larger impact of high food inflation on their coup probabilities, especially in SSA countries (SSA sample shown left)



A deterioration in political stability would lead to a much higher coup probability in countries with weaker governance, including voice and accountability and rule of law (2000-19 sample shown), among other structural characteristics.

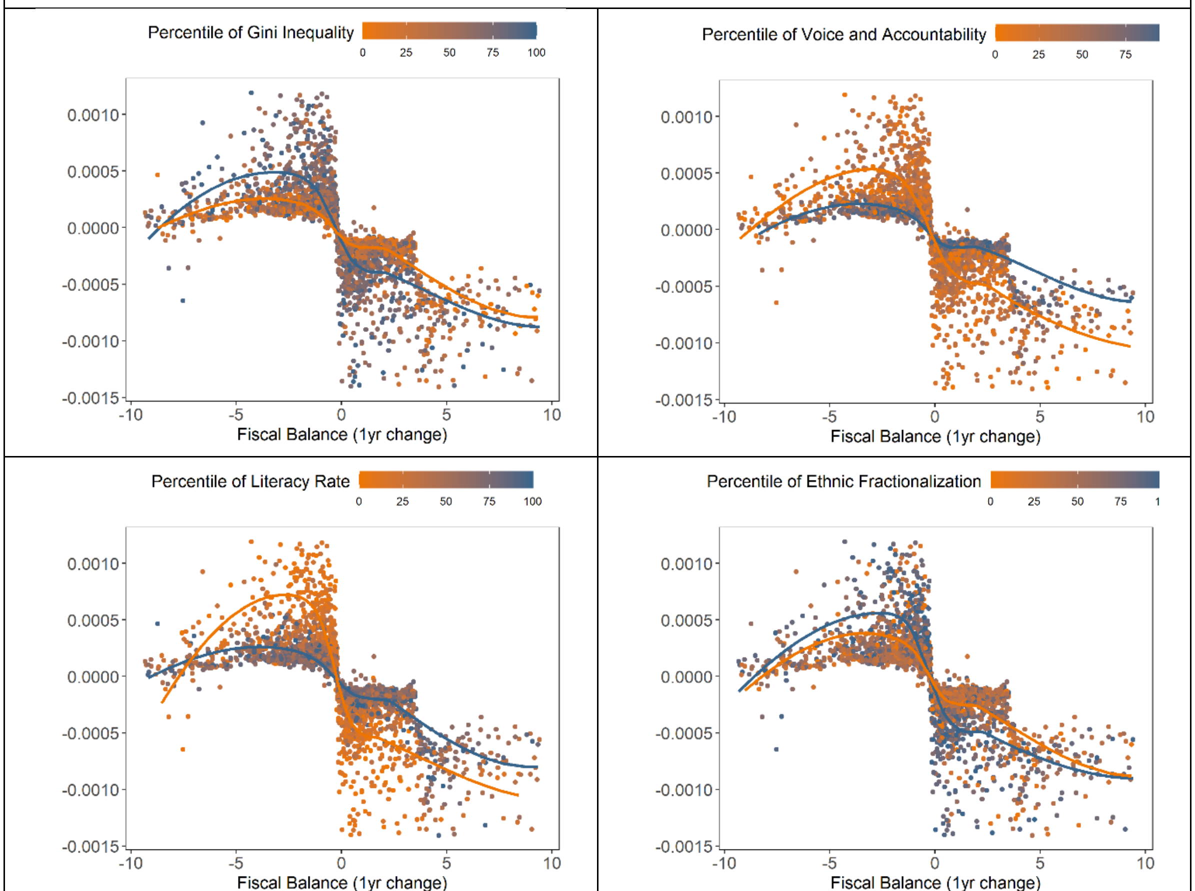


Notes: The y-axis shows the contribution to estimated coup probability, and the x-axis shows the value of the predictor, with color indicating the percentile of another predictor's value, blue for high and orange for low. To illustrate the trend better visually, outliers (observations with predictor value or Shapley value below the 2.5th percentile or above the 97.5th percentile of the respective sample) are not shown.
Sources: authors' calculations.

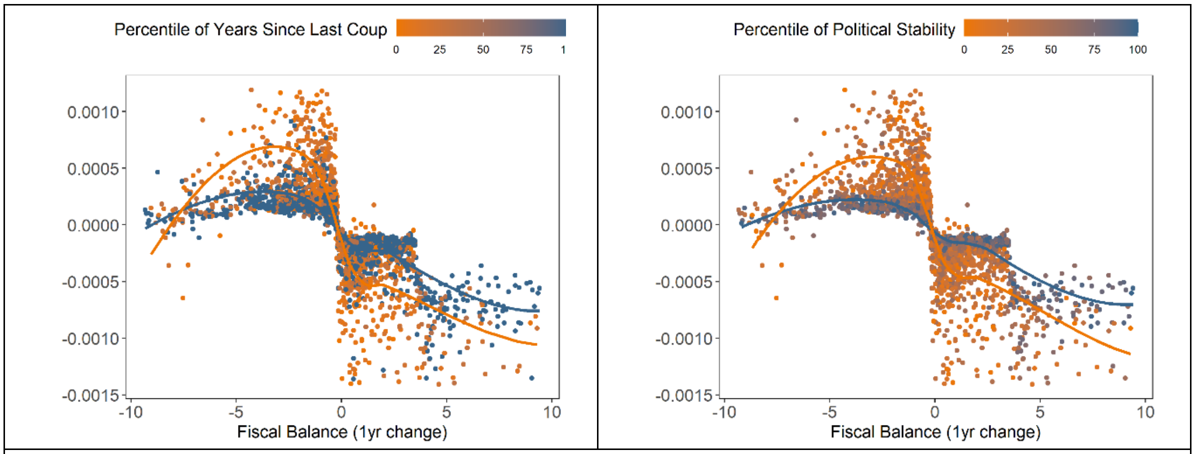
(ii) **Sources of fragility can also act as double-sided amplifiers of policies.** For example, deteriorations in the fiscal position or in the rule of law can increase coup probabilities by more in countries with weaker structural fundamentals (higher inequality, weaker governance, lower literacy, higher ethnic fractionalization, and lower political stability). Conversely, even moderate improvements in the policy environment can help reduce coup probabilities—an effect that is stronger when the sources of fragility are present (Figure 14b).

Figure 14b. Interaction Effects between Policies and Sources of Political Fragility

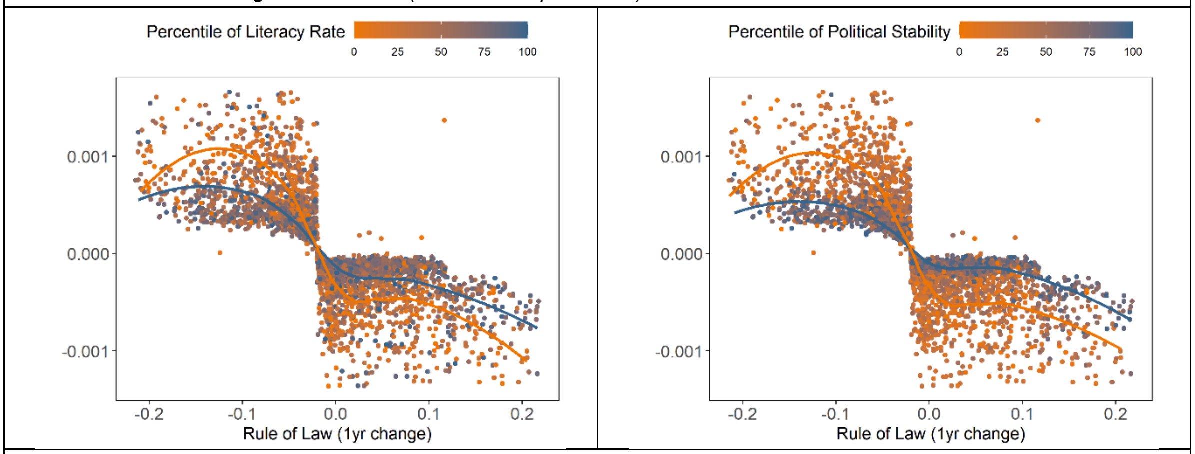
A deterioration in fiscal balance in countries with weaker fundamentals (higher inequality, weak governance, low literacy, higher ethnic fractionalization) is associated with larger increase in coup probabilities, while an improvement in fiscal balance in these countries would deliver stronger effects in terms of reducing coup probabilities (2000-19 sample shown).



A deterioration in fiscal balance in countries with weak political stability—proxied either by recent coups or low political stability index—is associated with larger increase in coup probabilities, while an improvement in fiscal balance in these countries would deliver stronger effects in terms of reducing coup probabilities (2000-19 sample shown).



Similar results for a change in rule of law (2000-19 sample shown).

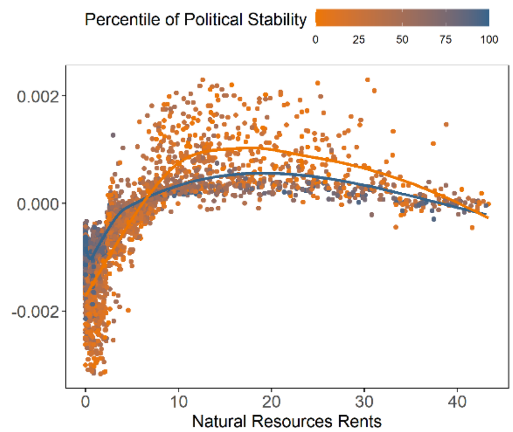


Notes: The y-axis shows the contribution to estimated coup probability, and the x-axis shows the value of the predictor, with color indicating the percentile of another predictor's value, blue for high and orange for low. To illustrate the trend better visually, outliers (observations with predictor value or Shapley value below the 2.5th percentile or above the 97.5th percentile of the respective sample) are not shown.
Sources: authors' calculations.

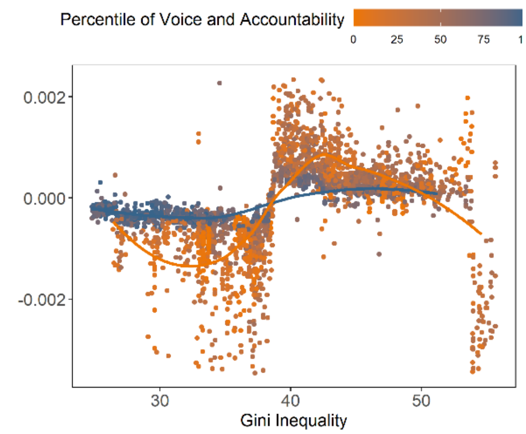
(iii) **Sources of fragility or stressors can also act as amplifiers of each other.** For example, higher natural resources rents increase coup probability more in politically unstable countries; and a lower degree of economic inclusion—proxied by higher Gini index—increases coup probability more in countries with weaker governance. This finding highlights that fragile countries may be especially prone to coups as they have weak structural fundamentals on multiple fronts which could amplify each other's effect. Similarly, negative shocks can also amplify each other's effects in terms of increasing the probability of coup. For example, weak growth can increase coup probability by more when demographic pressure (as measured by faster population growth) is higher (Figure 14c). These results suggest that in a situation of overlapping shocks—similar to the one that the world economy has been traversing in 2020–22 with the pandemic, the war in Ukraine and associated increase in food and energy prices—countries are more likely prone to fragilizing political systems, especially in countries with weaker fundamentals.

Figure 14c. Interaction Effects among Sources or Stressors of Political Fragility

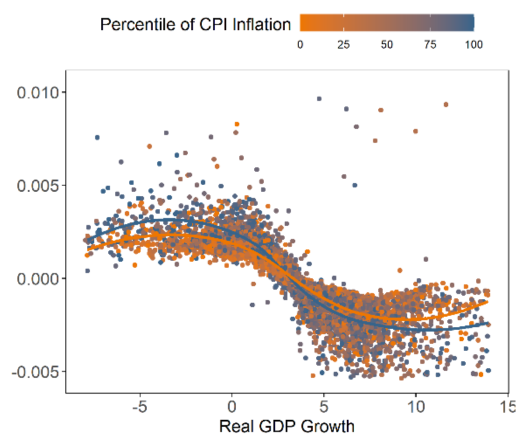
In countries with weaker political stability or more violence/terrorism, higher natural resources rents have a larger impact on increasing the probability of coups, while strengthened political stability helps reduce the sensitivity.



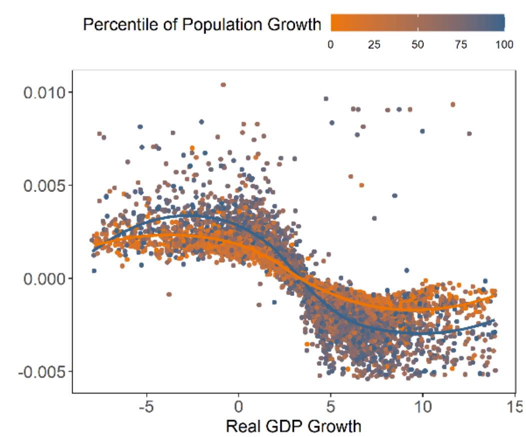
Countries with lower voice and accountability would see their coup probabilities increase more when income inequality is high, while those with higher voice and accountability barely see that impact.



When weak growth is coupled with high inflation (overall or food inflation), the likelihood of coups is higher.



Faster population growth exacerbates the stress of weak growth put on political stability, increasing the likelihood of coups more.



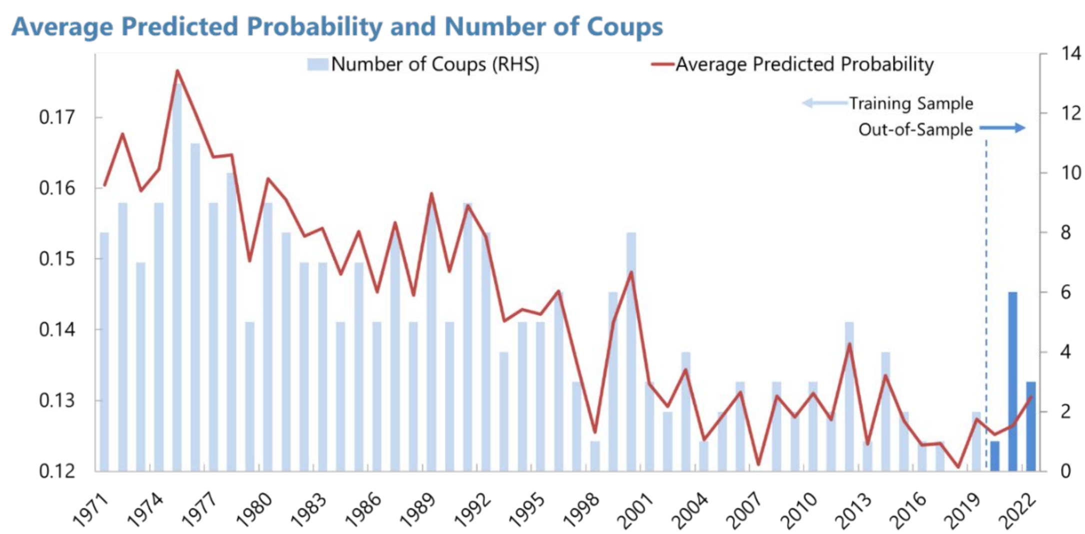
Notes: The y-axis shows the contribution to estimated coup probability, and the x-axis shows the value of the predictor, with color indicating the percentile of another predictor's value, blue for high and orange for low. To better illustrate the trend, outliers (observations with predictor value or Shapley value below the 2.5th percentile or above the 97.5th percentile of the respective sample) are not shown.
Sources: authors' calculations.

5. Predicting Coups with the Machine Learning Model

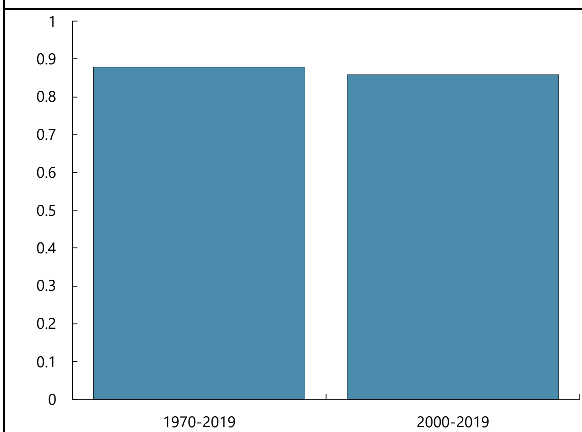
How well can the model predict coups?

We recall that the machine learning model is trained on the data from 1970-2019, hence we can do out-of-sample prediction for the period 2020–22—a period of high coup incidence—to gauge how the model performs. Figure 15 presents these out-of-sample prediction results. The top chart shows the increase in the predicted coup probabilities since 2020 broadly tracking the rise in coups during the same period. The bottom right chart shows that, of the 10 countries that had coups in the last 3 years, the model places 9 in the top 25 countries with highest coup probabilities (above the 80th percentile of the coup probability distribution). This captures all recent coups in sub-Saharan Africa, leaving out only Myanmar from the top probability countries. The out-of-sample area under the curve (AUC) for 2020-22 is estimated at 0.878 out of 1, which also suggests an overall good model prediction performance.

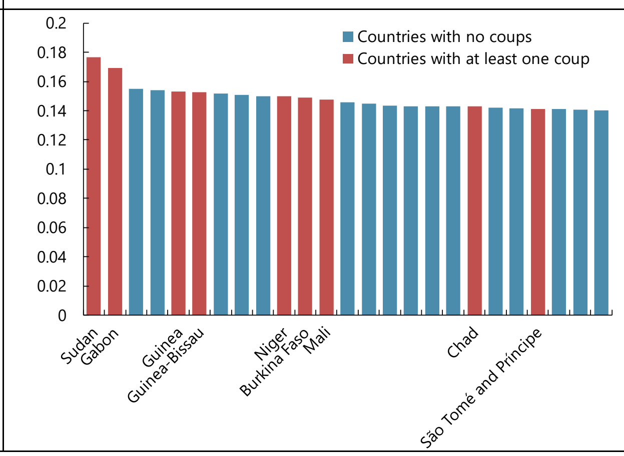
Figure 15. Coup Predictions for 2020-22



Out-of-Sample AUC of Different Samples
(Out-of-sample consists of coups during 2020-2022)



Predicted Coup Probability
(Average of 2020-22, Top-25 countries, red=countries that had coups during 2020-Sept. 8, 2023)

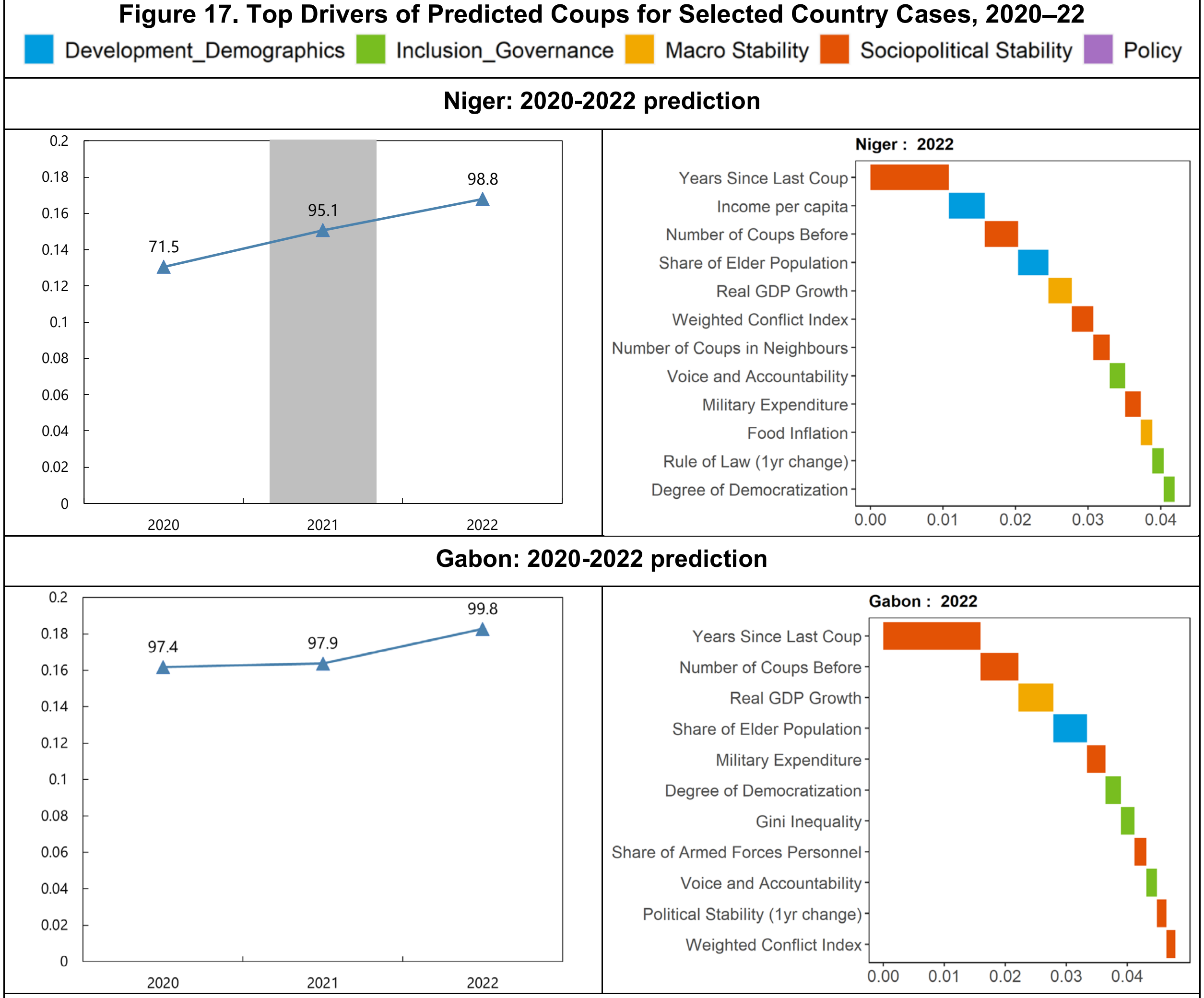


Source: Powell and Thyne (2011), and authors' calculations.
Notes: In the top chart, the LHS y-axis shows the year-average predicted coup probability in the training sample (using 1970-2018 data to predict coups during 1971-2019) and the out-of-sample (using 2019-2021 data to predict coups during 2020-2022), and the RHS y-axis shows the number of coups in each year. In the bottom-left chart, the y-axis shows the area under the ROC curve (AUC) for the out-of-sample prediction, and the x-axis shows the sample used for training. In the bottom-right chart, the y-axis shows the average out-of-sample predicted coup probability for the top-25 countries with highest coup probability over 2020-2022.

What are the main factors behind high predicted coup probabilities in recent cases?

We use two country cases where the drivers are likely to be different: Niger in the Sahel region and Gabon in Central Africa. Both had a coup in the summer of 2023, and we look at the latest years for which we could make predictions (2022) as indicative of the drivers that were at play prior to the coup. In both cases, recent coup incidence, weak growth and young demographics are among the top drivers (Figure 17). One main distinction between them is that in Niger conflict and more broadly weak socio-political stability is the main category driving high coup probability, whereas in Gabon the main category is weak inclusion (high inequality, weak democratization) and governance. In both cases, these groups of drivers are consistent with perceived contributors to coups (see Annex IV for a discussion of a few country cases, including Niger). It is worth noting that spillover effects from coups in neighboring countries emerge as an important driver in the case of Niger, consistent with the concentration of the recent coups in its Sahel neighbors Mali, Burkina Faso, and Chad.

Figure 17. Top Drivers of Predicted Coups for Selected Country Cases, 2020–22



Source: authors' calculations.
Notes: For each country case, the left chart shows its predicted coup probabilities during 2020-2022 on the y-axis and their percentiles (in the distribution of the out-of-sample during 2020-2022) in the labels, and the right chart shows the contribution of top predictors that account for the 70 percent of the increase in coup probabilty in 2022 (vis-à-vis sample average).

6. Conclusions

The paper seeks to understand the driving forces behind political fragility, focusing on coups d'état as symptomatic of such fragility. The surge in the incidence of coups during 2020–22—at a time of large overlapping global shocks of the covid pandemic, the war in Ukraine and commodity price surges—has provided the impetus for a deeper look into the sources of fragility and what can be done to mitigate them. With a vast literature devoted to the understanding of conflict (of which coups are usually a subset) and its drivers, the paper contributes to the literature through a sharper focus on coups and the use of machine learning to parse out the complex and nonlinear interactions between factors that could be contributing to coups, and to identify policies that could mitigate them.

The paper finds that the destabilization of the county's economic, political or security environment sets the stage for a higher likelihood of coups. This likelihood is further increased in the case of overlapping stressors as they amplify each other's effects. These shocks strain incomes, affect lives and livelihoods, and stoke discontent that weaker political and economic systems are unable to handle well, leading to higher risks of political breakdowns through unconstitutional power changes. The global shocks of 2020–22 have indeed produced a cocktail of lower growth, higher food, energy and overall inflation, and weaker external positions for food or oil price importers—all factors that the paper found to drive up coup probabilities.

While many countries have been exposed to large macroeconomic shocks, not all countries experience breakdowns in their political systems. The paper finds that underlying structural weaknesses such as poverty, poor inclusions, weak governance, and high political and security risks are the factors that account for a fragile response to shocks. This finding is consistent with both the large frequency of coup incidence in lower income countries and with the recent wave of coups in sub-Saharan African countries, including in the Sahel region, where such structural fragilities are present. While many of the SSA countries have been relatively resilient to the economic effects of the global pandemic, a deteriorating security situation and political instability in the region may have indeed increased the probability of coups.

Breakdowns are also more likely to occur when policies are weaker, especially the fiscal position. This could be due both to the limited fiscal space to mitigate shocks or more generally to lower confidence in the government. Higher resource rents, as during times of higher oil prices, also increase the benefits of being in power—the surest way of securing access to resources in many lower income countries—and with them the likelihood of coups.

Overall, fragile countries—however defined—are most vulnerable to coups, given the presence of multiple structural and policy weaknesses identified above, as well as heightened risks of a destabilized economic, political and security environment.

The model performs relatively well at predicting coups d'état, assigning a high probability of coup to all SSA countries that have experienced military takeovers during 2020–23, including Mali, Burkina Faso, Niger, Gabon, among others, picking up in particular on the cross-country structural fundamentals more than time-bound stressors. It can therefore be used to monitor countries in fragile political situations, although we do not report in the paper the predictive results for countries that have a high predicted coup probability but have not had one given understandable sensitivities around such predictions.

The main policy takeaways, however, stem from the finding that strengthened structural fundamentals—across macroeconomic, institutional, political, and social fronts—and policy outcomes have higher returns in structurally fragile environments in terms of staving off political breakdowns than they do in structurally more robust environments. Continued engagement by multilateral institutions and donors in fragile situations is therefore likely to have particularly high dividends, both because their financial support can help stabilize the economy and mitigate risks of coups, and because the stronger policies targeted in program designs bring additional benefits in terms of reducing political risks. In addition to the importance of strengthening fiscal policies, the results shed light on the importance of strengthening structural fundamentals—such as inclusion, governance, education—as this would not only eliminate the sources of political fragility but also reduce the sensitivity of political systems to negative shocks, and therefore bring larger dividends.

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Annex I. Data and Methodology

This annex describes the data and methodology for the event study and machine learning.

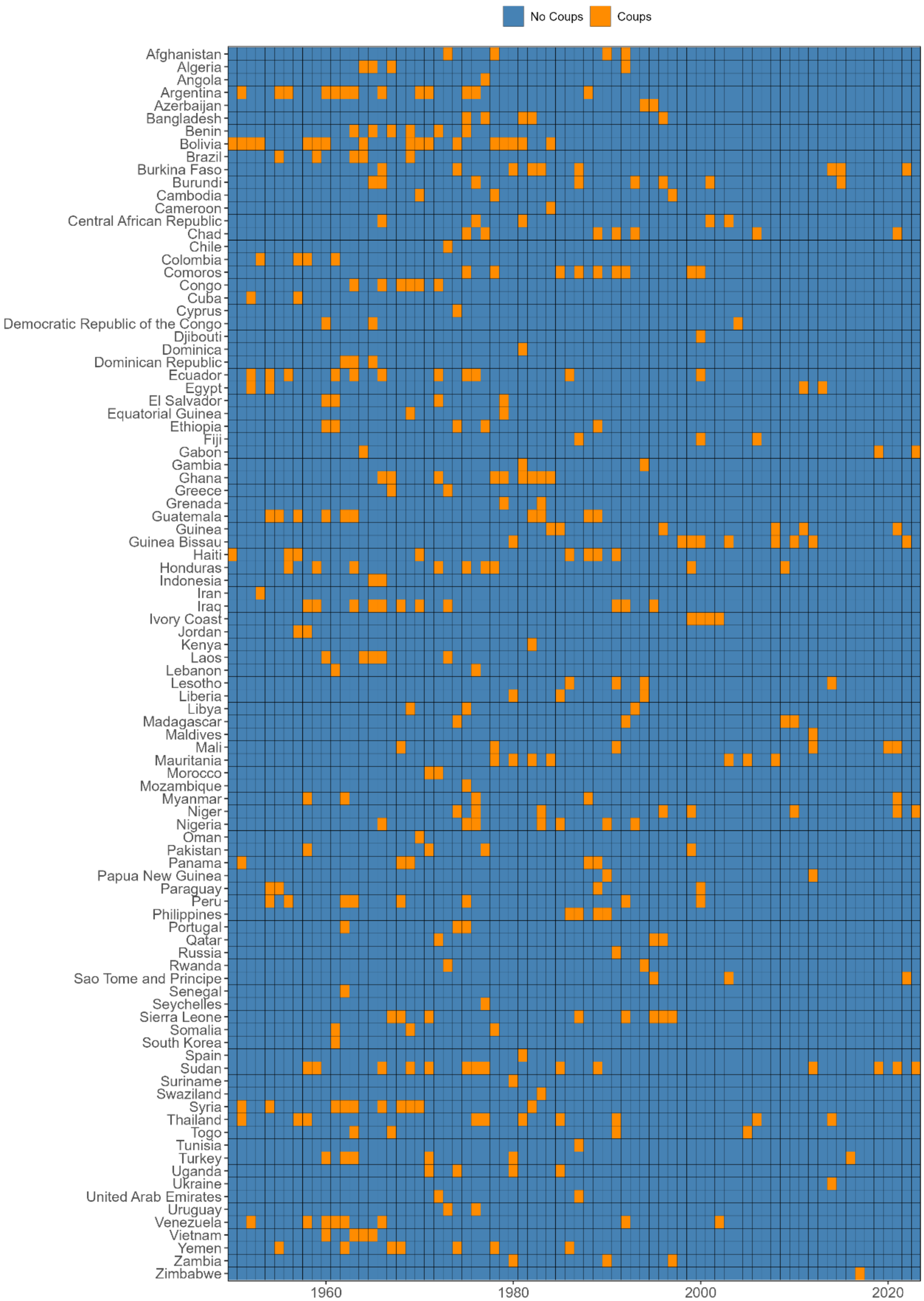
Data

Our sample covers 192 countries/economies over fifty years from 1970 to 2022, although the event study and the machine learning training sample use only the years 1970-2019 to avoid potential distortions introduced by the pandemic years 2020-22 and to account for data availability due to significant lags in some variables. For coups d'état, we use the database by Powell and Thyne (2011) that covers the period 1950-2023 September 8: Annex Figure 1 illustrates the distributions of these coups across country-years. For the 1970-2019 period we focus on, the database includes a total 293 coups, or 2.6 percent of all country-year observations during this period. Our main exercises include both coups and coup attempts.

For potential coup predictors, we focus on variables that capture demographic, development, governance, macro stability, and sociopolitical characteristics of countries and that are associated with interpretable channels—described in the literature discussed above—that could affect the likelihood of coups. Based on these variables, the actual numbers used in the event study and the machine learning exercises may vary.

- *In the event study*, we use the 86 variables shown in Annex Table 1a. Many of them capture similar concepts but are helpful to understand a finer breakdown of the channels affecting coups. The results for those variables that do not show statistically significant differences around coups relative to tranquil times are not reported in the paper.
- *In the machine learning exercise,* we use a total of 55 variables shown in Annex Table 1b. There are two main changes we make relative to the event study database. First, we drop several variables that may be collinear and could dilute the Shapley values and use instead the main variable that combines them for better interpretability. For example, we drop different types of political/social conflicts in favor of the weighted conflict index, or the number of major cabinet changes and major constitutional changes in favor of political stability and absence of violence/terrorism that is inclusive of them. It's also worth noting that in the main exercises we use nominal GDP per capita (in purchasing power parity (PPP) terms) as a proxy for economic development—including for the financial, labor, infrastructure, and other development areas. This allows us to minimize the number of predictors, given their high correlation (above 0.5) with the overall economic development level, although we also use alternative indicators of economic development in the robustness checks. Second, we add a few transformations of the variables used in the event study. For example, in addition to levels, we include—as appropriate—one-year change or percentage change for most of the variables to capture the short-term dynamics.

Annex Figure 1. Coups, 1950-September 8, 2023



Sources: Powell and Thyne (2011).

Annex Table 1a. List of Predictors and their Categories Included in the Event Studies

Variable	Category	Source
Income per capita	Development & Demographics	World Economic Outlook Database
Individuals using the Internet (% of population)	Development & Demographics	World Development Indicators
Literacy rate	Development & Demographics	World Development Indicators
Natural Resources Rents	Development & Demographics	World Development Indicators
Population Density	Development & Demographics	Cross-National Time-Series Data Archive (CNTS)
Population in urban agglomerations of more than 1 million (% of total population)	Development & Demographics	World Development Indicators
Population Size	Development & Demographics	World Development Indicators
Share of Elder Population	Development & Demographics	World Development Indicators
Share of Young Population	Development & Demographics	World Development Indicators
Competitiveness of Chief Executive Recruitment	Inclusion & Governance	Polity V
Competitiveness of Nominating Process	Inclusion & Governance	Cross-National Time-Series Data Archive (CNTS)
Competitiveness of participation	Inclusion & Governance	Polity V
Control of Corruption	Inclusion & Governance	World Governance Indicators
Degree of Democratization	Inclusion & Governance	Polity V
Degree of Parliamentary Responsibility	Inclusion & Governance	Cross-National Time-Series Data Archive (CNTS)
Economic Complexity Index	Inclusion & Governance	Atlas of Economic Complexity
Economic Freedom	Inclusion & Governance	Heritage Economic Freedom Index
Estimate of Gini index of inequality in equivalized household disposable income	Inclusion & Governance	SWIID
Ethnic fractionalization Index	Inclusion & Governance	Havard university
Executive constraints	Inclusion & Governance	Polity V
Head of State	Inclusion & Governance	Cross-National Time-Series Data Archive (CNTS)
Legislative Effectiveness	Inclusion & Governance	Cross-National Time-Series Data Archive (CNTS)
Legislative Selection	Inclusion & Governance	Cross-National Time-Series Data Archive (CNTS)
Number of active groups in this country	Inclusion & Governance	EPR (Ethnic Power Relations Dataverse)
Number of groups with regional autonomy in this country	Inclusion & Governance	EPR (Ethnic Power Relations Dataverse)
Number of relevant groups in this country	Inclusion & Governance	EPR (Ethnic Power Relations Dataverse)
Openness of Chief Executive Recruitment	Inclusion & Governance	Polity V
Party Coalitions	Inclusion & Governance	Cross-National Time-Series Data Archive (CNTS)
Party Fractionalization Index (Scaling: 0.0001)	Inclusion & Governance	Cross-National Time-Series Data Archive (CNTS)
Party Legitimacy	Inclusion & Governance	Cross-National Time-Series Data Archive (CNTS)
Regime Durability	Inclusion & Governance	Polity V
Regulation of Chief Executive Recruitment	Inclusion & Governance	Polity V
Regulation of participation	Inclusion & Governance	Polity V
Regulatory Quality	Inclusion & Governance	World Governance Indicators
Rule of Law	Inclusion & Governance	World Governance Indicators
Size of Legislature/Number of Seats, Largest Party	Inclusion & Governance	Cross-National Time-Series Data Archive (CNTS)
Sum of discriminated population as a fraction of ethnically relevant population	Inclusion & Governance	EPR (Ethnic Power Relations Dataverse)
Sum of discriminated population in this country (as a fraction of total population).	Inclusion & Governance	EPR (Ethnic Power Relations Dataverse)
Sum of the ethnically relevant population in this country (as a fraction of total population)	Inclusion & Governance	EPR (Ethnic Power Relations Dataverse)
Total population of all minority and excluded groups in this country (as a fraction of total population)	Inclusion & Governance	EPR (Ethnic Power Relations Dataverse)
Total population with regional autonomy in this country (as a fraction of total population).	Inclusion & Governance	EPR (Ethnic Power Relations Dataverse)
Voice and Accountability	Inclusion & Governance	World Governance Indicators
Agriculture, forestry, and fishing, value added (% GDP)	Macro Stability	World Development Indicators
CPI Inflation	Macro Stability	World Economic Outlook Database
Current Account Balance (% GDP)	Macro Stability	World Economic Outlook Database
Domestic credit to private sector by banks (% GDP)	Macro Stability	World Development Indicators
Energy inflation	Macro Stability	World Economic Outlook Database
Food Inflation	Macro Stability	World Economic Outlook Database
Gross domestic product, constant prices, National Currency, percent change	Macro Stability	World Economic Outlook Database
Gross fixed capital formation, current prices, (% GDP)	Macro Stability	World Economic Outlook Database
Labor force participation rate, total (% of total population ages 15-64)	Macro Stability	World Development Indicators
Manufacturing, value added (% GDP)	Macro Stability	World Development Indicators
National currency units per U.S. dollar, end of period	Macro Stability	World Economic Outlook Database
Net ODA received (% of GNI)	Macro Stability	World Development Indicators
Purchasing Power Parity per capita	Macro Stability	World Economic Outlook Database
Terms of trade, goods, US Dollars, percent change	Macro Stability	World Economic Outlook Database
Total external debt, percent of GDP	Macro Stability	World Economic Outlook Database
Total Reserve Assets	Macro Stability	World Economic Outlook Database
Unemployment, total (% of total labor force)	Macro Stability	World Development Indicators
Wage and salaried workers, total (% of total employment)	Macro Stability	World Development Indicators
Fiscal Balance	Policy	World Economic Outlook Database
Public Debt (% of GDP)	Policy	World Economic Outlook Database
Government Effectiveness	Policy	World Governance Indicators
Government Tax Revenue (%GDP)	Policy	World Economic Outlook Database
Anti-Government Demonstrations	Sociopolitical Stability	Cross-National Time-Series Data Archive (CNTS)
Armed forces personnel (% of total labor force)	Sociopolitical Stability	World Development Indicators
Assassinations	Sociopolitical Stability	Cross-National Time-Series Data Archive (CNTS)
Change in political regimes from last year	Sociopolitical Stability	Political Regime
General Strikes	Sociopolitical Stability	Cross-National Time-Series Data Archive (CNTS)
Government Crises	Sociopolitical Stability	Cross-National Time-Series Data Archive (CNTS)
Guerrilla Warfare	Sociopolitical Stability	Cross-National Time-Series Data Archive (CNTS)
Internally displaced persons, total displaced by conflict and violence (number of people)	Sociopolitical Stability	World Development Indicators
Military expenditure (% GDP)	Sociopolitical Stability	World Development Indicators
Number of conflict incidence	Sociopolitical Stability	UCDP/PRIO
Number of Legislative Elections	Sociopolitical Stability	Cross-National Time-Series Data Archive (CNTS)
Number of Major Cabinet Changes	Sociopolitical Stability	Cross-National Time-Series Data Archive (CNTS)
Number of Major Constitutional Changes	Sociopolitical Stability	Cross-National Time-Series Data Archive (CNTS)
Political Stability and Absence of Violence	Sociopolitical Stability	World Governance Indicators
Purges	Sociopolitical Stability	Cross-National Time-Series Data Archive (CNTS)
Refugee population by country or territory of asylum	Sociopolitical Stability	World Development Indicators
Reported Social Unrest Index	Sociopolitical Stability	Barrett et al. (2020)
Revolutions	Sociopolitical Stability	Cross-National Time-Series Data Archive (CNTS)
Riots	Sociopolitical Stability	Cross-National Time-Series Data Archive (CNTS)
Total fatalities due to conflict	Sociopolitical Stability	UCDP/PRIO
Total Number of People Affected by Natural Disaster	Sociopolitical Stability	EMDAT
Weighted Conflict Index	Sociopolitical Stability	Cross-National Time-Series Data Archive (CNTS)

Annex Table 1b. List of Predictors and their Categories Included in the Machine Learning Exercise

Variable	Category	Source
Economic Complexity	Development & Demographics	Atlas of Economic Complexity from Harvard University
Literacy Rate	Development & Demographics	World Development Indicator Database
Natural Resources Rents	Development & Demographics	World Development Indicator Database
Natural Resources Rents (1yr change)	Development & Demographics	World Development Indicator Database
Share of Elder Population	Development & Demographics	World Development Indicator Database
Income per capita	Development & Demographics	World Economic Outlook Database
Population Growth	Development & Demographics	World Economic Outlook Database
Economic Freedom	Inclusion & Governance	Economic Freedom Indicator from Fraser Institute
Share of Regional Autonomy Population	Inclusion & Governance	Ethnic Power Relations (EPR) Dataset
Ethnic Fractionalization	Inclusion & Governance	Historical Index of Ethnic Fractionalization (HIEF) Dataset
Degree of Democratization	Inclusion & Governance	Polity V Database
Degree of Democratization (1yr change)	Inclusion & Governance	Polity V Database
Gini Inequality	Inclusion & Governance	Standardized World Income Inequality Database
Control of Corruption	Inclusion & Governance	World Governance Indicator Database
Regulatory Quality	Inclusion & Governance	World Governance Indicator Database
Rule of Law	Inclusion & Governance	World Governance Indicator Database
Voice and Accountability	Inclusion & Governance	World Governance Indicator Database
Control of Corruption (1yr change)	Inclusion & Governance	World Governance Indicator Database
Government Effectiveness (1yr change)	Inclusion & Governance	World Governance Indicator Database
Regulatory Quality (1yr change)	Inclusion & Governance	World Governance Indicator Database
Rule of Law (1yr change)	Inclusion & Governance	World Governance Indicator Database
Voice and Accountability (1yr change)	Inclusion & Governance	World Governance Indicator Database
Energy Inflation	Macro Stability	World Bank Global Database of Inflation
Food Inflation	Macro Stability	World Bank Global Database of Inflation
CPI Inflation	Macro Stability	World Economic Outlook Database
CA Balance	Macro Stability	World Economic Outlook Database
Exchange Rate Depreciation	Macro Stability	World Economic Outlook Database
FX Reserves	Macro Stability	World Economic Outlook Database
FX Reserves (1yr change)	Macro Stability	World Economic Outlook Database
Real GDP Growth	Macro Stability	World Economic Outlook Database
Terms of Trade Percentage Change	Macro Stability	World Economic Outlook Database
Unemployment Rate	Macro Stability	World Economic Outlook Database
Unemployment Rate (1yr change)	Macro Stability	World Economic Outlook Database
Country Uncertainty Index	Macro Stability	World Uncertainty Index Dataset
Country Uncertainty Index (1yr change)	Macro Stability	World Uncertainty Index Dataset
Government Tax Revenue	Policy	World Economic Outlook Database
Fiscal Balance	Policy	World Economic Outlook Database
Public Debt	Policy	World Economic Outlook Database
Fiscal Balance (1yr change)	Policy	World Economic Outlook Database
Government Tax Revenue (1yr change)	Policy	World Economic Outlook Database
Public Debt (1yr change)	Policy	World Economic Outlook Database
Government Effectiveness	Policy	World Governance Indicator Database
Reported Social Unrest Index	Sociopolitical Stability	Barrett et al. (2022)
Reported Social Unrest Index (1yr change)	Sociopolitical Stability	Barrett et al. (2022)
Weighted Conflict Index	Sociopolitical Stability	Cross-National Time-Series Data (CNTS)
Weighted Conflict Index (1yr change)	Sociopolitical Stability	Cross-National Time-Series Data (CNTS)
Share of Natural Disaster-Affected Population	Sociopolitical Stability	EM-DAT The International Disaster Database
Number of Coups Before	Sociopolitical Stability	Powell and Thyne Coup Dataset
Years Since Last Coup	Sociopolitical Stability	Powell and Thyne Coup Dataset
Number of Coups in Neighbours	Sociopolitical Stability	Powell and Thyne Coup Dataset
Military Expenditure	Sociopolitical Stability	World Development Indicator Database
Military Expenditure (1yr change)	Sociopolitical Stability	World Development Indicator Database
Share of Armed Forces Personnel	Sociopolitical Stability	World Development Indicator Database
Political Stability (1yr change)	Sociopolitical Stability	World Governance Indicator Database
Political Stability	Sociopolitical Stability	World Governance Indicator Database

Methodology for Event Study

The event study is estimated based on the specification below that follows Gourinchas & Maurice (2012) and Catão and Milesi-Ferretti (2014):

$$\boldsymbol{Y_{ict}} = \sum_{p=-5}^{5} \boldsymbol{\beta_p D_{ic,t+p}} + \boldsymbol{number\_coups\_before_{ict}} + \boldsymbol{\alpha_{ic}} + \boldsymbol{\lambda_{ct}} + \boldsymbol{\varepsilon_{ict}} \tag{1}$$

where Y_{ict} represents the variable of interest for country i of continent c at time t; $D_{ic,t+p}$ represents a dummy variable taking the value of 1 when a coup or a coup attempt occurs in country i of continent c at time t, and 0 otherwise, for a total of 11 dummies per coup event spanning the 11-year window centered around the year t when there is a coup or a coup attempt. We also control how many coups happened in country i of continent c prior to time t by $number\_coups\_before_{ict}$ and include country-continent fixed effect α_{ic} and continent-specific time fixed effects λ_{ct}. The coefficients β_p therefore can be interpreted as the difference between the level of the variable when around a coup (within the 10-year window around it) and its average level during "tranquil" periods (outside the 10-year window around a coup) across countries. In other words, the coefficients measure how proximity to a coup affects the dynamics of the variables of interest and will be the focus of our reported results.

In cases where overlapping coup windows may occur if a country experiences two consecutive coups in a short timeframe, the coefficients for overlapping years are summed to measure the treatment effect for those specific years. For instance, if a country experiences coups in 2001 and 2002, the first coup window spans from 1996 to 2006, and the second from 1997 to 2007. This results in overlapping years from 1997 to 2006, and the treatment effect for these years is the sum of the effects of both coups as illustrated in the table below. For example, a decrease of Growth in 2003 will be attributed to its proximity to coups happened in 2002 (t+1) and 2001 (t+2) (see Annex Table 2).

Annex Table 2. Example illustrating the treatment effect calculation for overlapping events in the event study specification.

	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5
…											
1995											
1996	**1**										
1997	**1**	**1**									
1998		**1**	**1**								
1999			**1**	**1**							
2000				**1**	**1**						
2001					**1**	**1**					
2002						**1**	**1**				
2003							**1**	**1**			
2004								**1**	**1**		
2005									**1**	**1**	
2006										**1**	**1**
2007											**1**
2008											

Methodology for Machine Learning

Machine learning models have been widely applied to the prediction of complex economic and political events, given their ability to accommodate nonlinearities and interactions. In this paper, we employ two tree-based supervised machine learning models for the prediction of coups, i.e., the labelled prediction target—Random Forest and XGBoost—and conduct a horse race between them to select the winning model based on AUC scores. As tree-based ensemble methods, these models overcome overfitting that is common in binary classification trees by combining many single trees and introducing sampling and randomness for each tree or at each node.

To unpack the black box of machine learning models and understand the contributions of predictors, we report the results in terms of Shapley values (Strumbelj and Kononenko, 2010; Lundberg and Lee, 2017)—built on the concept of Shapley values from cooperative game theory (Shapley, 1953; Young, 1985)—which essentially measure the additive contribution of each predictor to the likelihood of a coup relative to the sample-average predicted probability of a coup (for a detailed description of the Shapley values algorithm see below).

To examine robustness and heterogeneity across different groups (across continents, income groups, and time periods), event studies on each variable of interest and machine learning exercises are conducted for the entire sample (covering all countries from 1970 to 2019) and for subsamples including a more recent time period (2000 to 2019), and regional subsamples (e.g., sub-Saharan Africa and Middle East and Central Asia).

Machine Learning Algorithms: Tree-Based Models

In the category of tree-based ensemble methods, this paper considers two different ensemble learning methods with the binary classification tree (BCT) as the base learner: Random Forests (Breiman, 2001) and XGBoost (Chen & Guestrin, 2016).

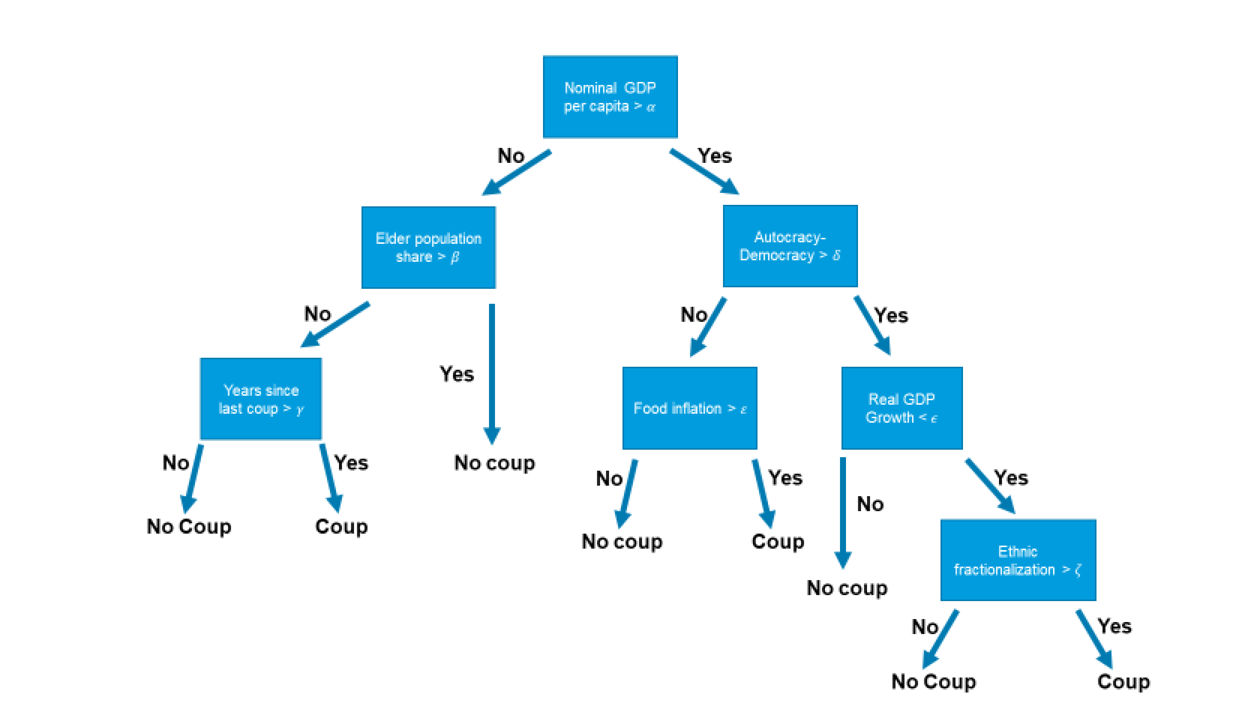
The binary classification tree method (Breiman et al., 1984) uses a decision tree to flag an observation by going from the original complex sample to smaller and purer subsamples. Each decision tree consists of a root node, branches departing from parent nodes and entering child nodes, and multiple terminal nodes which are also called leaves. In the structure of classification tree, leaves represent the flagged classes (determined by the class with the most votes within one leaf) and branches represent the conjunctions of indicators that lead to the classes. Observations in the root node are sent to left or right child nodes according to some splitting rules that identify indicators and corresponding thresholds. Once the whole sample is split into two subsamples, such process is repeated on each child node recursively until each leaf consists of observations in one class, or some stopping criteria are met (e.g., the maximum depth or the minimum leaf size of a tree is reached). In other words, a decision tree is made up by many splits, which consists of a parent node, two child nodes, and branches departing from the parent node and entering child nodes.[11] The indicator and threshold used to split the sample at each node are chosen based on some measures of impurity, such as the Gini impurity index. Because of the recursive algorithm, the binary classification tree structure partitions the classification (or prediction) space into multiple smaller spaces, which allows for a complex relationship between the classification (or prediction) outcome

[11] A child node of a split could be the parent node of another split in a deeper level of the tree.

and predictors, such as non-linearities, non-monotonicities, and interactions among indicators. An illustrative example of a binary classification tree is shown in Annex Figure 2.

Binary classification trees are prone to overfitting when a tree grows fully to fit all observations in the training sample, which results in a deep tree with small leaves containing only few observations with strict rules. Such a deep tree will fail to make accurate predictions for new observations because it includes too much noise from the training sample that is irrelevant to new predictions. To reduce overfitting of one single binary classification tree, ensemble models consisting of many binary classification trees were proposed (Annex Figure 3).

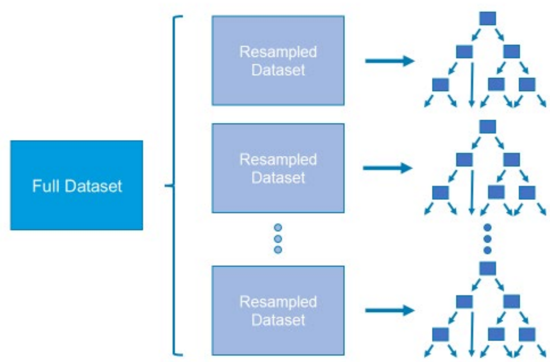
Annex Figure 2. An illustrative example of a binary classification tree for predicting coups



Random Forest: Among ensemble models based on binary classification trees, the simplest is Random Forests introduced by Breiman (2001), which applies the general techniques of bootstrap aggregating (bagging). The Random Forest consists of multiple binary classification trees, each of which is grown on a random sample selected with replacement from the training sample, which decreases the variance of the model without substantially increasing the bias. Additionally, it performs random feature sampling such that only a random subset of predictors selected from the entire set are considered at each split, effectively preventing strong correlations among trees. In the end, class predictions for new observations are made by taking the majority vote of classes determined by individual trees, and scores of new observations are calculated by taking the average of scores generated by individual trees. Bootstrap aggregating and feature sampling together help Random Forests prevent overfitting and thus achieve better prediction performance.

XGBoost: In addition to Random Forests, we also consider XGBoost (Chen & Guestrin, 2016), another ensemble learning algorithm with the binary classification tree as the building block. XGBoost employs gradient boosting, in which individual binary trees are trained sequentially. To be specific, each new binary tree is trained to learn the residuals of previous trees, which are the differences between the predicted and actual values of the target variable. Moreover, XGBoost adds a penalty term to the loss function used in training the model, which helps prevent overfitting by discouraging the model from becoming too complex. The complexity is measured by sum of the depth of all trees and the number of trees in the XGBoost model. The depth of a tree in an XGBoost model refers to the number of splits in the tree. A tree with more splits has a greater depth and can capture more complex interactions in the data but may also be more prone to overfitting. Also, the more trees you have in the XGBoost model, the more likely you will capture some "idiosyncratic" pattern only for this sample and suffer over-fitting problem when make prediction on another sample. Thus, the algorithm builds new trees to minimize the errors in the training set while controlling the complexity of the trees to ensure it has good generalization ability.

Annex Figure 3. Random Forests and XGBoost



Note: Both Random Forests and XGBoost are ensemble methods consisting of many binary classification trees, and each tree is built from a dataset resampled from the full dataset. In Random Forests, datasets and trees are generated independently, while in XGBoost, datasets and trees are generated sequentially such that the construction of a new tree considers the classification outcomes of previous trees.

Model Performance Evaluation

The area under the ROC curve (AUC) is used to measure and evaluate model performance. The AUC is calculated by plotting the true positive (i.e., an observation which has a coup and is predicted to have a coup) rate against the false positive (i.e., an observation which does not have a coup but is predicted to have a coup) rate for different threshold values of the model's predicted probabilities, and then calculating the area under the resulting curve. In other words, the AUC measures the ability of the model to distinguish between positive and negative samples, regardless of the specific threshold used to make the classification decision. A higher AUC indicates better overall performance of the model, with a score of 0.5 representing a model with random guessing ability and a score of 1 representing a perfect model.

Hyperparameter Tuning

We employ the block time-series cross-validation method based on Burman et al. (1994) and Racine (2000) to tune hyperparameters and evaluate model performance, which accounts for the cross-sectional dependence in the panel structure of our sample. Exact steps are as described below:

Step 1: Construct 5 {training set, validation set} pairs based on the entire sample, which consists of observations with years belong to {1970 - 2009, 2010 - 2011}; {1970 - 2011, 2012 - 2013}; {1970 - 2013, 2014 - 2015}; {1970 - 2015, 2016 - 2017}; {1970 - 2017, 2018- 2019}. Therefore, each training set consists of observations to predict with years since 1970 until the cutoff year (namely 2009, 2011, 2013, 2015, and 2017), and each test set consists of observations to predict in the next two years (namely, 2010-11, 2012-13, 2014-15, 2016-17, and 2018-19);

Step 2: For each ML algorithm, starting with a random set of hyperparameters, we train the model on the training sets and apply the model to the corresponding validation sets to get five AUCs. In each tree-based algorithm, 1000 trees are constructed, and the hyperparameters we choose to tune for each model are shown below:

1. Random Forest: maximum tree depth for base learners and subsample ratio of columns when constructing each tree.
2. XGBoost: L2 regularization term on weights and boosting learning rate.

Step 2 is repeated with different sets of hyperparameters which are chosen by Bayesian optimization over 100 iterations. For each ML algorithm, the set of hyperparameters that yield the highest average AUC across the five validation sets are chosen as the optimal set of hyperparameters.

Step 3. Finally, the ML algorithm with its optimal set of hyperparameters that yields the highest average AUC is chosen as our final selected ML algorithm and the corresponding hyperparameters.

Imputation

Given the wide coverage of countries and long span of years of our sample, there is missing data especially for some earlier years or some individual countries. We opt to let the machine learning algorithms impute the missing data as the models are trained.

Shapley Values

Beginning with linear models, Shapley value of a predictor for an observation is simply the estimated coefficient multiplied by the observation's value of the predictor. Specifically,

$$\hat{f}(x_i) = \phi_0(\hat{f}) + \sum_{k=1}^{n} \phi_k\left(x_i; \hat{f}\right) = \hat{\beta}_0 + \sum_{k=1}^{n} \hat{\beta}_k\, x_{i,k} \tag{3}$$

where $\hat{f}(x_i)$ is the model prediction for observation x_i, $\hat{\beta}_0$ is the estimated unconditional expected value of $\hat{f}(x)$, and $\hat{\beta}_k$ is the estimated slope coefficient for the kth predictor. Shapley value of the kth predictor for observation x_i is calculated as $\hat{\beta}_k x_{i,k}$, and the sum of Shapley values of all predictors for observation x_i is the difference between its model prediction and the average prediction in the training sample.

Shapley values for non-linear model draws on ideas from cooperative game theory, and is implemented in a model-agnostic way, i.e., it offers a way to decompose the model prediction into contributions of predictors for any machine learning algorithm. The idea is to think about a model prediction for an observation as a cooperative game where each predictor value of the observation is a "player" and the prediction is the "payout". In this way, the "gain" of this game is the difference between the payout and the average prediction for all observations, and all predictor values of the observation (all players in the game) collaborate to receive the gain. Then the Shapley value of a predictor for the observation is defined as the average marginal contribution of a predictor value for the observation across all possible coalitions, given the observation values for all other predictors. Specifically, a model prediction can be linearly decomposed as

$$\hat{f}(x_i) = \phi_0^S(\hat{f}) + \sum_{k=1}^{n} \phi_k^S(x_i; \hat{f}) \tag{4}$$

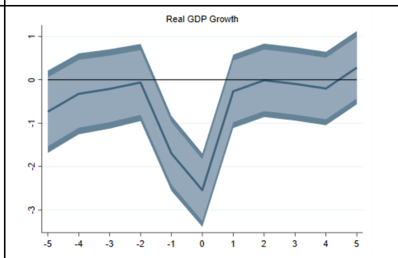
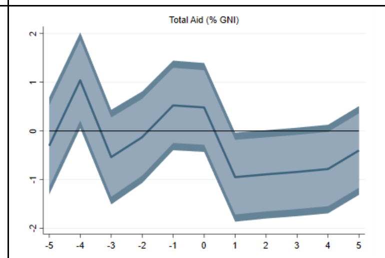
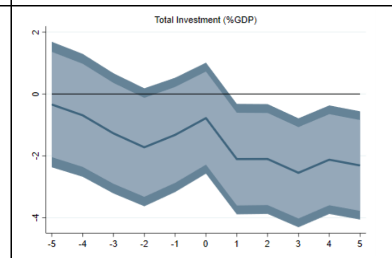
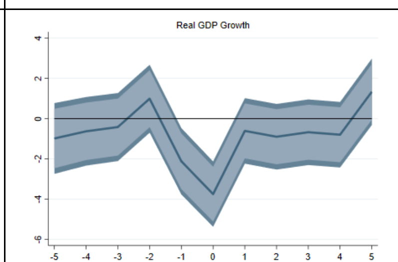
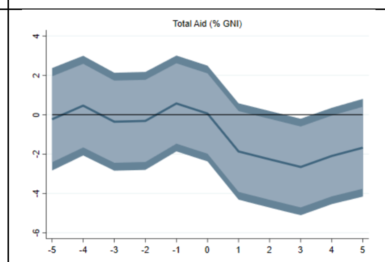
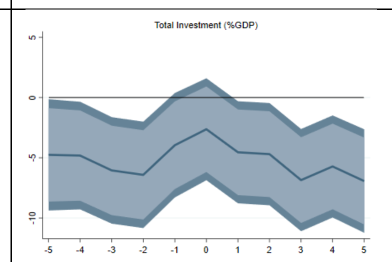
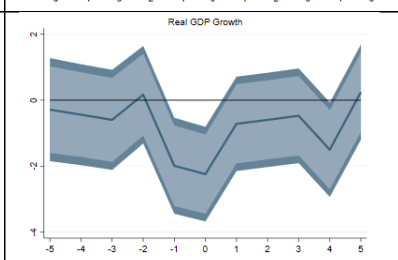
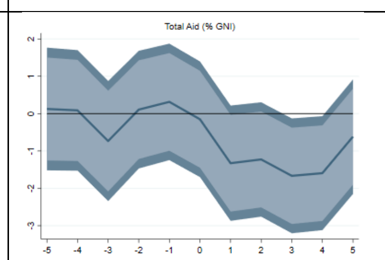
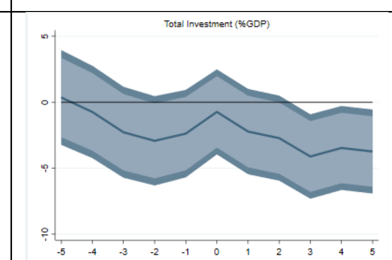
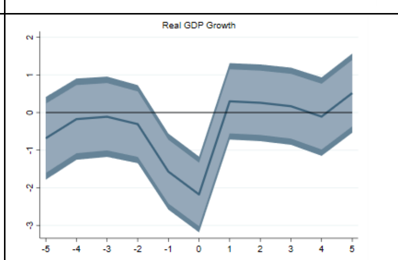
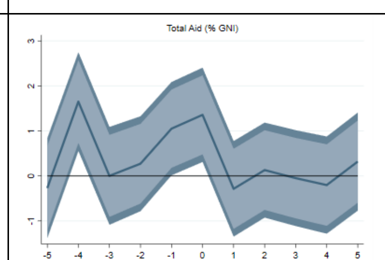
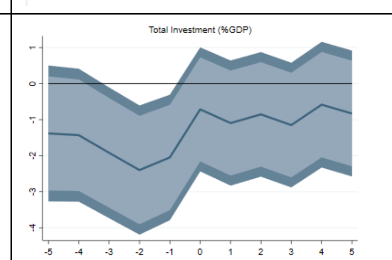
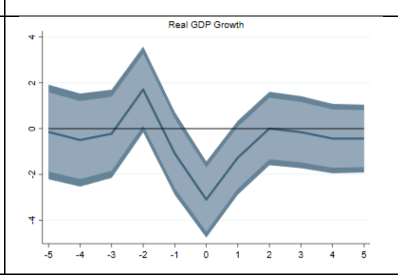
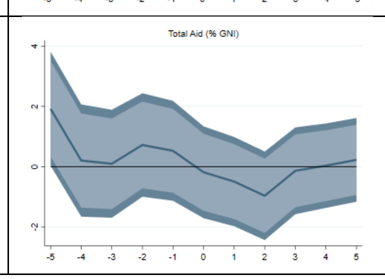
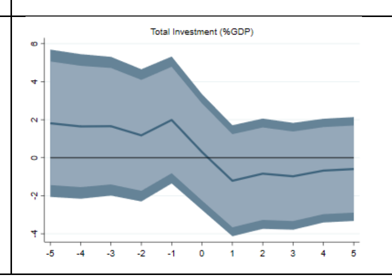
$$\phi_k^S(x_i; \hat{f}) = \sum\nolimits_{x' \subseteq \{x_1, x_2, \ldots, x_n\} \setminus \{x_k\}} \frac{|x'|!\,(n - |x'| - 1)!}{n!} \left(\hat{f}(x_i|x' \cup \{x_k\}) - \hat{f}(x_i|x')\right) \tag{5}$$

where $x' \subseteq \{x_1, x_2, \ldots, x_n\} \setminus \{x_k\}$ is the set of coalitions used in the model prediction consisting of all predictors but the kth predictor for which the Shapley value $\phi_k^S(x_i; \hat{f})$ is calculated, $|x'|$ is the number of predictors included in each coalition except the kth predictor, $\frac{|x'|!(n-|x'|-1)!}{n!}$ is the weighting factor, and $\hat{f}(x_i|x' \cup \{x_k\})$ and $\hat{f}(x_i|x')$ are the model prediction with and without the kth predictor conditional on the set of coalition consisting of all other predictors, which implies that the difference is the pay-off for including the kth predictor, i.e., x_k, in the coalition x'.

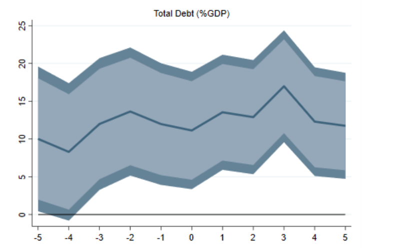
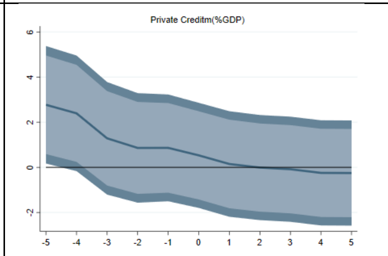
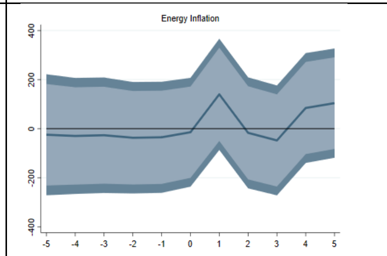
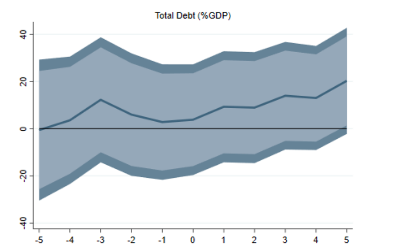
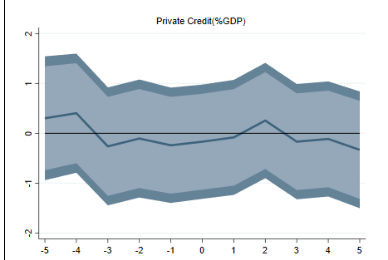
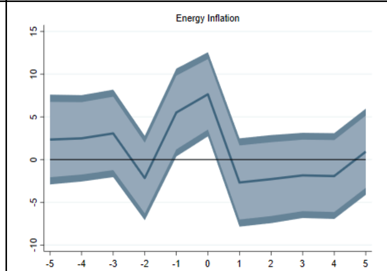
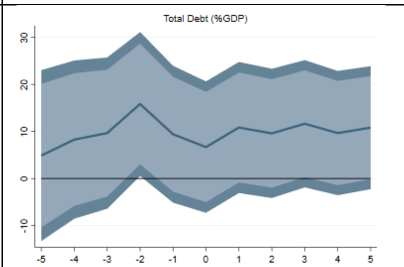
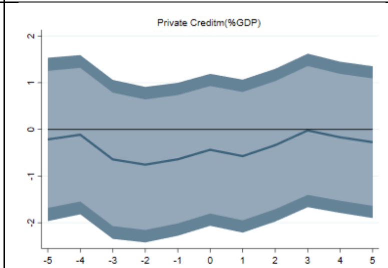
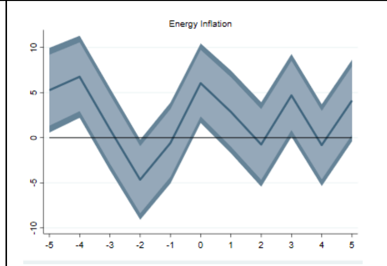
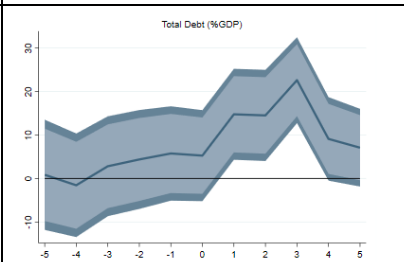
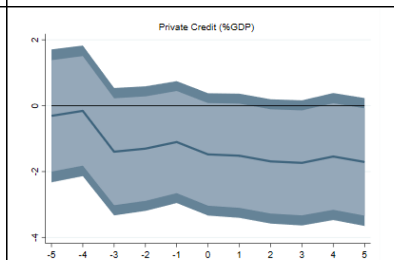
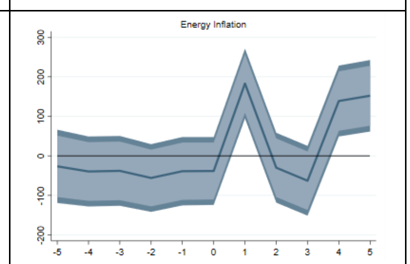
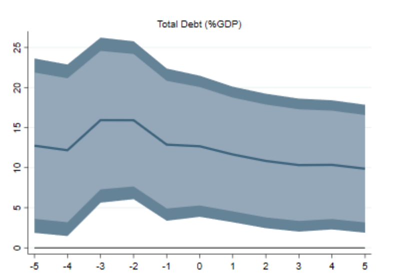
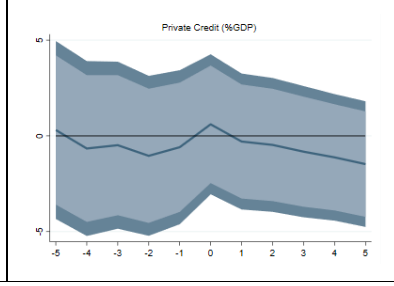
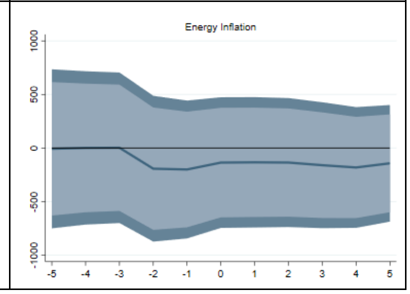
Annex II: Event Study Results

This annex reports the results of the event study analysis for those variables that show significant deviations around coups (including coups and attempted coups) relative to tranquil times either in the full sample or the in regional, time, or income subsamples.

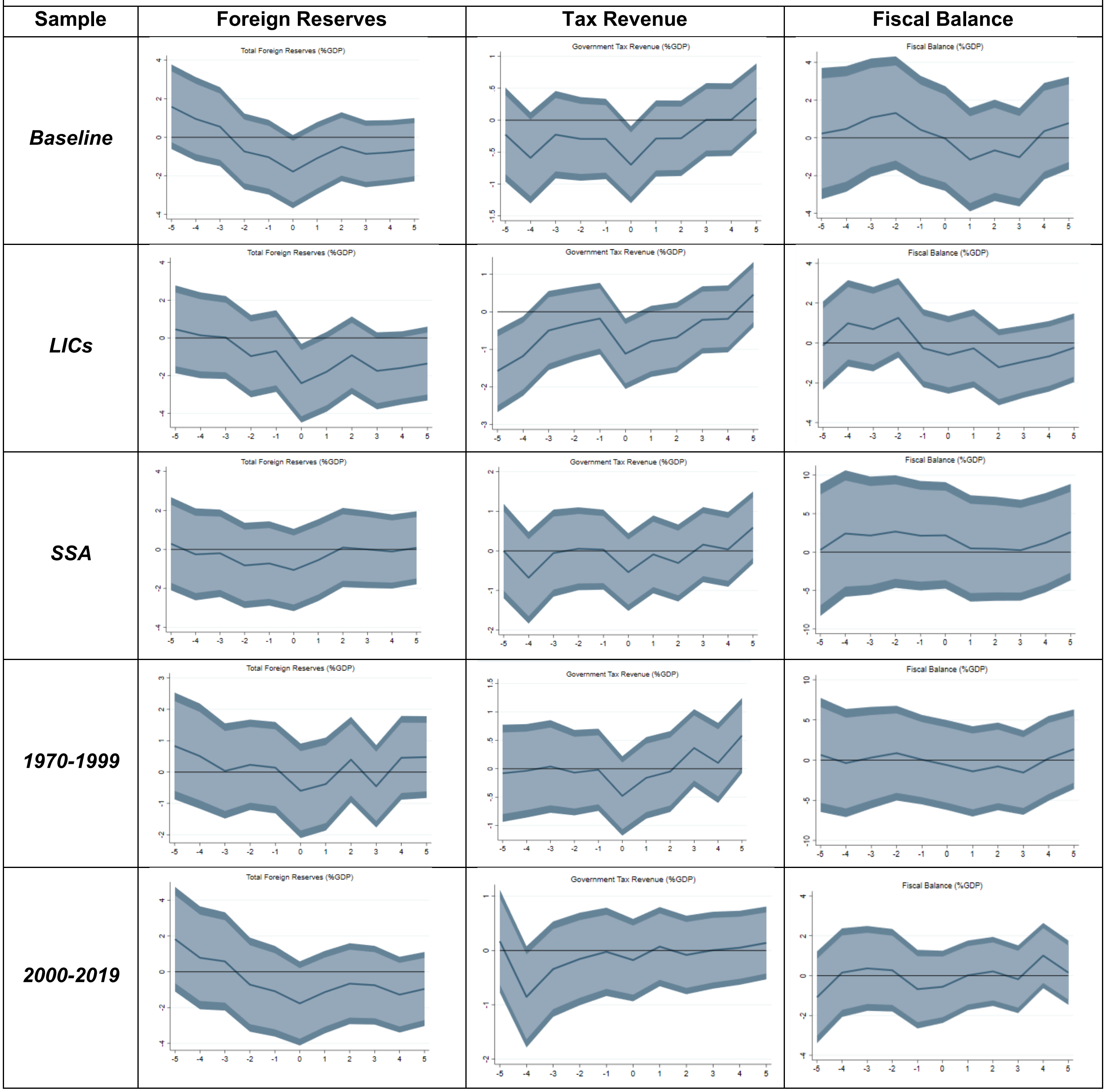
Annex Figure 4a: Event Study Results for Selected Indicators and by sub-Sample: Economic Indicators

Sample	Growth	Aid (% of GNI)	Investment
Baseline			
LICs			
SSA			
1970-1999			
2000-2019			

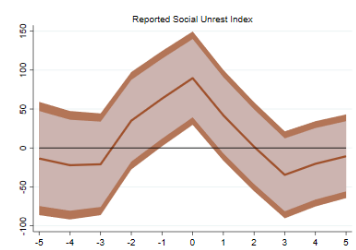
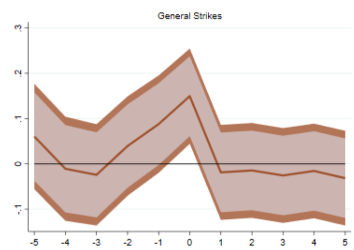
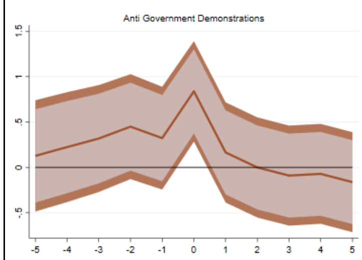
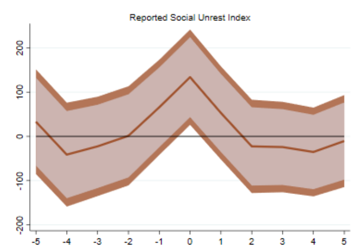
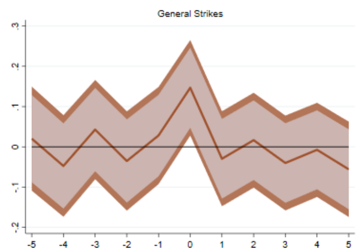
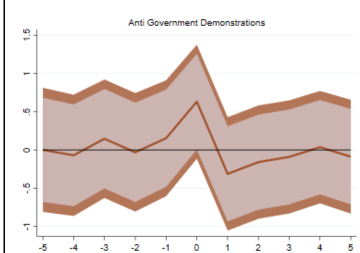
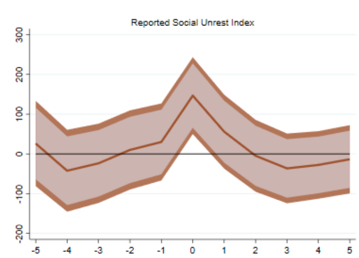
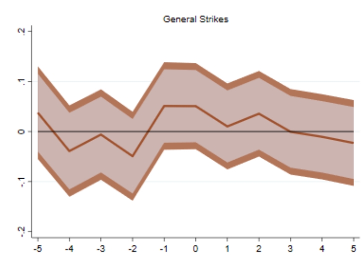
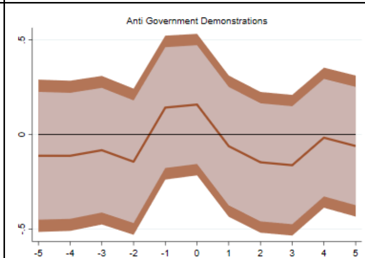
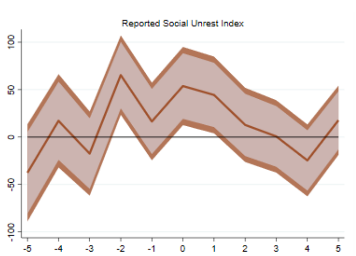
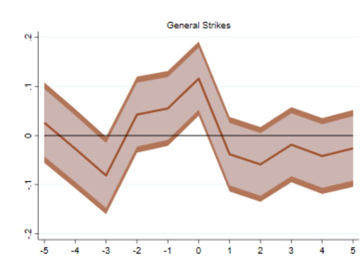
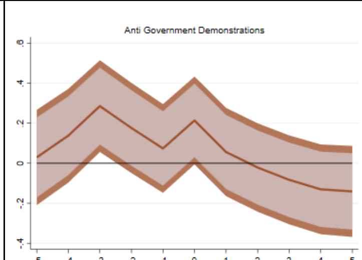
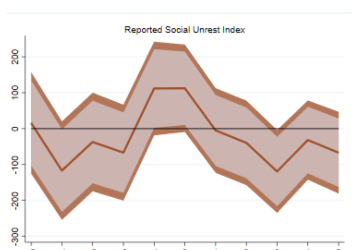
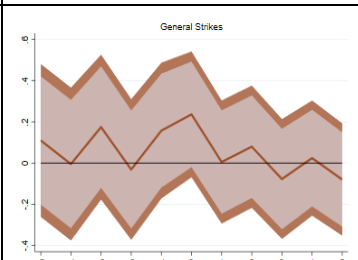
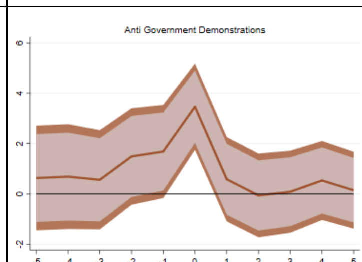
Annex Figure 4b: Event Study Results for Selected Indicators and by sub-Sample: Economic Indicators

Sample	Debt	Private credit	Energy inflation
Baseline			
LICs			
SSA			
1970-1999			
2000-2019			

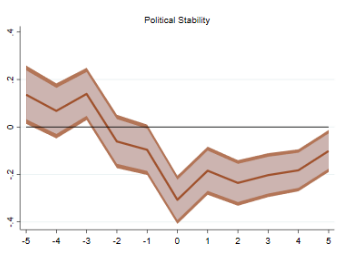
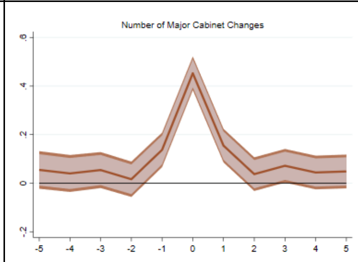
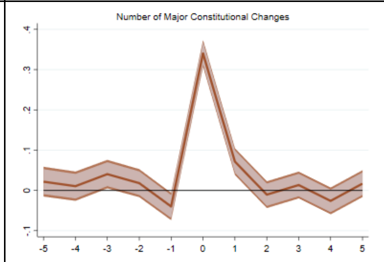
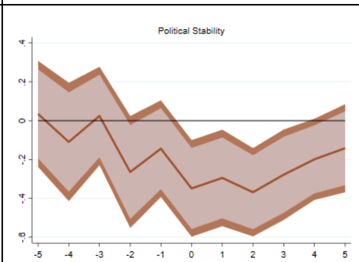
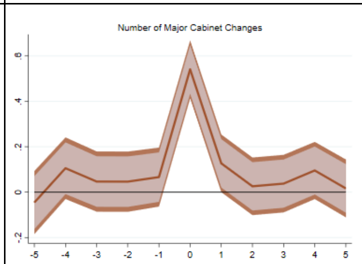
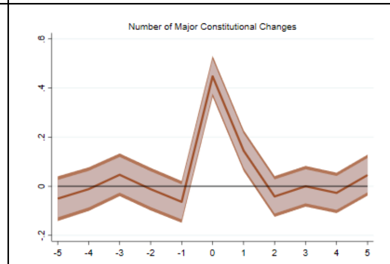
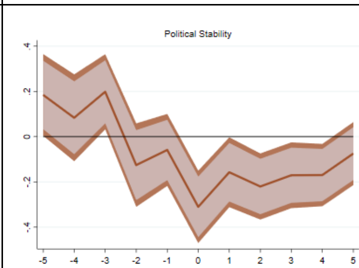
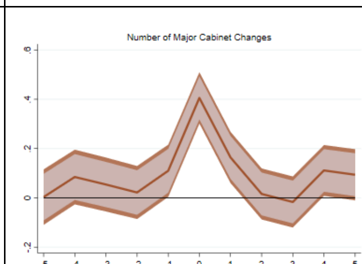
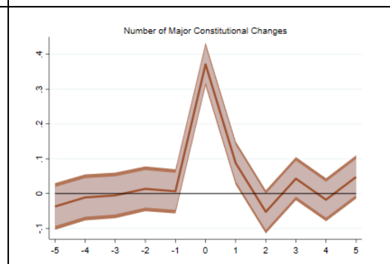
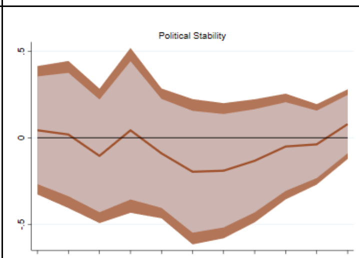
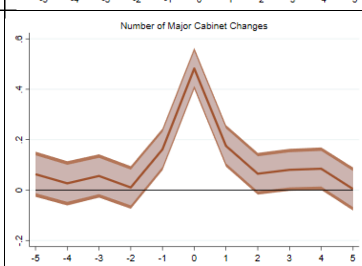
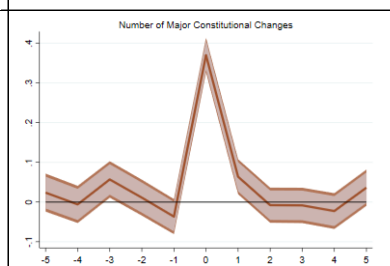
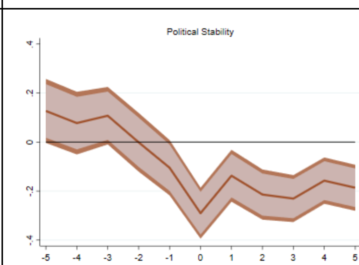
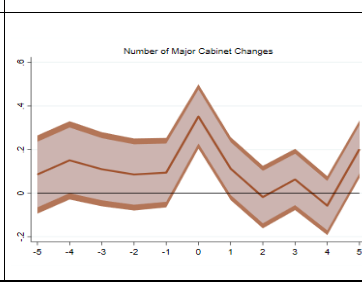
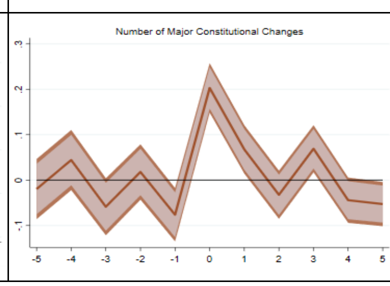
Annex Figure 4c: Event Study Results for Selected Indicators and by sub-Sample: Economic Indicators



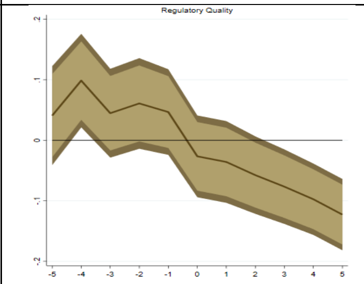
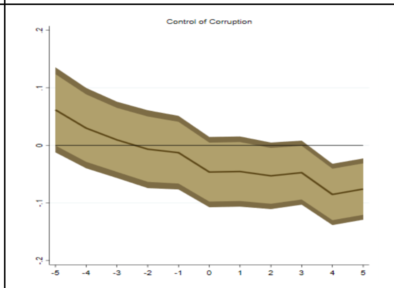
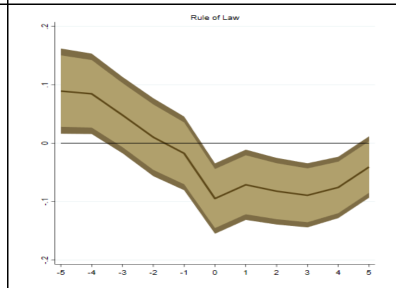
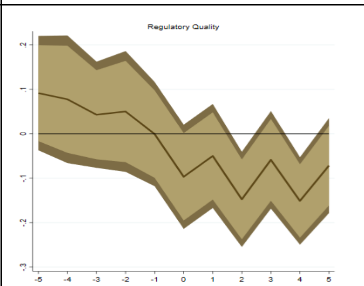
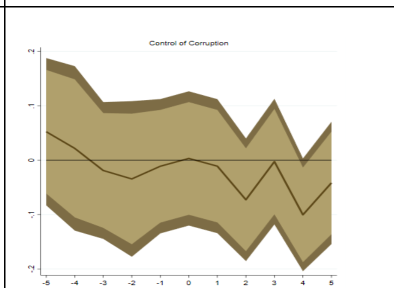
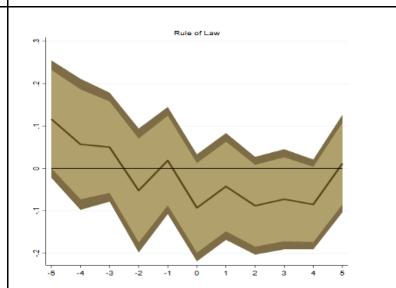
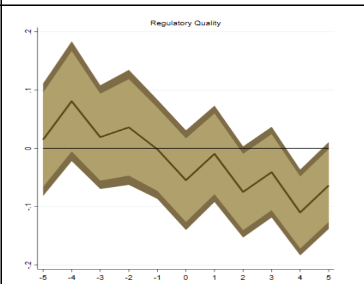
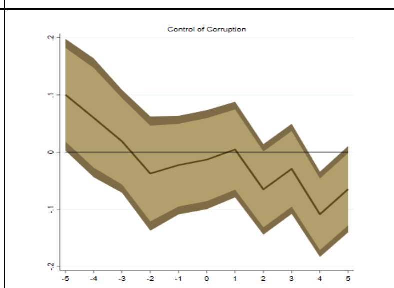
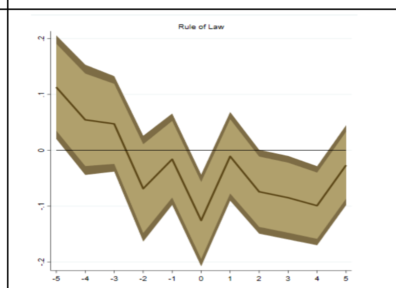
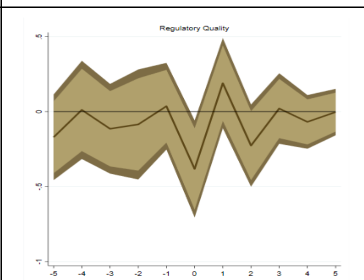
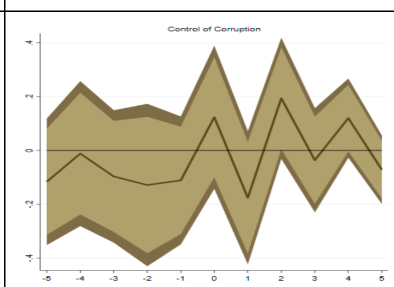
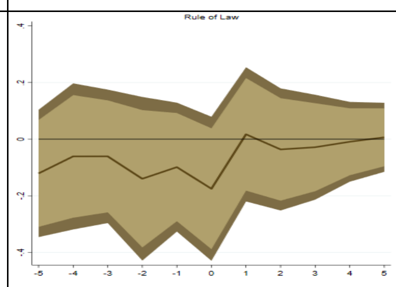
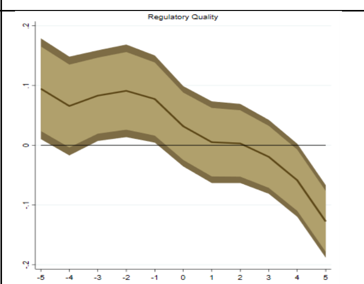
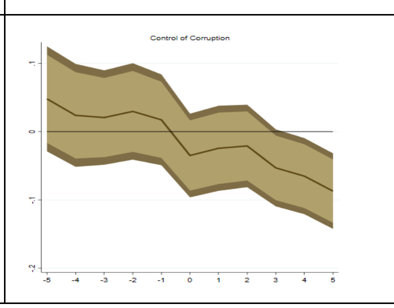
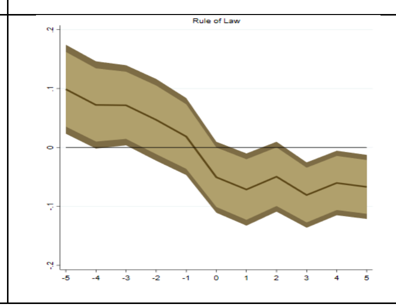
Annex Figure 5a: Event Study Results for Selected Indicators and by sub-Sample: Socio-Political Stability Indicators

Sample	Reported Social Unrest	General Strikes	Anti Government Demonstration
Baseline			
LICs			
SSA			
1970-1999			
2000-2019			

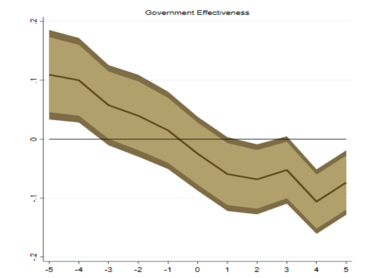
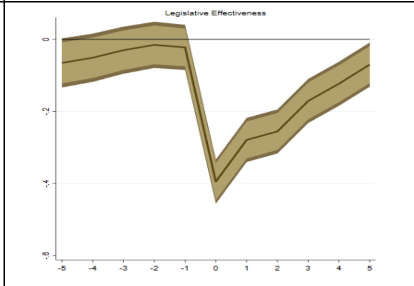
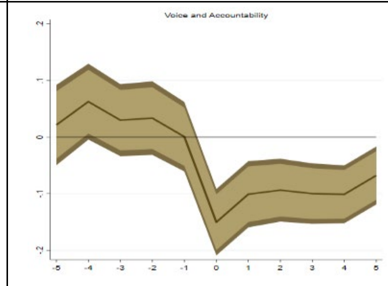
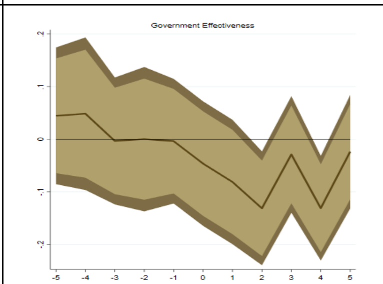
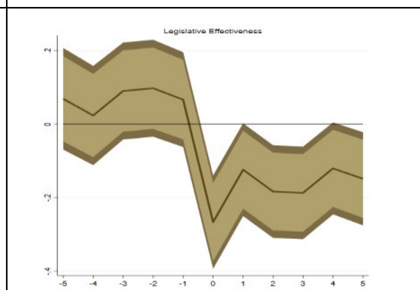
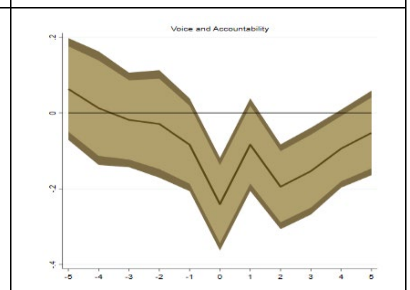
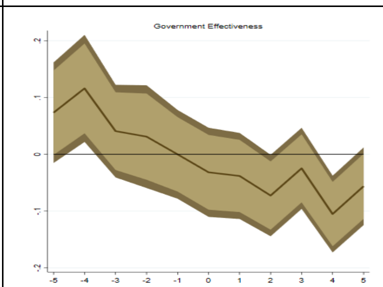
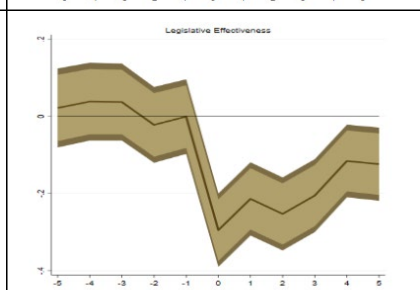
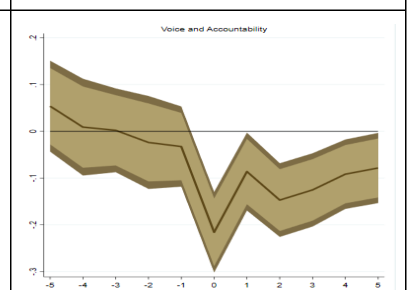
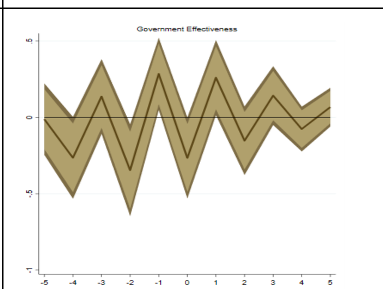
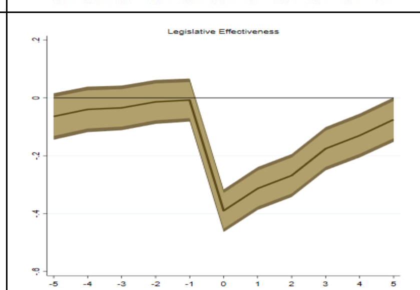
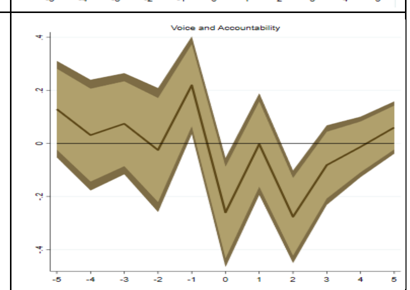
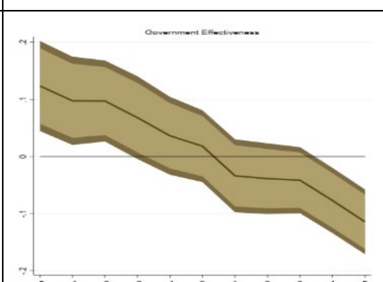
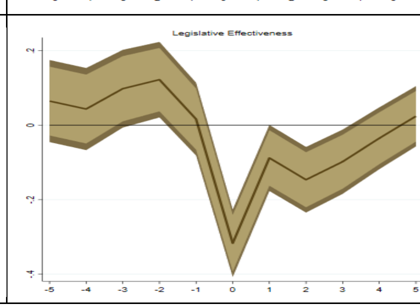
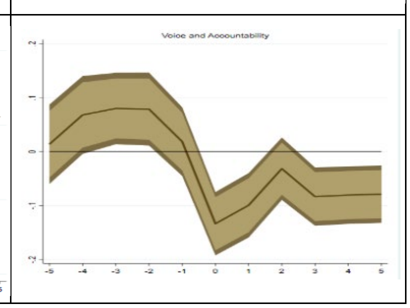
Annex Figure 5b: Event Study Results for Selected Indicators and by sub-Sample: Socio-Political Stability Indicators

Samples	Political Stability	Number of Major Cabinet Changes	Number of Major Constitutional Changes
Baseline			
LICs			
SSA			
1970-1999			
2000-2019			

Annex Figure 6a: Event Study Results for Selected Indicators and by sub-Sample: Governance Indicators

Samples	Regulatory Quality	Control of Corruption	Rule of Law
Baseline			
LICs			
SSA			
1970-1999			
2000-2019			

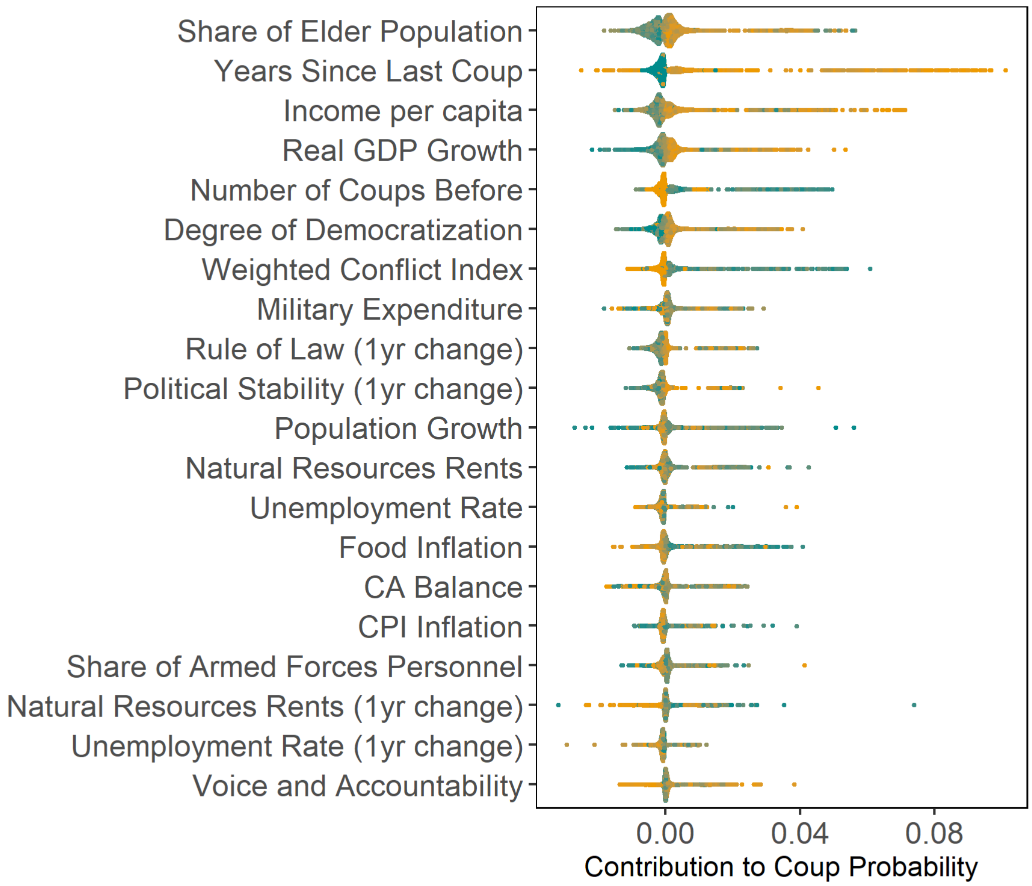
Annex Figure 6b: Event Study Results for Selected Indicators and by sub-Sample: Governance Indicators

Samples	Government Effectiveness	Legislative Effectiveness	Voice and Accountability
Baseline			
LICs			
SSA			
1970-1999			
2000-2019			

Annex III. Machine Learning Results

This annex reports the results of the machine learning exercise in terms of the Shapely Values for the top-20 predictors of coups for (i) the full sample (Annex Figure 7); (ii) the subsample covering the most recent two decades 2000-2019 (Annex Figure 8); (iii) the sub-Saharan African sample over fifty years from 1970 to 2019 (Annex Figure 9); and (iv) the Middle East and Central Asia sample over fifty years from 1970 to 2019 (Annex Figure 10). The guidance for reading the charts is in the notes to each chart.

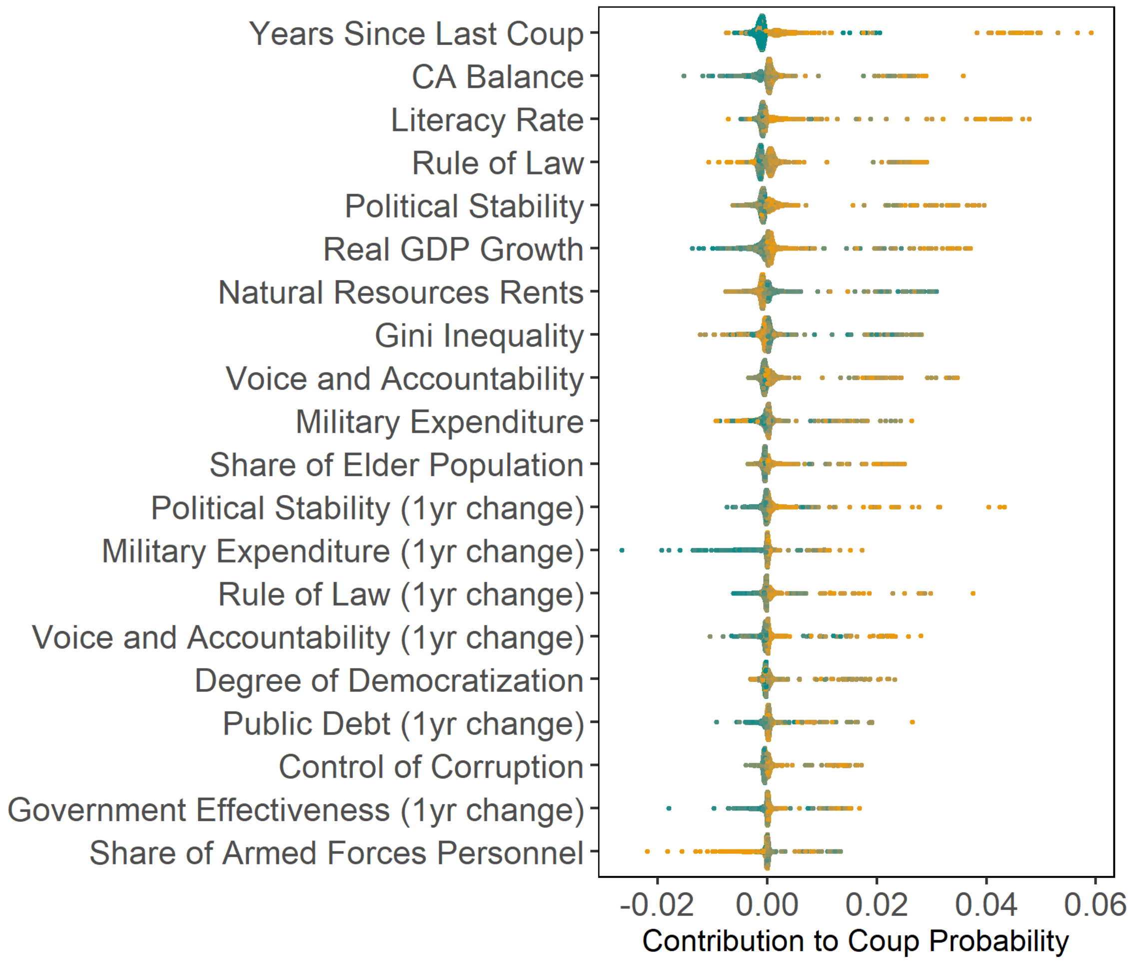
Annex Figure 7. Shapley Values of Top 20 Predictors for Coups in the Global Sample for 1970-2019



Source: authors' calculations.

Note: The chart shows the contribution to coup probability (as measured by the Shapley value) for the top 20 drivers of the coup probability for the sample. Each dot represents one observation (one country-year pair), and its color indicates the predictor value, with orange being low and green high. Therefore, the value of the contribution (and its negative or positive sign) and color together illustrate how the predictor value affects the coup probability. For example, for the share of elder population, the top predictor in the full sample, most green dots (observations with higher share of elder population) are to the left (i.e., reduce coup probability, relative to the sample average) and most orange dots (observations with lower share of elder population) are to the right (i.e., increase coup probabilities, relative to the sample average).

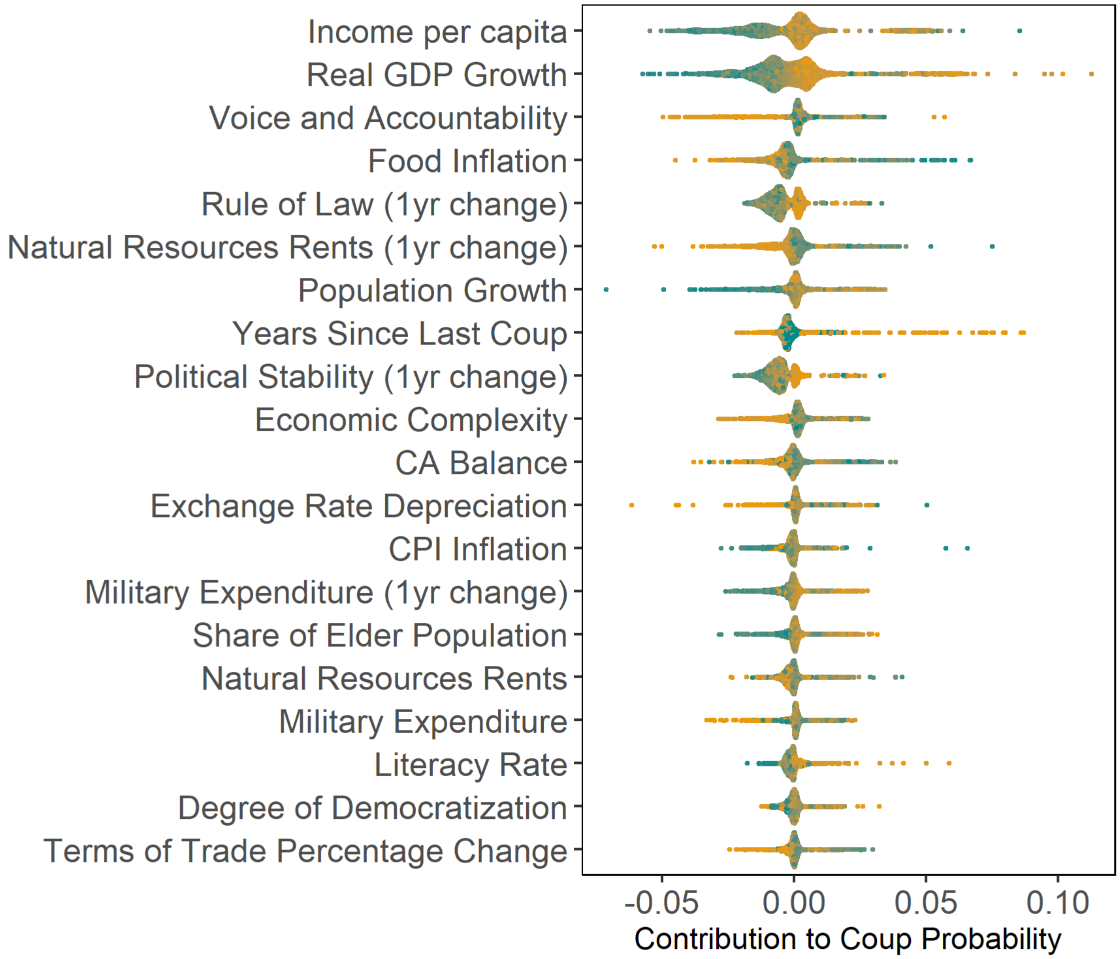
Annex Figure 8. Shapley Values of Top 20 Predictors for Coups in the Global Sample for 2000-19



Source: authors' calculations.

Note: The chart shows the contribution to coup probability (as measured by the Shapley value) for the top 20 drivers of the coup probability for the sample. Each dot represents one observation (one country-year pair), and its color indicates the predictor value, with orange being low and green high. Therefore, the value of the contribution (and its negative or positive sign) and color together illustrate how the predictor value affects the coup probability. For example, for the years since the last coup, the top predictor in the sample, most green dots (observations with higher number of years since the last coup) are to the left (i.e., reduce coup probability, relative to the sample average) and most orange dots (observations with a lower number of years since the last coup) are to the right (i.e., increase coup probabilities, relative to the sample average).

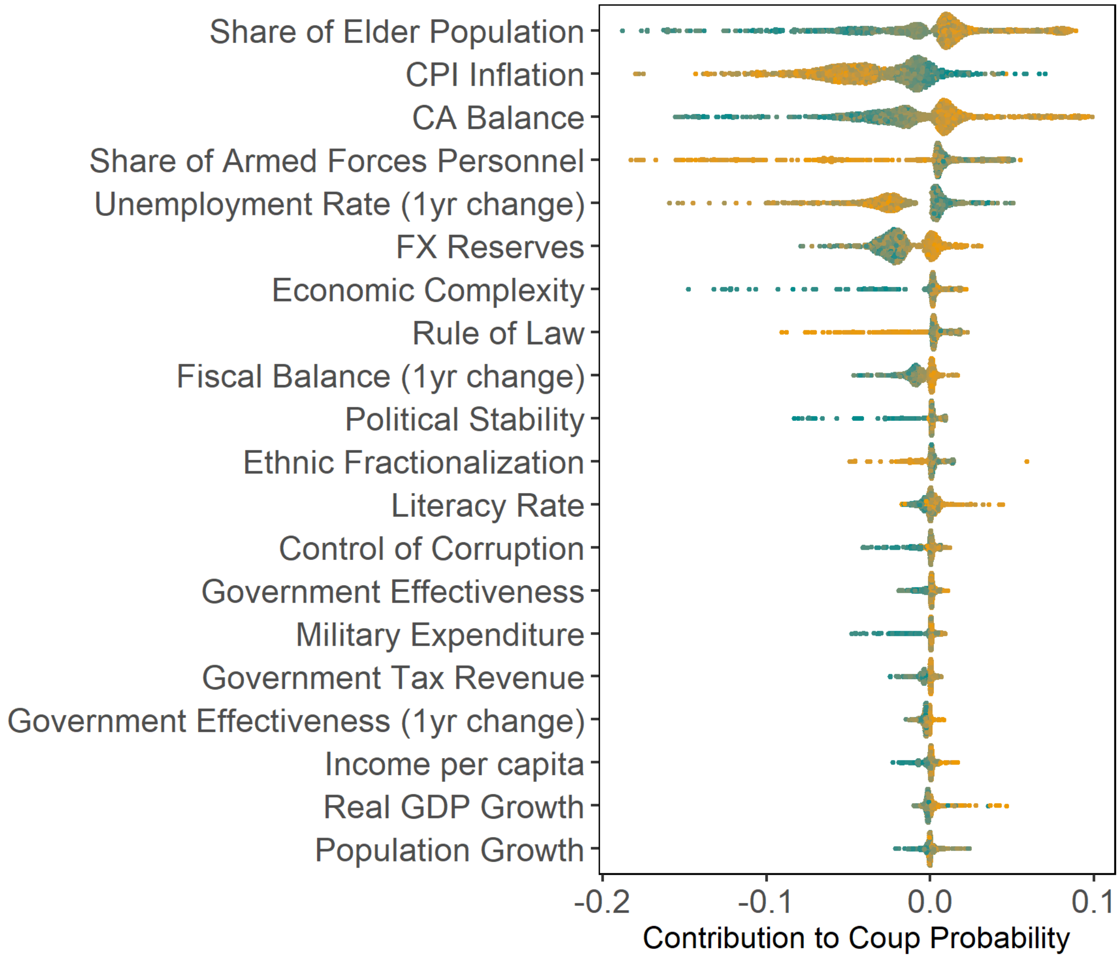
Annex Figure 9. Shapley Values of Top 20 Predictors for Coups in the Sub-Saharan African Sample for 1970-2019



Source: authors' calculations.

Note: The chart shows the contribution to coup probability (as measured by the Shapley value) for the top 20 drivers of the coup probability for the sample. Each dot represents one observation (one country-year pair), and its color indicates the predictor value, with orange being low and green high. Therefore, the value of the contribution (and its negative or positive sign) and color together illustrate how the predictor value affects the coup probability. For example, for the income per capita, the top predictor in the sample, most green dots (observations with higher income per capita) are to the left (i.e. reduce coup probability, relative to the sample average) and most orange dots (observations with lower income per capita) are to the right (i.e., increase coup probabilities, relative to the sample average).

Annex Figure 10. Shapley Values of top 20 Predictors for Coups in the Middle East and Central Asia Sample for 1970-2019



Source: authors' calculations.

Note: The chart shows the contribution to coup probability (as measured by the Shapley value) for the top 20 drivers of the coup probability for the sample. Each dot represents one observation (one country-year pair), and its color indicates the predictor value, with orange being low and green high. Therefore, the value of the contribution (and its negative or positive sign) and color together illustrate how the predictor value affects the coup probability. For example, for the share of elder population, the top predictor in the sample, most green dots (observations with higher share of elder population) are to the left (i.e., reduce coup probability, relative to the sample average) and most orange dots (observations with lower share of elder population) are to the right (i.e., increase coup probabilities, relative to the sample average).

Annex IV. Coups d'État: Selected Cases

This annex focuses on the social, economic and political developments in the runup to a number of coups, including in the Sahel region, Sudan, and Venezuela. These developments are consistent with the coup determinants identified above and serve as a helpful illustration.

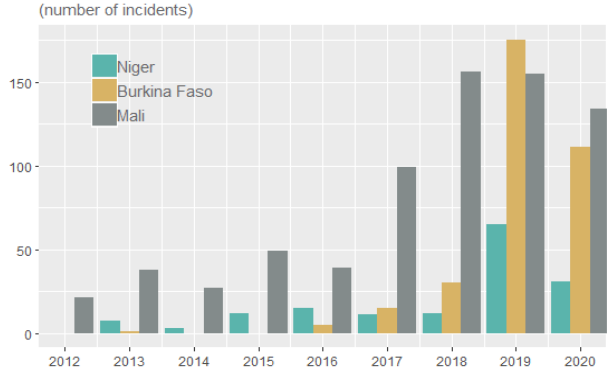
The Sahel Region, 2020–23

Following the fall of Muammar Gaddafi's regime in 2011, the Sahel countries entered a period of heightened political fragility, in part due to the outflow of armed groups that fled Libya to relocate into the Sahel. The rise of armed conflicts and jihadist movements contributed to escalating political instability across the region. Mali, Burkina Faso, and Niger, which share contiguous borders, have had grappled with heightened terrorism against the backdrop of already severe developmental challenges, including extreme poverty, low education levels, weak governance and institutions and a dearth of public services in many areas. By 2020–23, the security situation has deteriorated further despite support from France, the UN, and other international partners and a decade of conflict in the region has led to a decline in people's wellbeing, large population displacements, while corruption within administrations has weakened security and public financial management. Lack of progress in improving security have also stoked anti-French sentiment in several countries, especially Mali. Against this backdrop, the coup in Mali in 2020 was the first in a string of seven coups or coup attempts in the Sahel region: two in Burkina Faso in 2022; one in Chad in 2021; another in Mali in 2021; two in Niger in 2021 and 2023. While a common motivation of recent coups in Sahel countries has been a deterioration of security situation, post-coup conditions have not demonstrated a subsequent amelioration (Annex Figure 11).

Annex Figure 11. Terrorism and Social Unrest in the Sahel Region, 2012-23

Terrorism in the Sahel region, 2012-2020 1/

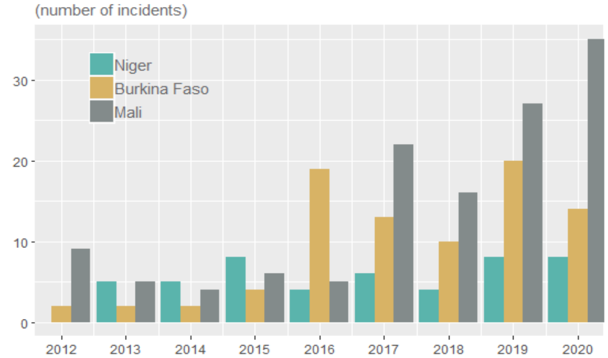
(number of incidents)



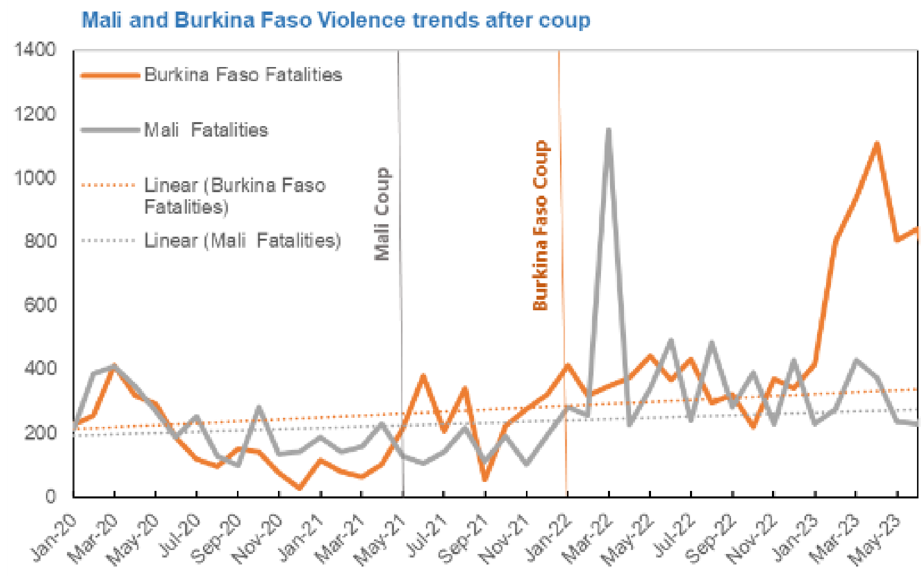
Source: Control Risks.
1/ Does not show Chad and Mauritania. Data captures incidents from January unitl July.

Social unrest in the Sahel region, 2012-2020 1/

(number of incidents)



Source: Control Risks.
1/ Does not show Chad and Mauritania. Data captures incidents from January until July.



Source: ACLED database (2023), and authors' calculation.

- **Mali (2020, 2021).** Mali faced eight coups since its independence in 1960 (five of them successful) and four coups since 2012. The 2012 coup led to the election of President Keïta in 2013 (he was re-elected in 2018) on a mandate to tackle the incipient security crisis and corruption in the public sector. In the event, delays in disarming the Tuareg rebels who colluded with jihadists and the continued deterioration in security conditions gave rise to a spiral of violence and intercommunal clashes, displacing thousands and leaving large parts of the country outside the perimeter of government control and basic public services. This strife, in turn, eroded national cohesion and raised socio-political tensions around 2020. Before the 2020 coup, social unrest intensified in response to the perceived rigging by the Constitutional Court of the latest parliamentary elections in favor of the ruling party of President Keïta, with corruption scandals and nepotism recriminations, as well as frequent turnover of high-level officials all contributing to public discontent. The proximate causes of the coup, thus, ran deep into the multifaceted systemic fragilities facing Mali at the time.

- **Burkina Faso (2022).** Burkina Faso experienced its first coup in 1966 followed by a period of intense political instability from 1980 to 1987, marked by six successful coups. The country achieved some political stability until the surge in conflict and terrorist attacks in 2012, which started to spread from Mali to some of its border areas. In 2014, President Blaise Compaoré, in power since 1987, was ousted due to popular discontent with his attempt to revise the constitution for re-election. The election of Roch Kaboré in the 2015 democratic elections did not alleviate tensions, and by 2022 the pre-coup environment resembled that of Mali in 2020. Security challenges persisted under Kaboré's leadership, fostering public and military dissatisfaction, in the case of the latter due to the failure of the administration to supporting military forces with needed equipment to fight against terrorist group. Over 2,000 lives were lost and 1.5 million were displaced since 2015 and intercommunity group conflicts (farmers vs livestock breeders) escalated due to terrorist presence. The worsening living conditions of the population and the failure of the international community to combat terrorism in the country have led to an increase in public sentiment against the international forces present in the country and a sharp fall in public confidence in the government's management of the security crisis. This catalyzed support for a January 2022 military coup. Yet, further security deterioration caused division within the army, resulting in another coup months later.

- **Niger (2021, 2023).** Since gaining independence in 1960, Niger has experienced a total of six coups, five of them successful, all orchestrated by military factions. The election of President Mohamed Bazoum in 2021 marked the country's first democratic transition through a conventional electoral process. Despite this progress, a failed coup attempt occurred a few months after his election. This coup attempt came just after (i) the opposition's legal appeal against the election results was rejected by the Constitutional Court and (ii) terrorists had killed around 137 people in a village a week before. The most recent coup occurred at end-July 2023 against the background of widespread conflicts across the country, a multitude of developmental challenges, including a high poverty rate, and heightened insecurity in the west along the borders with Burkina Faso and Mali, and in the southeast along the border with Nigeria, where the Boko Haram group operates. The disruptive jihadist activities caused significant displacements, adversely affected economic activities and led to the closure of numerous schools. The National Council for the Safeguarding of the Homeland (CNSP) — formed by the military group behind the coup— invoked the persistent deterioration of the security situation and inadequate economic and social governance as the motivation for the seizure of power. However, it has been speculated that the proximate cause may have been the alleged planned dismissal of the head of the Presidential Guard (who led the military coup) and/or the forced retirement of five army generals.

Sudan, 2021

Sudan has experienced a complex and often tumultuous socio-economic and political context since its independence in 1956, deeply intertwined with a history of conflicts and authoritarian rule. The country experienced seventeen coups in total since 1956—among the highest in the world and the highest in the Middle East and North Africa region—with six of them successful. Moreover, the country has grappled with numerous civil wars—between 1955 and 1972 (First Sudanese War) and between 1983–2005 (Second Sudanese War)—which tragically led to over 1 million casualties and the displacement of approximately 2 million people. In 2019, following a series of extensive public demonstrations lasting several weeks, President Omar al-Bashir, who had maintained his leadership since the 1989 coup, was overthrown by the military forces. Demonstrations organized by civilians continued for several months until a power-sharing agreement was reached between civilians and the military. This agreement led to the creation of a Sovereignty Council, which provided for the transfer of power from the military to civilians in November 2021. However, continued political wrangling over representation in the legislative body, increasing and open criticism by the military of the civilian members of government all added to the fragility of a military-civilian coalition government. After weeks of escalating political crisis in the run up to the slated shift from military to civilian leadership of the Sovereign Council, the military staged a successful coup in October 2021, on the heels of an unsuccessful coup one month earlier. The government was dissolved, and a state of emergency was declared. Since the second quarter of 2023, the country is facing an armed conflict between two rival fractions of the military Government. The political crisis was already having a significant impact on the economy and welfare of the population, and the military coup further adversely impacted economic activity, inflation, and the fiscal position.

Venezuela: a long history of political fragility

After oil wealth was discovered in 1914 and a 21-year rule by General Juan Vicente Gómez ended in 1935, the country started experiencing a protracted period of political fragility. For twenty years after 1945— despite generating and sustaining growth, rapid urbanization, important migration inflows, and strong state building—Venezuela registered one successful political assassination and 14 coup attempts, of which only three were successful. During this period, political fragility was likely driven by lower social and political inclusion in the transition to more inclusive political institutions amid political antagonisms between and within conservative, and progressive military and civilian coalitions in the mist of the cold war (Thinker Salas, 2015, pp.75–91). During the next period from 1966 to the early 1990s, the socio-political system saw relative stability with no coups, after the implementation of coup-proofing strategies including policies to reward military loyalty and defend against dissent (Norden, 2021). However, an important feature of the recent history of Venezuela is severe underperformance of the economy, with a long recession over 1978-1989, an extended period of growth stagnation over 1990-2003, and a growth collapse (or depression) over 2012–20. As coined by Cebotari et all (forthcoming), this chronic fragility is characterized by low or negative growth and weak structural fundamentals including high levels of debt, high commodity dependency, governance weaknesses, lower social inclusion, rising poverty, and political polarization between conservative and leftist coalitions. Negative shocks may have acted as amplifiers, with overlapping crises in the stagnation and depression periods further fragilizing the political system in the presence of weak fundamentals. Indeed, the last four attempted coups documented in Chinn et.al (2021,2022) happen within the periods of long recession (in February and November 1992), stagnation (in 2002) and depression (in 2019).

It is worth nothing that the growth recovery during 2004–11 was driven by overspending during a resource boom under exchange rate and price controls, which induced macroeconomic imbalances and fragility conditions (Rodriguez, 2021). This growth recovery transitioned to a depression as a result of a series of events, including the death of President Hugo Chavez in early March 2013, the large negative 2014–16 terms-of-trade shock and the unprecedented domestic political confrontation amid geopolitical divide that ended in the imposition of escalating sanctions in August of 2017 by a block of western countries and in government duality (from January 2019-February 2024). Rodriguez (2021) and Kronick and Rodriguez (2023) argue that the depression period was a symptom of breaking the country's trade and financial links with the global economy as a result of the decision by political actors to adopt winner-takes-all strategic interactions leading to an equilibrium of political conflict and international economic sanctions with large adverse aggregate economic and social spillovers. The civilian population was mostly impacted by the sanctions, with reduced "public's caloric intake, increased disease and mortality (for both adults and infants), and displaced millions of Venezuelans who fled the country as a result of the worsening economic depression and hyperinflation" (Sachs and Weisbrot, 2019). In this context of chronic fragility and complex interactions within the sociopolitical structure, acute political conflict was an important stressor of the political system over time.

PUBLICATIONS

Political Fragility: Coups d'État and Their Drivers
Working Paper No. WP/24/34