Resilient Democracies

Pablo Beramendi[†] Carles Boix[‡] Daniel Stegmueller[§]

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Abstract

Despite prevalent concerns about elites' attempts to capture democratic institutions potentially leading to their collapse, contemporary democracies seem highly resilient to breakdown. We study the conditions under which backsliding is likely to translate into democratic breakdowns. We focus on inequality and development as the key drivers of voters and elites' incentives, both economic and political, to backslide. We agree with the literature that, on average, inequality fosters social and political strife. However, the incentives of elites to manipulate (and ultimately get rid of) democratic institutions are conditional on a country's level of development. To test our argument, we examine the survival of democracies over the last 100 years using semiparametric survival models. In a novel extension, we also jointly model the co-evolution of backsliding and democratic survival and show that it, too, is conditioned by development.

[†]Department of Political Science, Duke University, Durham, NC, USA. pablo.beramendi@duke.edu

[‡]Department of Politics, Princeton University, Princeton, NJ, USA and IPErG-University of Barcelona. cboix@princeton.edu

[§]Department of Political Science, Duke University, Durham, NC, USA. daniel.stegmueller@duke.edu

1 Introduction

Coinciding with rapid technological change, globalization and rising inequality in the last decades, a fair number of countries have experienced considerable political polarization and various forms of populist challenges to democratic representation. As a matter of fact, several incumbents have been increasingly willing to bend rules and manipulate institutions to retain power—a process known as *democratic backsliding* (Bermeo 2016; Foa and Mounk 2016; Levitsky and Ziblatt 2018; Haggard and Kaufman 2021; Grillo et al. 2024). And yet, despite pessimistic forecasts about the future of democracy, competitive elections and representative institutions have proved quite resilient across the board. Governments continue to be chosen in relatively free and fair elections, parties compete on valence and policy to obtain the support of the majority, and incumbents remain accountable, even if imperfectly, to voters. Figure I plots the evolution of democratic breakdowns in the long run by reporting both the total number of collapses of democracy and the percentage of breakdowns over democratic country−years per decade between 1900 and 2019. The data comes from Boix et al. (2013) as well as Polity V (defining the breakdown as any instance where a country drops both below 6 and below 7 in the polity scale of -10 to 10). Democratic breakdowns peaked in the 1930s and in the 1960s. Following the third democratization wave, they fluctuated around 1 percent of all democratic country-years. This behavior is in line with the recent empirical explorations of Treisman (2023) and Meng and Little (2024) showing that already democratic countries appear to have rather robust representative institutions.

Democratic backsliding, understood as the outcome of a deliberate manipulation of rules, processes, information (media) and institutions by a subset of elites to enhance their relative power (sometimes to the point of suffocating democracy), is hardly new. Hitler infamously used Weimar's own constitutional procedures to dismantle its institutions. Yet he was not alone in the interwar period. Pilsudski's dedemocratized Poland with the support of a broad political coalition that included agrarian, socialist and communist parliamentarians. Dollfuss engaged in a systematic strategy of executive aggrandizement in Austria in 1932-33. Both the Estonian and Latvian prime ministers staged each a self-coup in 1934. A year later, part of the Greek government took over the state in collaboration with the army. Historically, these attempts intensified in periods of high social and economic polarization and often ended in a process of regime collapse. What is new today, and one of the motivations of this paper, is the coexistence of high levels of social and economic stress (including rising inequality) and increasing instances of backsliding with resilient democratic regimes—understood as regimes where parties lose elections and still accept the results and compete again (Przeworski 1991).

In the last decade, democratic backsliding theorists have described the process of democratic degeneration in detail. However, the social and economic conditions under which elites choose

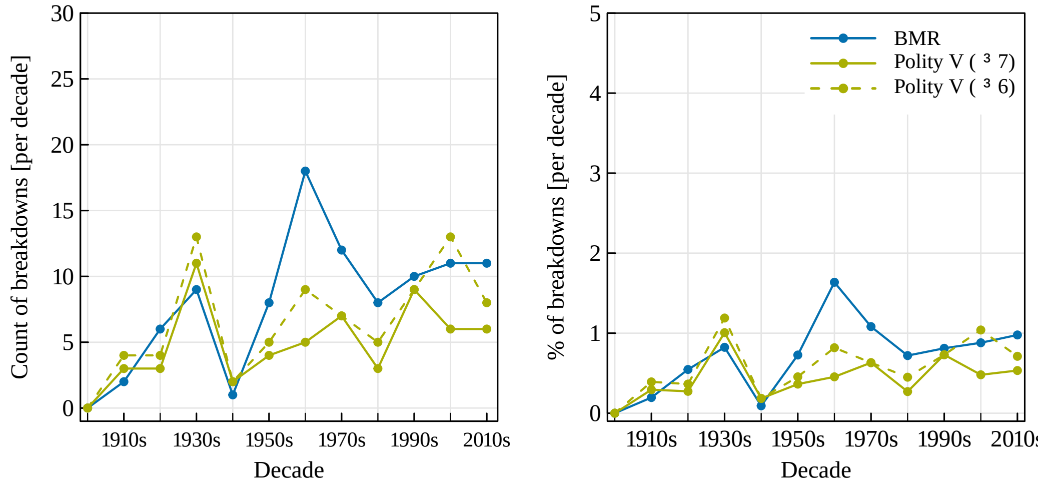


Figure I
Democratic breakdowns, 1900-2019

Source: Boix et al. (2013); Marshall and Gurr (2020)

to undermine democracy remain less well understood, both theoretically and empirically. Here we offer an analytical framework that captures the causes and context triggering institutional backsliding as well as the conditions under which democratic backsliding leads to an actual breakdown of the regime.

We analyze both events as different moments in the life of a democratic regime. Backsliding results from the intentional undermining of rules and procedures to extend the control of power within the regime. It is, as it were, a disease spreading within a living body. In turn, democratic collapse implies the actual death of the constitutional regime governing the polity. More precisely, we model the conditions under which democratic backsliding may happen and the extent to which it may lead to a regime breakdown by taking two main steps. First, we consider the electoral and policy incentives of political incumbents and of voters in a democratic setting. We do this by partly relying on recent work on how political incumbents may engage in democratic backsliding (Bermeo 2016; Svolik 2020; Graham and Svolik 2020; Grillo et al. 2024). Second, we link those incentives (and the choices of incumbents) to the economic and social context in which elections take place. Here, we revisit and amend the existing literature that integrates democratic consolidation with the way in which structural conditions shape regime choices (Przeworski 1991; Weingast 1997; Boix 2003). We then test our argument, which combines earlier studies of democratic breakdowns as the outcome of elites' strategies (Linz 1978) with modern analyses characterizing democracy as an equilibrium (Przeworski 2005), on a panel of sovereign countries that extends over a period of almost 120 years.

In a nutshell, we show that, on average, inequality fosters social and political strife. However, the incentives of elites to manipulate (and get rid of) democratic institutions are conditional on a country's level of development. At low and intermediate levels of development, higher levels of inequality exacerbate distributive conflict to the point of endangering democracy. To maintain themselves in power (and to safeguard the economic interests and policy preferences of their allies), political elites engage in backsliding by manipulating institutions to their advantage. In the extreme, they may support doing away with democracy altogether when they perceived any threat to their position to be existential. In contrast, at high levels of development, efforts to capture rules and institutions, which do, in fact, take place, are unlikely to lead to coordinated attempts to overthrow democracy. Rising incomes attenuate the negative effects of inequality—mainly by reducing the disutility potentially associated with a higher level of redistribution triggered by inequality. This increases social toleration for elections, and stabilizes representative democracies. In short, the level of prosperity in a society modifies the extent to which democratic backsliding actually translates into a full collapse of democracy. Understanding this conditionality helps disentangle the instances under which backsliding makes democracies worse from the conditions under which backsliding makes democracy stop.

We make several contributions to the existing research on the stability and strength of democratic institutions – substantively and methodologically. Theoretically, we integrate current work on democratic backsliding (Bermeo 2016; Mainwaring and Bizzarro 2019; Svolik 2020; Haggard and Kaufman 2021; Meng and Little 2024) and on democratic survival (Miller 2012; Treisman 2015, 2023) as follows. We tie the process of institutional manipulation that political incumbents may engage in to the extent of ideological and electoral polarization of a country, in line with current work by Svolik (2020); Luo and Przeworski (2023); Grillo et al. (2024). We then proceed to endogenize that polarization to changes in both the structure of the economy and the nature of the electorate.

By examining how the social and economic fabric of a given country affects the likelihood of democratic backsliding and breakdown, we shed light on the relationship between economic growth, its social distribution, and democratic stability since the inception of industrial capitalism. While economic inequality erodes democracy—sometimes to the point of collapse—its impact is mediated by the level of development.[5] Our explanation arguably accounts for the absence or short duration of democratic regimes before the second industrial revolution (starting at the turn of the twentieth century) began to equalize economic conditions and put the foundations of the so-called golden age of democratic capitalism. It also connects the most recent democratic strains of advanced countries with the social and economic transformations brought by accelerating technological change and globalization in the last decades. Our model allows us also to situate the

[5]For previous empirical work on the relationship between inequality instability, see, among others, Boix (2003, 2011), Ansell and Samuels (2014) and Haggard and Kaufman (2012) and the work cited therein.

current democratic tensions experienced by the United States in a longer and broader historical perspective. The stability of American democracy (positively noted by some backsliding theorists) that followed the Civil War rested in part on the exclusion of Blacks. Their electoral incorporation following the Civil Rights Act effectively widened inequality within the American electorate and therefore the extent of redistributive conflict. The latter was then compounded by the rise of digital technologies, foreign trade competition and immigration.

Empirically, we do not limit ourselves to recent episodes of democratic backsliding as is common in most recent research. Instead, we examine the fortunes of democratic institutions over more than one century. We depart from the existing literature on democratization by measuring inequality as both a function of the distributions of assets and flows and the relative weight of different assets in the overall structure of production. In addition, taking heed from existing biomedical research, our modeling approach integrates two disparate strands of democracy scholarship (models of symptoms of backsliding and models for the death of democracy) into a joint semi-parametric longitudinal survival model that allows us the study the conditional relationship between backsliding and democratic survival. In those models, we implement flexible semi-parametric duration models that capture the potentially non-linear interplay between inequality and development in shaping the probability of democratic survival over time, while allowing for unobserved heterogeneity and state dependence. It is worth noting from the onset that our findings are robust to the use of different measures of democracy and regime dynamics, including V-Dem. Finally, we develop an approach to account for the potential role of spatial dependencies in our analysis.

2 The Argument

We model the possibility of democratic backsliding and the risk of democratic breakdown (linking both of them as different moments within a range of institutional outcomes) as a function of the behavior of both politicians and voters as follows.

We consider a polity in which voters, who vary in terms of their income, choose, based on their preferences for tax policy, between competing candidates offering different tax platforms. Due to the redistributive structure of taxes, support for higher tax rates declines with the voter's income. Besides proposing a specific tax policy, candidates are associated with some degree of non-democratic behavior. In principle, voters care about democracy but they may tolerate some democratic violations by an undemocratic politician if the latter's policies benefit them financially. Their willingness to accept undemocratic behavior rises with the intensity of their policy and partisan preferences. Hence, as political polarization increases, voters become more willing to support anti-democratic actions to secure their interests. In turn, the extent of political polarization (and, therefore, the level of democratic backsliding and the possibility of a transition to authoritarianism) is shaped by both the level of development and the extent of inequality, which jointly determine the redistributive preferences of voters.[6]

Notice that, in this section, we examine the mechanics of internal (or incumbent-led) challenges to democratic norms and institutions—they have been the main focus of attention of the literature on democratic backsliding. Historically, democracies have also collapsed as a result of actions taken by non-incumbents either in reaction to incumbent actions (such as a military coup) or for reasons unrelated to the behavior of political elites (such as wars or foreign occupation). For the sake of simplicity, we state the idea that 'non-incumbents' may respond to political incumbents to the point of staging an authoritarian coup (and that is could be embedded in our model), without developing it formally.

2.1 Political Economy

To fix ideas, consider a political economy where a finite population of individuals i earn each income y_i (with y potentially varying across individuals). A central authority imposes a linear tax rate on all incomes and, after keeping a fraction σ (for $0 \leq \sigma \leq 1$) of the revenue to pay for some general services, distributes all the remaining revenue equally to all citizens. Formally, each individual's utility from its final income $\hat{y}_i$ will be:

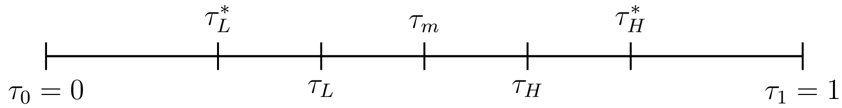
$$U(\hat{y}_i) = (1-\tau)log(y_i) + (1-\sigma)\tau log(y_a) - \frac{log(y_a)\tau^2}{2} \tag{1}$$

where y_a denotes average income, the last term models the distortionary effect of taxes on income, and income is written in log terms to indicate its diminishing marginal utility.[7]

Under the assumption that the fraction σ spent on common services benefits all individuals equally, that is, it is income-neutral, we can set σ to 0 for the purposes of simplification (and without incurring any loss of information). Individual i maximizes income at tax $\tau_i = 1 - log(y_i)/log(y_a)$, where y_i/y_a denotes the difference between individual income and average income. Two features define the relationship between individual income and taxes here. First, i's preferred tax declines with income, reaching 0 whenever $y_i \geq y_a$ (a point at which i becomes a net contributor). Second, and also central to our model and its results, because of income's declining marginal utility, the

[6]The support of citizens may take place by either electoral and non-electoral means. Although we focus here on an electoral model to relate our insights to the recent backsliding literature, its basic intuition can be applied to non-electoral settings too.

[7]Recent work on the relationship between income and life satisfaction has found higher incomes are correlated with more happiness—with the former driving the latter in those cases where individuals get richer by chance (i.e., through lotteries). However, income's contribution to satisfaction has a concave structure, flattening after a given income threshold (Layard et al. 2008; Frey 2008). For recent and more direct evidence (derived from conjoint experiments) that, everything else equal, democracy has a higher value among higher income earners arguably pointing to a decreasing marginal utility structure of income, see Adserà et al. (2023).



τ_m	policy position of median voter
τ_L	policy position of fully democratic candidate L
τ_H	policy position of fully democratic candidate H
τ_L^*	position of partially democratic candidate L
τ_H^*	position of partially democratic candidate H

Figure II
Policy platforms

welfare loss from some fixed τ falls in intensity when income grows.

2.2 Electoral Dynamics

Taxes are determined, in principle, by a policy-maker elected democratically. At election time t_1, two candidates, H and L, compete for office on a single policy issue, the tax rate τ and, therefore, the level of redistribution. Both candidates (one of them already the incumbent elected at election t_0) can be thought of as individuals drawn with equal probability from the pool of all citizens—with H and L drawn from the right and left segments of the policy space with respect to the median voter. As such, they enter the political game with their own ideal tax policy. Because they care about policy (in addition to winning the election) and there is uncertainty about the position of the median voter, their electoral platforms do not converge fully (see Wittman (1983); Calvert (1985); Alesina (1995) for a formal derivation of partial divergence). Accordingly, candidates offer platforms τ_H and τ_L respectively, with $\tau_H > \tau_L$. Figure II draws the policy space and the position of the two policy platforms from democratic candidates, τ_j. The platforms of candidates entering the electoral race vary with the distribution of voters in terms of their preferences: as the latter become more polarized, tax platforms diverge from each other. Once elections take place and voters select one of the two candidates, the winner implements the announced tax rate.

Following Svolik (2020), the incumbent (one of the two candidates) may engage in some manipulation of the electoral process, denoted by μ, where a higher μ implies a more antidemocratic strategy – with μ over some threshold $\bar{\mu}$ implying the collapse of democracy.[8] Take H to be the

[8] This threshold captures Linz's distinction between semi-loyal elites, engaging in strategies and alliances potentially jeopardizing the regime from within, and fully anti-democratic ones, willing to do away with the regime altogether (Linz 1978).

incumbent.[9] Formally, the payoff of voter i is:

$$U_i(\tau_i, \mu_i) = \begin{cases} -(\tau_i - \tau_H)^2 - \delta(\mu_H + \dfrac{\mu_H^2}{2}) & \text{if the incumbent wins} \\ -(\tau_i - \tau_L)^2 & \text{if the challenger wins} \end{cases} \tag{2}$$

where $\delta \geq 0$ indicates the weight that voters attach to democracy.[10] Voter i will vote for candidate H if:

$$-(\tau_i - \tau_H)^2 - \delta\left(\mu_H + \frac{\mu_H^2}{2}\right) \geq -(\tau_i - \tau_L)^2 \tag{3}$$

Solving for τ_i,

$$\tau_i \geq \frac{\tau_H + \tau_L}{2} + \frac{\delta\left(\mu_H + \frac{\mu_H^2}{2}\right)}{2(\tau_H - \tau_L)} \tag{4}$$

To determine the candidates' vote shares and the level of manipulation chosen by the incumbent, consider the indifferent or decisive voter (with an ideal policy τ_d^*) that marginally satisfies expression (4):

$$\tau_d^* = \frac{\tau_H + \tau_L}{2} + \frac{\delta\left(\mu_H + \frac{\mu_H^2}{2}\right)}{2(\tau_H - \tau_L)} \tag{5}$$

Voters vote for their most preferred candidates with some stochastic perturbation ϵ. With policies fixed (as a function of voter (and income) polarization), the incumbent politician only has to choose how much manipulation to engage in and still be reelected. The resulting vote shares of H and L are:

$$\begin{aligned} V_H &= 1 - \tau_d^* \pm \epsilon(\kappa_H) \\ V_L &= \tau_d^* \pm \epsilon(\kappa_H) \end{aligned} \tag{6}$$

where the perturbation ϵ of H is some function of κ_H. Think of the latter as some tools that—even within full democracies—any office-holder or incumbent can take advantage of, e.g., setting the election date or managing policy and business cycles.

[9] Results apply equally to the scenario where L is the incumbent.

[10] Voters may value democracy (denoted by the parameter δ) for two main classes of reasons. The first are normative in the sense that voters see democracy as having an intrinsic value. Within models of democratic backsliding, this is, for example, the route taken by Svolik (2020). The second are instrumental. In this case, although voters could support an authoritarian politician aligned with their interests, they also care about democracy (and prefer democratic politicians) to the extent that it holds the policy-maker accountable and allows voters to achieve better policy outcomes in the future—see, for example Luo and Przeworski (2023) when modeling democratic backsliding. Adserà et al. (2023) (and partly Chu et al. (2024)) show that voters care about democracy as a form of government in the context of conjoint experiments, where respondents choose different societies. Likewise, using candidate choice set-ups, Graham and Svolik (2020), Carey et al. (2022), Gidengil et al. (2022), Frederiksen (2022) and Saikkonen and Christensen (2023) show that toleration for democratic violations varies rather consistently with the severity of the violation, hence pointing to the fact that voters understand the potential effects of manipulation.

The incumbent chooses a total level of manipulation μ to maximize her probability of victory $Pr(V_H - V_L)$. Substituting expression (5) in $Pr(V_H - V_L)$, and maximizing with respect to μ, the level of antidemocratic behavior by H will be:

$$\mu_H = \frac{\tau_H - \tau_L}{\delta} \tag{7}$$

Notice that the platforms of candidates H and L coincide with the ideal policy positions of a low-income (or poorer) individual i^H_{poor} (with income y^H_{poor}) and a high-income (or richer) individual i^L_{rich} (and income y^L_{rich}) respectively. We then can build on (1) to express tax preferences (in (8)) in terms of the income of those voters whose ideal tax rate coincide with each candidate's platform:

$$\mu_H = \frac{1}{\delta} \frac{log(y^L_{rich}) - log(y^H_{poor})}{log(y_a)} \tag{8}$$

The result implies that democratic backsliding (and breakdowns) are a function of three factors:

1. The level of inequality, captured by the gap $y^L_{rich} - y^H_{poor}$, shapes, via the tax and redistribution policy preferences of individuals, the incentives of political elites to pursue non-democratic strategies. The higher the level of inequality, the stronger the incentive to follow a backsliding strategy while retaining enough popular support to win.[11]
2. The level of development (captured by y_a). This parameter works to reduce the incentives to engage in democratic backsliding, even under high levels of inequality. A growing income, due its diminishing marginal utility structure, moderates the welfare losses of taxes and, therefore, the undermining effects of economic inequality on the workings of democracy. For sufficiently high income levels, even with growing inequality (and more potential polarization), democratic institutions do not necessarily collapse—provided $\mu \leq \bar{\mu}$.
3. The third factor of interest, how much weight δ voters put to having democratic institutions also works as a counterweight on the deleterious consequences of inequality. For simplicity we take δ as given.

2.3 The Model in Context: Broad Historical Trends

To elaborate how the model clarifies the relationship between backsliding and the survival of democracy in the long run, and before we test our propositions more rigorously, we discuss our theoretical implications in light of the political and economic conditions that dominated what may be seen as three distinctive periods since the emergence of modern representative democracies.

[11]As we pointed out earlier, a democratic breakdown may result from the actions of non-incumbents elites, from opposition parties to the military, in response to actual or potential backsliding actions by the incumbents. We have not formalized an opposition move in our model for the sake of simplicity.

Low to Medium Development, High Inequality. Prior to the industrial revolution, economies were stagnant, wealth was extremely concentrated, and most of the population lived at the margin of subsistence.[12] The system of privileges, personal favors and side-payments that generated those outcomes was sustained by autocratic political institutions under the control of a narrow elite. At least initially, the first industrial revolution did not reduce existing inequalities (Kuznets 1955). In fact, by encouraging the substitution of unskilled workers employed in the modern factory for artisans working in small workshops, it resulted in lower wages and rising profits (Allen 2009; Feinstein 1998).

Under conditions of high inequality and substantial social and political tensions, both pre-industrial elites and the new industrial capitalists had little incentive to grant influence to broader sectors of society. Political elites extended voting rights to, at most, well-to-do urban strata holding moderate distributive demands and/or engaged in a variety of non-democratic strategies ranging from the coercion of voters and the tampering with election procedures to the direct manipulation of ballots and ballot counting (Mares 2015; Basu et al. 2022).

When fully democratic regimes were established, often as a result of critical shocks such as popular revolutionary events (France in 1848) or military defeat (France in 1870 or the Central empires in 1918), opening the door to popular and progressive forces that advocated the radical overhaul of the economic and political system, political elites (and the societal groups behind them) bet on the complete suspension of electoral processes, supporting fully authoritarian (and, sometimes, totalitarian) movements. Already in 1850, the French National Assembly voted to exclude half of the electorate, Thiers' "vile multitude", from the ballot box. A year later, Louis Napoleon staged a self-coup that would end up in a monarchical restoration. In response to the political violence unleashed by the Paris Commune of 1871, the founders of the Third Republic, among them Thiers, who would become its first president, established a conservative order based on an exaggerated overrepresentation of conservative rural interests in the Senate. In the interwar period, substantial wealth disparities and the economic and social dislocations generated by war led the formation of mass socialist and communist movements, the countermobilization of fascist parties, extreme political polarization, and the eventual breakdown of democratic regimes in Central, Eastern and Southeastern Europe (Linz 1978; Luebbert 1991).

High Development, Equalizing Conditions. A second industrial revolution, triggered by the extensive use of electricity and the invention of mass production techniques, eventually attenuated the economic inequalities and social tensions of nineteenth-century capitalism. Starting at the turn

[12]Employing income distribution data for 28 preindustrial societies, Milanovic et al. (2011) estimate that elites captured over two thirds of all the resources available after excluding the total sum of the minimum subsistence wage for all the population. Right before the French Revolution, the French top decile received 55 percent of all income (Morrisson and Snyder 2000).

of the twentieth century and over the course of several decades, semi-skilled and skilled employees replaced unskilled workers as the main type of labor. Wages grew across the board, particularly among middle social strata. Average income growth accelerated and the distribution of earnings became more equal. In addition, the consolidation of moderate levels of fiscal progressivity after World War Two and the expansion of public services helped to curb inequality.[13] The political strife of the past gave way to political moderation, catch-all parties, and a robust social consensus around the value of elections. Non-democratic interludes in advanced industrial economies were rare and brief. De Gaulle's soft 'coup' of 1958 responding to the Algerian war resolved itself in a new constitution and the call for elections in a matter of months.

High Development, High Inequality. The so-called golden age of democratic capitalism started to unravel at some point between the mid 1970s and the collapse of Soviet Union. The introduction and development of digital technologies (computer systems, software, mobile telephones, robotics, AI, etc.) affected employment and wage structures in critical ways. Computerization allowed firms to reassign many routine tasks performed by humans to machines, reducing the demand for middle-skilled workers while increasing the need for high-skilled workers (Cortes et al. 2017; Katz and Margo 2014). In addition, digital technologies cut communication costs, enabling the emergence of global value chains (where production has often been relocated to the Global South), deepening globalization, and further eroding the position of low-skilled workers in the North. A changing labor market went hand in hand with a shifting wage and income distribution. Labor productivity and median earnings, which had trended together until 1975, diverged afterwards. While wages for US workers dropped in real terms for individuals in the bottom quintile of the earnings distribution and stagnated for those around the median, they doubled for individuals with postgraduate education (Autor 2010). In addition, the rising financialization of capital exacerbated earnings inequality. A more mobile capital dented the capacity of the state to tax an important fraction of wealth holders (Atkinson 2015; Zucman 2015).

As economic inequality and social polarization rose, politics grew contentious again. Policymakers and economic elites redoubled their efforts at controlling specific mechanisms of policy influence, lobbying the state regulatory machine, and/or capturing judicial arbiters. Recent attempts to control election boards and courts in the United States illustrate this tendency. Parties began to tamper with electoral procedures to undercut the opponents' mobilization capacity, as illustrated by the proliferation of gerrymandering also in the United States. Nevertheless, it is unclear that the political consequences of ever-growing levels of inequality are mirroring those of the interwar period (Figure I). Higher levels of average income have attenuated the existential threat that democracy poses to their economic and political elites, arguably decoupling the process

[13] The Gini coefficient, which was around 0.5 or higher in the late nineteenth century, declined in North Atlantic economies throughout the middle decades of the twentieth century to about 0.3.

of democratic backsliding from the full breakdown of representative institutions.

2.4 Summary of Testable Implications

To summarize, our argument about the relationship between development, inequality, and the crises of democracy yields the following testable implications:

1. The (negative) relationship between inequality and the survival of democracy is conditional on the level of development. As development increases, the association between inequality and the risk of a democratic breakdown declines.
2. The relationship between economic inequality and democratic backsliding is conditional on the level of development. As development increases, the association between inequality and the incidence of democratic backsliding declines.
3. By implication, the link between democratic backsliding and the breakdown on democracy is conditional on the level of development. The higher the level of development, the weaker the link between the two.

3 Inequality, Development, and the Crisis of Democracy in the Long Run

We turn to examine our theory more systematically, through a battery of econometric tests employing a data set that covers the lifetime of political regimes from 1900 to 2019.[14] Appendix A provides details on data sources and calculations as well as descriptive statistics for all variables included in our analyses. It is important to note that when studying regime survival, the correct unit of analysis are country spells of democracy. For example, a survival analysis of democracy in Germany includes the first spell of democracy during the years of the Weimar Republic and the second spell of democracy beginning in 1949, but it excludes the autocratic spell under the Nazi Regime. In other words, analyses of democratic breakdowns should only include spells where democracy is actually at risk. Appendix Table A.2 illustrates the resulting data structure. All our survival analyses account for the fact that countries can experience more than one spell of democracy.

Our key explanatory variables of interest are development and inequality. To capture development we employ the log value of real GDP per capita in Maddison's historical data set (Maddison 2010). Measuring inequality over a long time-span is far more challenging. The period of interest involves several waves of industrialization, which have taken place at different times across world regions (Beramendi and Rogers 2022), as well as, in recent decades, the rise of the digital economy and the spatial reallocation of manufactures around the world.

[14]While our data on political regime type covers 1800 to 2019, we focus on the post-1900 period, because some important covariates (most notably, agricultural employment shares used in the construction of our measure of inequality) are not available in prior years.

This has direct implications for how we measure inequality. Over the long run, overall inequality is a complex phenomenon that reflects three dimensions: the relative importance of factors (land, capital, labor) in the economy, the distribution in the ownership of land and capital, and the distribution of income derived from each. In an ideal world we would have precise measurements of each of these dimensions of inequality. It is a well known fact in comparative research that we are forced to work with imperfect data to approximate these distributions across units and over time.

In the absence of comparable micro-data covering the whole period, we propose the construction of a measure of overall inequality (g_t^o) that captures each of these dimensions. Our approach captures the insights of Smith, Ricardo, and to a large extent Marx, for whom inequality was determined by the weight of each factors of production, under the assumption that land, capital and labor were internally homogeneous. However, with modernization, this assumption needs to be relaxed as the returns to labor and capital have a higher variance. Accordingly, we strive to capture their internal dispersion as well. The main advantage in this approach is that it allows us to approximate both changes in the sectoral composition of the distributions of income and wealth and changes in the distribution of returns within sectors. This is an important feature given the period (1900-2020) for which we study the political implications associated with the evolution of inequality. The measure integrates several components and captures how their relative importance changes over time.

First, we (partially) capture the distribution of assets through a measure of the distribution of land property. Empirically, we employ the index of rural inequality (g_t^r) developed by (Ansell and Samuels 2014: p.116). Second, we capture the distribution of income derived from each type of asset through an index of income inequality (g_t^i) that captures the distribution of income from all sources (returns to land, returns to capital, labor wages), using data from the Standardized World Income Inequality Database (SWIID), which covers 1960 to 2020 (Solt 2019). For countries where we need inequality data before SWIID coverage begins, we extrapolate (predict) the inequality series using a Bayesian semi-parametric time-series model described in more detail in Appendix A.4.[15]

Finally, we weigh each measure by the relative importance over time of land as share of the economy relative to other forms of industry and capital. We weight g_t^r by the share of labor working in the agricultural sector (Wingender 2014), denoted by π_t and g_t^i by the complementary share of workers working in industry and services. This allows to incorporate the changes in the structure of factors in our measure of inequality. Our index of overall inequality, $g_t^{(o)}$, is

[15] We conduct several specification analyses of this model (Appendix A.3.2) and we provide results for extrapolation models that employ additional information on changes in the income share of the Top-1 percent. In Appendix A.3.4 we provide a range of survival estimates delaying the starting point of the analysis (so that the fraction of extrapolated inequality information is reduced). We also compare our measure to the high-quality subsample of the Deininger and Squire (1996)'s inequality database (the correlation is about 0.8; see Appendix A.3.3).

therefore the weighted sum of income inequality and rural inequality, where the weights capture the changing importance of the agricultural sector (AES) over time:

$$g_t^o = \pi_t g_t^r + (1 - \pi_t) g_t^i. \tag{9}$$

The measure is necessarily conditioned by the implicit assumptions in the construction of each of its components, including the extrapolation of missing data. Critically, our results are robust to alternative choices on both dimensions and do not hinge on any specific definition, assumption, or extrapolation choice. In the analyses that follow, we also conduct robustness test showing that our results are substantively similar when only employing a measure of income inequality instead of our measure of total inequality (see Appendix C.6).

3.1 Inequality, Development, and Backsliding

We proceed to test our hypotheses in three sequential steps: we examine first the covariates of backsliding; we move, in the following subsection. to examine the factors behind the survival of democracies; and we conclude by exploring the relationship between backsliding symptoms and democratic collapse.

According to the literature on democratic backsliding, democracies may perish not by a sudden collapse of the overall institutional framework but through the accumulation of small acts by key players, acts that slowly undermine the very fabric of free and fair elections and democratic norms (Bermeo 2016; Levitsky and Ziblatt 2018). The key idea here is that, in isolation, these acts do not constitute a collapse of democracy per se, but that, cumulatively, they lead to its potential death in ways that are undetectable to analysts with a radar biased towards the old forms of institutional crises. Heeding this literature, we first analyze a dependent variable generally understood to be a key *symptom* of democratic erosion: the refusal of losing parties or candidates to accept their electoral defeat (Meng and Little 2024). Without losers' consent, there is no explicit agreement that the rules of the game are widely accepted by all parties and, therefore, democracy is unlikely to remain in place. We also analyze four other indicators of democratic erosion, including the freedom of elections and judicial independence.

We estimate a series of models relating the backsliding indicators to levels of inequality, development, and their interaction. Losers' consent is defined as the losing parties or candidates accepting the result of an election within three months of its occurrence. Values for each country-election pair are based on expert ratings collected by the V-Dem project. Model details for all indicators as well as estimates are available in Appendix B.1. Here we present graphically the results of three specifications, all of which are linear models with two-way fixed effects (for country and year) with robust standard errors. Panel (a) of Figure III shows the first specification, which only includes basic controls capturing societal conflict (V-Dem's level of societal polarization) and a measure of the equal distribution of resources. We plot the marginal effect of inequality (with 95% confidence intervals) at varying levels of logged GDP per capita on the lack of consent. We find that at low levels of development increasing inequality raises the extent to which election losers refuse to acknowledge election results. However, the impact of inequality diminishes as development increases. In highly developed societies, the marginal effect of inequality is statistically indistinguishable from zero. Note that the transition takes place in an area with data support in the conditional variable, and that, therefore, it is not an artifact of the declining number of observations at the tail of the measurement of development. Overall, the findings on loser's consent follow a very similar pattern than the ones on binary definitions of democracy.

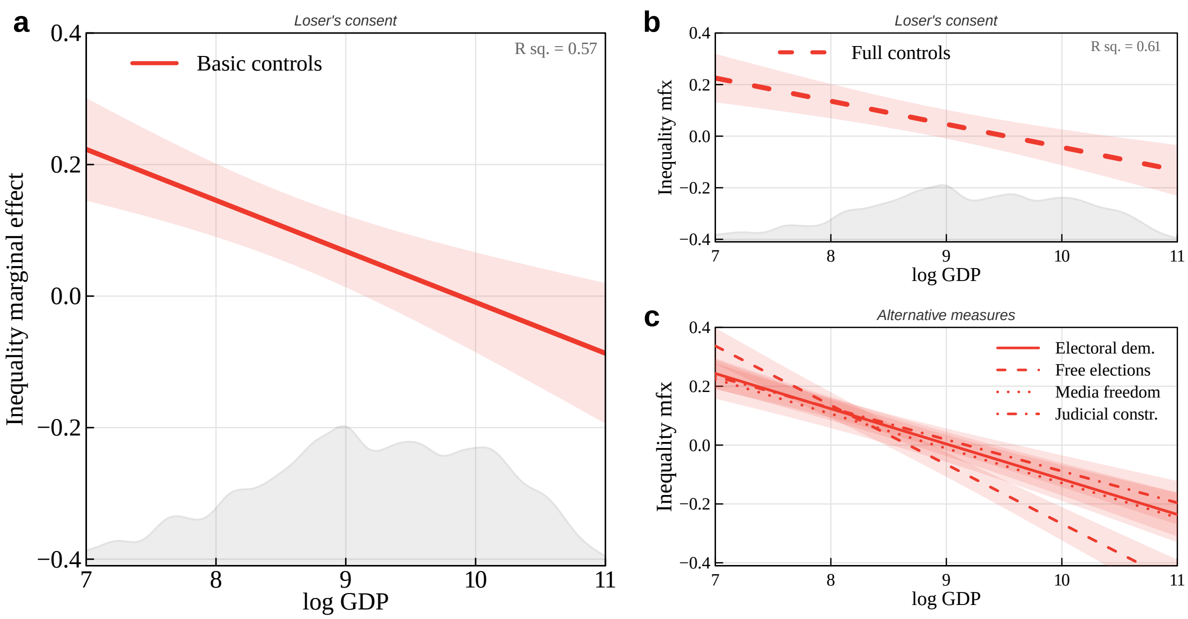


Figure III
Marginal effect of inequality on democratic backsliding at varying levels of development

This figure plots the marginal effect of inequality over the range of logged GDP per capita (density shown as shaded polygon). Based on linear two-way fixed effects models. 95% confidence interval calculated from robust variance covariance matrix. The shaded polygons show the density of logged GDP per capita in the respective estimation sample. Panels (a) and (b) display effects for lack of losers' consent, while panel (c) shows four alternative popular V-Dem measures of backsliding (cf. Appendix B.2).

In panel (b) we add a number of controls: average education, the percentage of enfranchised adults, and two indexes capturing the extent to which all social groups equally enjoy civil liberties and access to government jobs. This extended model shows the same pattern of a decreasing corrosive effect of inequality at increasing levels of development.

Even though the lack of consent from electoral losers is one fundamental feature or symptom of democratic backsliding, there are other signs of democratic erosion, such as encroachments on the separation of power, political attempts at controlling the media, or strategizing to undermine the opposition. Accordingly, panel (c) repeats the analysis in the previous panel using four different V-Dem indicators of democratic backsliding: the high-level measure of electoral democracy and two of its subcomponents: indices of free and fair elections and of media freedom, and finally an index capturing judicial constrains on the executive. The model and set of controls is as in the previous panel. We find that both the negative impact of inequality and the moderating effect of development apply to these other measures as well (Appendix B.2 provides more details and estimates).

3.2 Democratic Survival

We now turn to a set of analyses that focus on *survival* of democracy. Our models relate the instantaneous rate of survival of democracy at a point in time to changing inequality and development. We estimate a range of flexible proportional hazard models, where the baseline hazard of democratic survival is estimated semiparametrically (Royston and Parmar 2002), and we adjust for both time-constant and time-varying confounders. For presentational reasons, we focus on graphical display of key quantities of interest. Appendix C provides model details and maximum likelihood parameter estimates (see Table C.1). There we also show that our results are substantively robust to both relaxing the proportional hazard assumption and estimating the model using the popular Cox proportional hazard formulation. Appendix C also shows that accounting for country "frailties"—the fact that unobservable characteristics (such as civic culture or institutional legacies) make some countries more or less susceptible to democratic failures—does not change our key results.

All our models include fixed effects for major political world regions (see A.1 for their definition) in order to allow for potential spatial clustering in the evolution of political regimes during certain periods (e.g., West-European transitions or crises of democracy in Latin America). In extended analyses (further below), we will explicitly account for spatial correlations in unobservables. All our models include a variable capturing a country's (running) number of past democratic breakdowns in order to account for the fact that the experience of past breakdowns might affect the probability of future failures. Standard errors and confidence bands are based on robust variance-covariance estimates.

We display predicted (democracy) survival functions at various levels of development and inequality, which are the key quantities of interest of our analysis, in Figure IV.[16] Panel (a) plots the effect of a one standard deviation increase from median levels of total inequality and real

[16]The graphical representation of results is easier to interpret than raw coefficient estimates or hazard ratios (for an excellent exposition of the latter point see Hernán 2010).

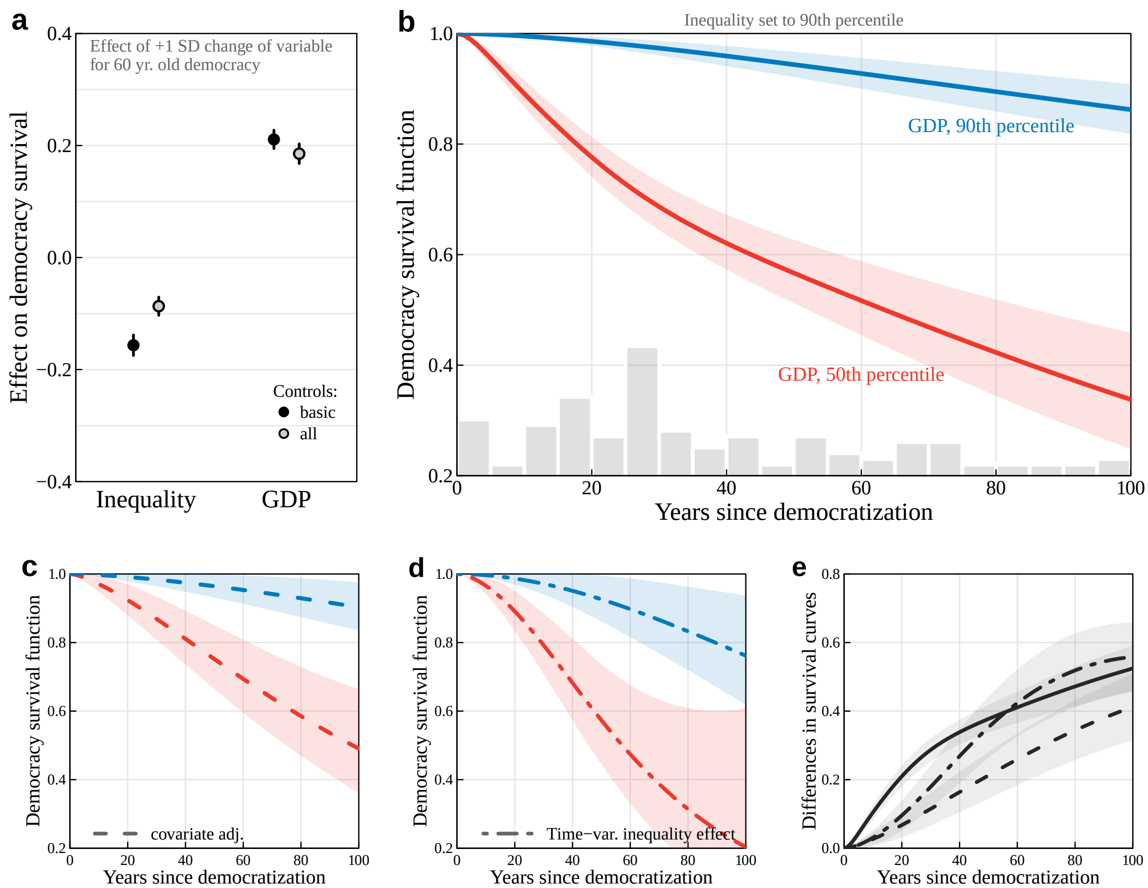


Figure IV
Inequality, Development, and Survival of Democracy.

Survival predictions from flexible proportional hazard model with baseline hazard rate estimated via cubic regression splines (*df=3*). Panel (a) plots the effect of a standard deviation increase from median levels of total inequality and GDP, respectively, on the predicted survival of a mature democracy (a democracy of 60 years without a previous breakdown). Panel (b) examines the impact of high inequality (90th percentile) on the over-time survival of democracies via conditional survival curves (see Appendix C.2 for their definition and calculation) and corresponding 95% confidence intervals with GDP fixed at the 50th and 90th percentile, respectively. Panel (c) adds a larger set of controls (see text). Panel (d) relaxes the proportional hazard assumption by allowing for time-varying effects of inequality. Panel (e) plots differences (with 95% confidence intervals) of conditional survival curves, i.e., the change in survival probability when moving GDP from the 50th to the 90th percentile conditional on high inequality. Distribution of democracy spell durations (in 2018) shown as gray histogram.

income per capita on the predicted survival of a mature (60-year-old) democracy. We find that higher levels of development have a strong stabilizing effect. Inequality has the exact opposite effect. Panel (b) turns to examine the impact of (high levels of) inequality at varying development stages. The likelihood of democratic survival falls below 0.8 after 20 years in a country with inequality at the 90th percentile in the world distribution and a real per capita income equal to the world median. By contrast, it stays close to 1 in a country with the same level of inequality but a per capita income at the 90th percentile of the world distribution.

Panel (c) again displays the survival function of a high inequality society with per capita income at the 90th and 50th percentile after adding a set of controls capturing observable differences in social and economic development: average years of education, a measure of the abundance of natural resources (a country's petroleum, coal, natural gas, and metals production), and an indicator for a country's involvement in an armed international conflict. Furthermore, we include two V-Dem measures capturing the equal distribution of resources in society (an index including particularistic public goods provision and inequalities in health and education) as well as societal polarization (see Appendix A.1 for sources and details). We find that the resulting covariate-adjusted survival functions do not differ substantively. Panel (d) relaxes the proportional hazard assumption by allowing for time-varying effects of inequality. Again, we find our basic pattern confirmed. However, the predictions now carry considerably more uncertainty. So far, we have examined the contrast between median and high GDP societies graphically (by contrasting the two survival curves). A more formal test can be conducted by calculating the difference of the two curves. Accordingly, panel (e) shows estimated differences in survival curves (between the 50th and 90th percentile of development) for all previous models together with their corresponding 95% confidence intervals. In all cases, we see that the difference in statistically different from zero along the (predicted) life-cycle of a democracy. This indicates that development acts as a statistically significant moderator of the inequality effect, thus limiting the corrosive effect of inequality on the survival rate of high income democracies.[17]

Figure V presents a more fine-grained analysis of the interplay between inequality and development. We estimate a duration model with a tensor product of semiparametric inequality and GDP terms. This setup estimates the smooth interaction surface of inequality and development in shaping the probability of democratic survival. The underlying spline terms are penalized cubic regression splines. By avoiding too abrupt function jumps, this penalization, which is estimated from the data, enables a more meaningful interpretation of the plot. Appendix D presents the model in detail. The z axes of Figure V report the probability of a breakdown in the full range from 0 to 1 for combinations of semi-deciles of development and democracy, reported on the x

[17]Appendix F reports our estimations restricting the democratic spells to those where women had the right to vote. Finally, Appendix G estimates our models employing a measure of democracy based on the Polity 5 database.

and y axes, respectively. The specification in panel (a) adjusts for previous democratic breakdowns and includes political region effects. We find that in highly developed, relatively equal economies, the probability of a democratic breakdown is essentially zero. As inequality increases, the collapse of a democracy becomes increasingly likely. However, for wealthy countries, the negative impact of inequality kicks in relatively late and is of a more moderate magnitude. In contrast, democratic regimes in poor countries are highly unstable, even when inequality is low. The combination of poverty and high inequality is associated with a high risk of democratic breakdown.

The specification underlying panel (b) is more involved. It includes country frailties or random effects because some countries might be more prone to experience democratic breakdowns (i.e., be more "frail") than others based on unobserved or unmodeled characteristics. For details on the random effects specification, see Appendix D. The predicted survival probabilities from this extended specification confirm our finding that higher levels of GDP limit the corrosive link between high inequality and democratic failure. Indeed, when accounting for country unobservables, the moderating role of development is even more marked: at the highest decile of GDP per capita, the probability of a failure of democracy is rather low in both societies with low and high levels of total inequality.

In Appendix D.1 we present a further extension of this analysis, where we allow for spatial correlation in country unobservables. Thus, the model allows for the fact that the unobserved characteristics that put a country more at risk of democratic breakdown are correlated with unobserved at-risk characteristics of other countries that are close in space. This analysis reveals a rather similar substantive pattern to the one discussed here.

3.3 A Joint Model of Backsliding Symptoms and Democratic Survival

In the previous subsections we have studied how inequality and development shape symptoms of democratic backsliding (such as losers' consent to election results) as well as the predicted survival of democracies. We now turn to a further implication of our argument: the relationship between symptoms of democratic backsliding and the ultimate collapse of a democratic regime. We examine if (and by how much) increases in democratic backsliding translate into an increasing risk of democratic breakdown. To do so, we specify a Bayesian joint longitudinal survival model, which simultaneously models both the dynamic evolution of backsliding and the survival of democracy. We specify this analysis in two ways. In the first, we capture backsliding simply as lack of losers' consent to election results. In the second, we employ a measurement model that combines the four indicators of backsliding (free and fair elections, judicial independence, media freedom, electoral democracy) used previously into one measure. The substantively important estimate arising from the joint model is the parameter that links the two processes. This setup is borrowed from the medical literature, where it has been employed to evaluate the relationship of

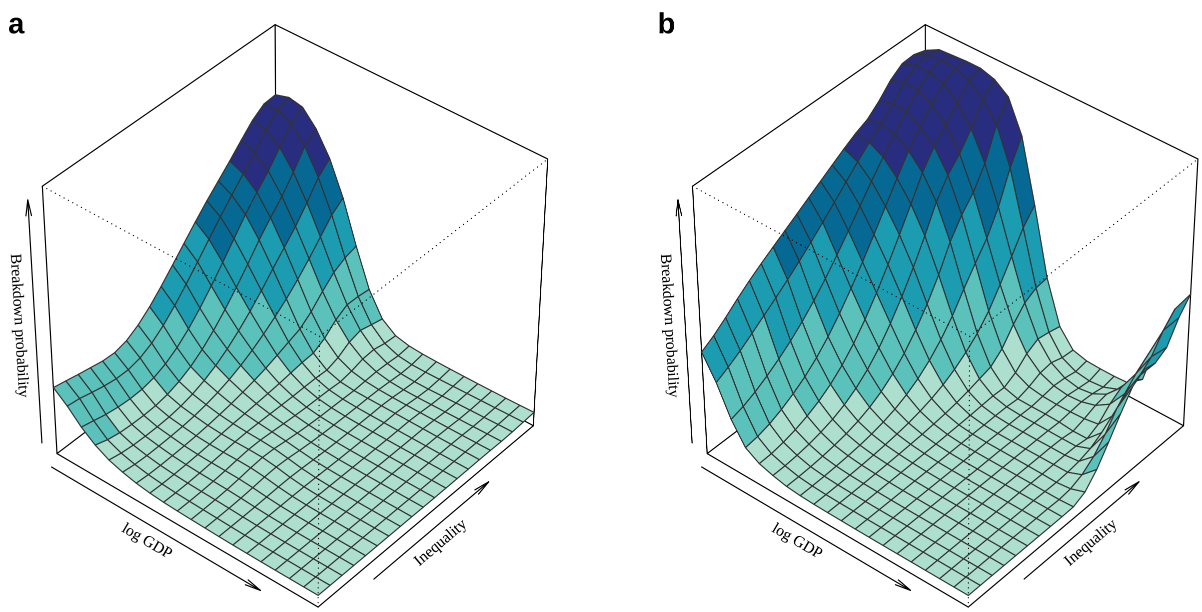


Figure V
Probability of democratic breakdown for semi-deciles of inequality and GDP.

This figure plots the interaction surface of the probability of a breakdown ($1 - P(T > t)$) for a democracy of median age (that has not previously failed) both without (a) and with (b) country frailties. Both the GDP and inequality axis are subdivided into semi-deciles yielding predicted non-survival rates in 400 GDP–inequality cells shown on the z-axis (ranging from 0 to 1). Calculated from a semi-parametric model using a tensor product of cubic penalized splines of inequality and GDP (cf. Appendix D). The model generating panel (a) adjusts for previous failures and includes political region effects. The model generating panel (b) includes a complete set of country frailties (specified as Gaussian random effects.)

changing biomarkers and the onset of disease (e.g., Lawrence Gould et al. 2015; Köhler et al. 2017; Rizopoulos 2023).

Our model has two important features. First, it takes into account that backsliding indicators are measured with error and models the evolution of the underlying smooth trend of democratic erosion. It considers also the heterogeneity in backsliding dynamics across societies and time by estimating country-specific non-linear trends using functional random effects (Guo 2002). Second, we specify the parameter linking the process of democratic erosion to the survival of democracy as a (possibly nonlinear) function of development. This allows us to examine if the relationship between backsliding and democratic failure is conditioned by levels of development as stated in our second hypothesis. A full description of the statistical model, its assumptions, and its estimation can be found in Appendix E.

Figure VI plots the parameter linking the process of democratic erosion to the hazard rate of democratic failure (on the y-axis) as a function of development (on the x-axis). Clearly, the relationship between backsliding and the risk of regime breakdowns is not constant. At low levels

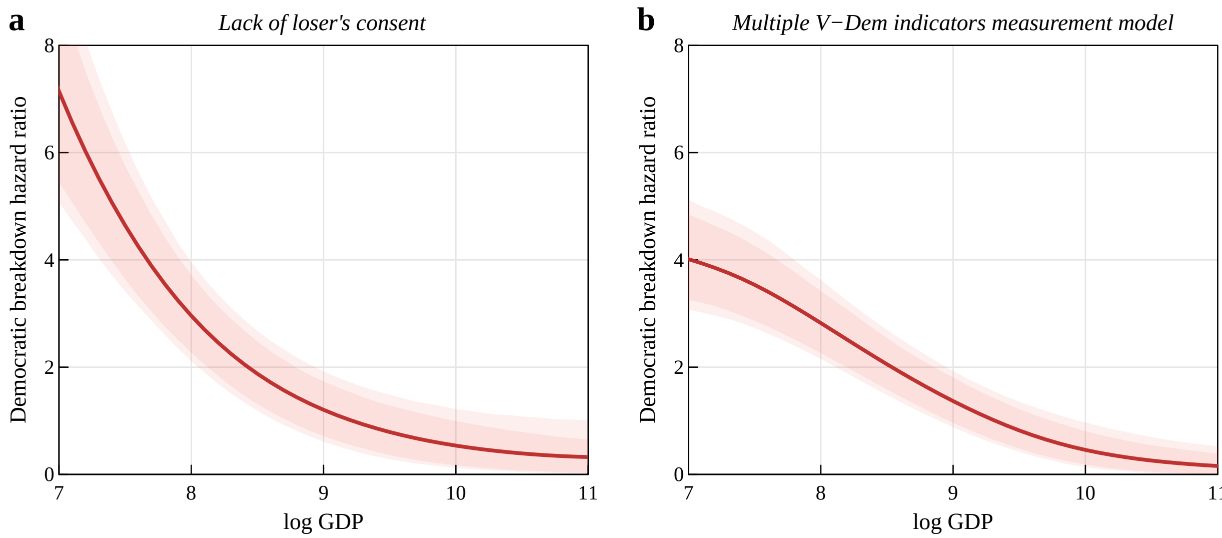


Figure VI
Association between backsliding and democratic failure as function of development.

This figure plots the relationship between indicators of democratic backsliding and the hazard ratio of democratic breakdown as a function of logged GDP per capita estimated via a joint Bayesian model of a semiparametric longitudinal process and survival outcomes. See Appendix E for details. Panel (a) uses a single indicator, lack of losers' consent to election results. Panel (b) combines four backsliding indicators via a dynamic semiparametric measurement model. Shaded areas represent 95% credible intervals.

of development increasing democratic erosion poses a great threat to the survival of democracy (note that our sample contains only few observations with very low levels of development). Even middle income democracies, up until a GDP per capita of about US$ 18,000, are at risk of democratic breakdown as backsliding intensifies (with hazard ratios between 2 and 4). On the other hand, and in line with the hypothesis developed in section 2.4, for democracies with a GDP per capita above US$ 30,000 the relationship between incumbents' refusal to accept defeat and the ultimate survival of democracy is much more limited.

4 Concluding Remarks: Backsliding and Democratic Resilience in Context

We close with a general reflection on the implications of our findings for the "crisis of democracy"—an expression that has come and gone from the academic scene several times in the last decades.[18] A majority of today's crises appear to be internal, set off by the decision of political incumbents to undermine democratic institutions and norms from within. In an increasingly polarized environment, political elites begin to perceive adversaries as enemies, questioning the shared norms that sustain democracy—mainly, toleration for rivals as well as respect for the

[18] For one of its first incarnations, see Crozier et al. (1975)

principle of fair elections, and the peaceful transition of power. What previously consisted of a shared ideational and institutional ground unravels and politics turns into the manipulation of norms (such as electoral procedures) and the capture of institutions (such as the judiciary). Slowly, democracies degenerate and death creeps up silently, until it may be too late to prevent it.

This process of democratic degeneration has well described by democratic backsliding theorists (see, among others, Bermeo (2016); Levitsky and Ziblatt (2018); Haggard and Kaufman (2021)). Yet, the conditions under which elites choose to undermine democracy, that is, the scope conditions of democratic backsliding and breakdown, remain less well understood. There is no gainsaying that politicians want to maximize power and to hold it with no temporal limits – for its own sake or to achieve policy goals they deem relevant. As recently put by Przeworski (2019: 19), "the dream of all politicians is to conquer power and to hold on to it forever". Yet, if that were the original cause of manipulating electoral institutions, we should see backsliding everywhere and at all times. This, however, we do not. Many countries have democratized in the last decades. Most of them, at least in developed regions, still enjoy robust liberal institutions. Hence, democratic backsliding, if and when it exists, requires that (naturally power-hungry) politicians operate in a permissive context—an institutional or economic setting facilitating the success of authoritarian practices.

In this paper, we have provided an analytical framework to understand the conditions under which elites' anti-democratic practices are more likely to emerge and, ultimately, lead to a full democratic breakdown. We have theorized backsliding as a continuum that goes from the strategic undermining and capture of institutions and norms to, at the extreme, the refusal to accept electoral defeat and the removal of free and fair elections as a mechanism for the selection of rulers. This is the point we consider democracy, in a minimalist sense, to break down (Linz 1978; Przeworski et al. 2000). We have then tied the incentives and behavior of politicians to the political and electoral environment in which they operate. The level of development and the incidence of inequality condition the latter and, hence, through the incentives and the strategic interactions of elites, the health and ultimate survival of democracy as a regime.

Building on a new approach to measure inequality in the long run, we have reached three main conclusions. First, inequality incentivizes elites to engage in democratic backsliding across a broad range of measures. Second, the link between inequality and backsliding weakens at higher levels of development. Adjusting duration models to account for prior instances of democratic breakdown, we find that inequality increases the likelihood of democratic collapse, but, again, only at low and intermediate levels of development. Our results are robust to region and period fixed effects and to a wide range of period, measurement, and specification choices. Finally, we model explicitly, in the context of the duration framework, the conditions under which instances of democratic backsliding actually lead to a breakdown of the regime. We establish that the deleterious consequences of backsliding for the operation of representative democracies translate into actual regime collapse primarily at low (and perhaps middle) levels of development. By contrast, at high levels of development, democratic backsliding is not only less prevalent but also less likely to lead to a full collapse of democracy. Unequal democracies are more prone to experience political turmoil and to see their elites engage in undermining democratic institutions. Yet whether those tensions lead ultimately to the collapse of the regime depends on the level of development.

Beyond addressing current debates on democratic backsliding, we believe that our analysis sheds light on two important topics in the discipline: the nature of democratic crises under different historical conditions; and the evolution of democracy in the United States. In his groundbreaking study on the breakdown of democracy, Linz (1978) claimed that, given comparable levels of prosperity, democracies were more prone to collapse in countries where both the left and the right saw representative democracy as a tool to pursue forms of social and political organization that transcended democracy itself. Yet Linz's work captured the relationship between democracy, development and elite behavior only partially. His study, focused on Europe's interwar period and several Latin American countries, examined what, from our vantage point, were still middle-income countries. Today's fully developed economies are five to six times richer, in per capita terms, than they were before World War Two. In the 1930s, both communism and fascism challenged young democracies. Overwhelmed by a massive economic crisis and still in their path to full development, many collapsed. They were Carl Schmitt's "democracies without democrats," threatened by organized forces that, both from the left and the right, proposed alternative political and economic regimes. In today's democracies, the extreme left are the old social democrats. With most electors much richer than in the past and with welfare programs that shelter them against economic volatility and the risks inherent to their life cycle, there is a strong social consensus around the institutional pillars of democracy. Indeed, our results, based on a more comprehensive sample than Linz', show that democracies functioning at high levels of development are more likely to survive even under high levels of inequality.

Our approach also allows us to situate the current democratic troubles in the United States within a longer historical perspective. Part of the country's institutional stability and elite forbearance (praised by some backsliding theorists) that prevailed until the 1970s rested on the federal acquiescence to the tampering of voting rights in the South. The exclusion of the majority of Black Americans effectively compressed or equalized the income distribution of the enfranchised electorate. In 1960, the median Black man's earnings corresponded to about the 25th percentile of the white earnings distribution and the 90th percentile man in the Black earnings distribution was ranked at slightly above the median of the white earning distribution (Bayer and Charles 2018). Recent work on the historical distribution of wealth among Black and white Americans shows that the ratio of the average wealth of Black Americans and white Americans wealth ratio was at around 7:1 and that the median Black household was at the 20th percentile of the wealth distribution of white households in the 1950s (Derenoncourt et al. 2023). The passage of the Civil Rights Act triggered the electoral realignment of the American South and a process of political polarization that, at least at the legislative level, had been previously absent. To put it in terms of our theoretical model, the electoral incorporation of Blacks expanded the franchise mainly among the poorest strata of Americans, increasing the level of inequality within the electorate, and, therefore, the demand for higher levels of redistribution. In the following decades, globalization and the rise of digital technologies, which we described in subsection 2.3, would exacerbate that inequality, eventually intensifying political disagreement.[19]

Our empirical results lead us to be cautious about the gloomiest positions espoused by some backsliding voices. Postindustrial democracies are characterized by conditions, in terms of wealth (and the kinds of public welfare or compensatory institutions and policies wealth can buy), that should shelter them from democratic collapse. Consider the political ramifications of the Great Recession of 2008-9 in a comparative perspective. As Bermeo and Bartels (2014: 2-3) note, they "appear a good deal less momentous than those of the Great Depression era"—with "popular reactions (...) surprisingly muted and moderate". Economic losses were inflicted on individuals with much higher living standards. Perhaps more fundamentally, governments could afford a massive level of governmental intervention that did not meet with any of the resistance it did seventy years before.

All this does not mean, however, that democracies may not eventually deteriorate, even to the point of collapse. If they do, we believe that this process will happen through two potentially different paths – worth exploring in future research. The first one falls squarely within our theory. A significant increase in inequality could cancel out the attenuating effects of development. Inequality could be the result, in turn, of either a growing labor supply (and a concomitant fall in wages) due to immigration and globalization or to a process of capital-labor substitution driven by automation (Boix 2019). (Notice, however, that this outcome is to a great extent endogenous to politics. Policy-makers may establish mechanisms to address the sources of that 'crisis', for example, curtailing globalization, if that is what generates most anxiety among voters. They could also employ the massive wealth of today's advanced countries to compensate the losers of economic change.) The second path lies outside our modeling choices, which emphasized economic considerations and relied on a one-dimensional policy space. The rise of a highly polarized second dimension, say around cultural and social issues or on climate change, could push both incumbents and opposition to engage in institutional manipulation. Here, economic growth would not be able to reduce their incentives – either because it can not compensate losses on a cultural issue or

[19]See McCarty et al. (2016) for the effects of a change in the US voting population on tax policy outcomes.

because it would be directly in conflict with environmental concerns.

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Supplementary Material

Contents

A. Data details

A.1. Data sources

Our base data set is created starting from a regular grid of countries from 1800 to 2019 to which we merge several data sets of regime classifications and covariates (not all countries provide information on all years). From this we create the analysis dataset used in our survival analyses and the analyses of losers' consent. The analysis dataset contains country-years between 1900 and 2019 for which a country is a democracy (i.e., it is at risk of democratic breakdown). Below we detail the data sources for our key variables and controls.

Regime status Data on regime status is taken from Boix et al. (2013), version 3.0 updated to cover years until 2019. An alternative classification used in some of the robustness tests is based on the Polity5 database. Here, a country is classified as a democracy if its polity score is greater or equal to 6 on the -10 to 10 polity score.

Development (GDP) Our measure of development is a country's real gross domestic product per capita (in 2011 USD) based on the Maddison project database, revision 2020 (Maddison 2010; Bolt and van Zanden 2020). We interpolate missing observations in a country-time-series using a flexible semiparametric model (with model terms tailored to each specific country) described in more detail in subsection A.4 below.

Inequality The data used in the construction of our total inequality measure are country time-series on (i) rural inequality as defined by Ansell and Samuels (2014), (ii) disposable household income inequality from the SWIID database (Solt 2016), and (iii) the share of the labor force employed in agriculture (Wingender 2014). We detail its construction in subsection A.3 below. Our data cover a wide range of inequality. Our combined Gini for total inequality ranges from 23 at the 5th percentile (for example, the Netherlands in the beginning of the 1950s and Zambia in 2017) to 55 at the 95th percentile (Finland in the late 1910s and Honduras in the mid-2000s).

Losers' consent Data on losers' electoral consent is taken from the V-Dem database v11.1 (Coppedge et al. 2021). The underlying V-Dem item asks country experts to rate the extent that election losers accept the results of a given election using the following scale: "None of the losing parties or candidates accepted the results the election, or all opposition was banned (0); Some but not all losing parties or candidates accepted the results but those who constituted the main opposition force did not (1); Some but not all opposition parties or candidates accepted the results, but it is unclear whether they constituted a major opposition force or were relatively insignificant (2); Many but not all opposition parties or candidates accepted the results and those who did not had little electoral support (3); All parties and candidates accepted the results (4)." We use the median ordinal version of this measure, but model it using a linear model to reduce complexity. In our analysis we reverse the direction of the measure, such that higher values indicate lack of losers' consent, in order to bring it in line with our other outcomes (democratic failure).[1]

Further measures of backsliding Further measures of backsliding are also taken from the V-Dem database. (i) The *electoral democracy index* captures to which extent the "ideal of electoral democracy in its fullest sense is achieved" (Coppedge et al. 2021). The next two measures are sub-components of this index: (ii) the *conduct of free and fair elections* and (iii) *freedom of expression and information.* The latter captures to what extent the government respects press and media freedom, the freedom of ordinary people to discuss political matters at home and in the public sphere, as well as the freedom of academic and cultural expression. (iv) The *judicial constraints on the executive index* captures the degree of independence of the judiciary (or lack thereof) and the extent to which government respects court rulings.

Political world regions Major political world regions are defined by both geographic proximity and political development paths, following Teorell et al. (2020). The corresponding regions are (1) Eastern Europe and Central Asia, (2) Latin America and the Caribbean, (3) Middle East and North Africa, (4) Sub-Saharan Africa, (5) Western Europe and North America, (6) Asia and Pacific. Australia, New Zealand, and Cyprus are classified as (5).

Table A.1
Descriptive statistics

	Mean	SD	N
GDP per capita [log]	9.126	0.972	4960
Inequality [/10]	35.592	9.928	4329
Political polarization	−0.599	1.300	5249
Equal distribution of resources	0.674	0.266	5435
Civil liberties social groups	1.095	1.181	5436
Engaged in internat. conflict [0, 1]	0.064	0.244	5431
Average education [years]	7.590	3.090	4869
Natural res. abundance [real $ pc /100]	4.212	18.286	5039
Enfranchised adults	0.936	0.184	5433

Note: Data are for country spells at risk (i.e, when a country is a democracy). 1900-2019.

Controls Several of our controls are provided by the V-Dem database. These include:

- the degree of political polarization,
- equal civil liberties for all social groups (defined by language, religion, race, caste etc.),
- the equal openness of state jobs to all social groups,

[1] As one of our reviewer points out, while the ratings of multiple experts are combined using a sophisticated measurement model by the V-Dem team, it is in principle possible for all raters to exhibit uniform bias correlated with our key variables, for example, rating backsliding more severely for low versus high income countries. In this sense, more 'objective' measures of backsliding are indeed preferable (Meng and Little 2024). However, in this paper we need to rely on the longer time-series coverage provided by the V-Dem project.

- the equal distribution of resources in a society measured as a composite index of expert ratings of: (i) the extent of particularistic public goods provision, (ii) the extent of means-testing in welfare delivery, (iii) health inequality, (iv) education inequality

Furthermore, we employ a measure of suffrage extension as the percentage of de facto enfranchised adults. Conflict is captured by an indicator variable equal to one if the country was involved in an international armed conflict in a given year. However, data in V-Dem is only provided up until 2000 (limited by the underlying data source). We use the database of Uppsala's Conflict Data Programme to code a country's involvement in interstate conflicts past the year 2000.[2] We measure resource abundance by the real value of a country's total production of petroleum, coal, natural gas, and metals and interpolate missing time-series observations from a fitted ARIMA model as described below. We capture education levels by the average years of education among citizens older than 15. Data on average years of education is missing completely for Guinea-Bissau, Indonesia, Iceland, Papua New Guinea, Sudan, and Taiwan. We use data compiled by Barro and Lee (1996), which uses the same definition (average years of education among citizens 15 and older). Table A.1 provides descriptive statistics for key covariates in our sample of democracies at risk of breakdown.

A.2. Data structure for survival models

Our survival analyses of democracies use a country-spell format for a sample of democracies at risk of democratic breakdown. Table A.2 shows this data structure for a hypothetical country that became a democracy in 1900 but experienced a democratic breakdown at the end of 1910 followed by a period of autocracy lasting until 1979. Starting in 1980, it became a democracy again until the end of our observation period. In other words, this country experienced two spells of democracy (where it was at risk of democratic breakdown) lasting 11 and 40+ years, respectively. Spell lengths are captured by the duration variable t_i. The event indicator δ_i is equal to 1 when the country experienced a democratic breakdown, and 0 when it is right censored. Clearly, during its autocratic spell between 1911 and 1979 the country is not at risk of a breakdown of democracy and these data points should be excluded from a duration analysis of democratic stability.

A.3. Computation of inequality time series

The construction of our total inequality measure requires country time-series on (i) rural inequality (Ansell and Samuels 2014), (ii) disposable household income inequality (Solt 2016), and (iii) the share of the labor force employed in agriculture (Wingender 2014). As illustrated in Figure A.1 our combined measure of inequality for any given country results from the weighted combination of time series for rural (g_t^r) and income (g_t^i) inequality. The weights π_t vary over time. Across all societies studied here, the relative weight on rural inequality decreases as time progresses, but the rate of change varies substantially across countries.

[2] This predominantly covers countries involved in the wars in Iraq and Afghanistan, as well as conflicts between India and Pakistan

Table A.2
Illustration of data structure

			Democracy sample			
Country	Year	Regime	Spell	t_i	δ_i	at risk
1	1900	Dem	1	1	0	yes
1	1901	Dem	1	2	0	yes
1	1902	Dem	1	3	0	yes
1	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
1	1910	Dem	1	11	1	yes
1	1911	Aut	–	–	–	no
1	1912	Aut	–	–	–	no
1	1913	Aut	–	–	–	no
1	$\vdots$	$\vdots$	–	–	–	$\vdots$
1	1979	Aut	–	–	–	no
1	1980	Dem	2	1	0	yes
1	1981	Dem	2	2	0	yes
1	1982	Dem	2	3	0	yes
1	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
1	2019	Dem	2	40	0	yes

Any dataset covering more than a century will encounter time-series with some missing information. This is the case for the constituent variables of our inequality measure (income inequality, rural inequality, and agriculture employment share), which end before the end of our analysis period (e.g., the measure of rural inequality ends in 2000) and/or do not extend back in time far enough. Thus, we extrapolate each key time series by combining two pieces of information: (1) a flexible estimate of its time dynamics, and (2) an assumption that the trend in its changes parallels those of the historical Maddison (2010) GDP per capita series (which is observed over our whole analysis period).

A.3.1. Model-based extrapolation of components of total inequality

More precisely, we estimate, for each country and variable y_t, the following semiparametric model

$$y_t = f_1(t) + f_2(x_t) + \epsilon_t. \tag{A.1}$$

We fit this model to the data to obtain plausible time-series model-based forecasts that avoid discontinuities at the boundary between observed and interpolated values and respects local

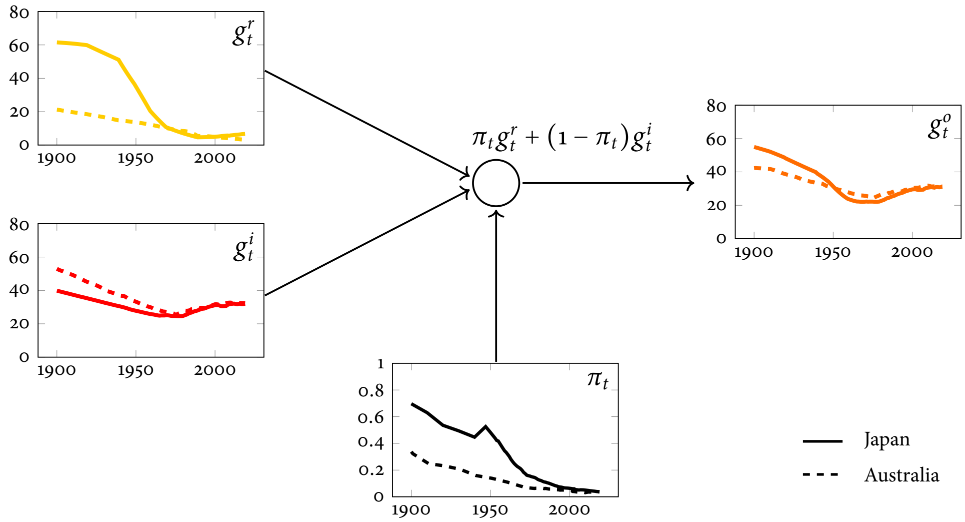

Figure A.1
Illustration of total inequality computation

This figure illustrates the computation of total inequality (g_t^o) from rural (g_t^r) and income (g_t^i) inequality by weighting the income inequality component by π_t, the employment share in agriculture. Displayed data series are from Japan (solid line) and Australia (dashed line).

trends.[3] To estimate the flexible function of time, $f_1(t)$, we use a smoothing spline representation (Ruppert et al. 2003; Wood 2004)

$$f_1(t) \approx \sum_{l=1}^{L} \zeta_l B_l(t), \tag{A.2}$$

where $B(t)$ are B-spline basis functions and ζ_l are the corresponding spline coefficients penalized using a quadratic penalty to induce a preference for smoothness. Penalization is implemented using a hierarchical prior

$$\boldsymbol{\zeta} \sim N\left(0, \left[\frac{1}{\omega_\zeta^2}\boldsymbol{K}_\zeta\right]^g\right) \tag{A.3}$$

where the penalty matrix $\boldsymbol{K}_\zeta$ is specified as $\boldsymbol{K} = \boldsymbol{D}_2'\boldsymbol{D}_2$ and $\boldsymbol{D}_2$ is a second order difference matrix (Eilers and Marx 1996).[4] The inverse of the variance parameter ω_ζ^2 thus controls the abruptness of function jumps (the "non-linearity" of the estimated relationship between the covariate and time) and we can estimate it from the time-series data. Similarly, we estimate the flexible time-varying

[3]Approaches that do not take into account the time-series nature of the data (e.g., simple "mean replacement" or regression imputation based on covariates) are likely to produce drastic jumps at the boundary of observed and interpolated values. We also examined more sophisticated approaches, such as multivariate normal imputation based on the joint distribution of several country-specific time-series or imputation using random forests, and found them similarly inadequate for this kind of data.

[4]A^g denotes the generalized inverse of A

function of GDP per capita, $f_2(x_t)$, using the smoothing spline representation

$$f_2(x) \approx \sum_{m=1}^{M} \eta_m B_m(x) \tag{A.4}$$

with basis functions $B_m(x)$ and associated coefficients ζ_m and a penalization prior as above with variance parameter ω_η^2. Finally, ϵ_t is an IID normal white noise term.

We estimate these models in a Hierarchical Bayesian framework. We assign (hyper-) priors to all remaining model parameters. The most important choice concerns the hyperpriors for the smoothing variances, ω_ζ^2 and ω_η^2. We use the prior proposed by Klein et al. (2016) which prioritizes a simpler functional form unless a deviation is clearly indicated by the data (for more details see the discussion around equation (D.9) below). The prior for the variances of the residuals ϵ is inverse gamma priors with shape and scale set to 0.001. We estimate all model parameters using MCMC sampling. We run our sampler for 8,000 MCMC iterations discarding the first 2,000 samples as transient phase. Based on the estimated functional forms of f_1 and f_2 we then extrapolate y_t by calculating predicted values of its future (or past) realizations from equation (A.1).

A.3.2. Sensitivity analyses

We ensure that our substantive results are not sensitive to specific modeling choices. Panel (a) Figure A.2 shows estimated survival (akin to those presented in Figure III in the main text) when using different specifications for the splines in equations (A.2) and (A.4). The solid line shows estimates obtained using the penalized spline specification used for all results presented in the paper. The dashed line shows that results are quite similar when changing the number of knots (5) for the B-splines. The dotted line shows results when using a different spline construction using thin plate regression splines (Wood 2017: 217).

Panel (b) of Figure A.2 shows that different prior choices for the variance parameters $(\omega_\zeta^2, \omega_\eta^2)$ have no meaningful impact on our results. The solid line shows results when using the scale-dependent prior Klein et al. (2016) used in the main text; while the dashed and dotted lines show results when using Cauchy and Normal prior distributions (truncated to positive values).

A.3.3. Comparison to Deininger-Squire high quality sample

Our empirical strategy and inequality data choices are driven by the goal to attain good coverage in both space and time. In order to get a sense of the quality of our extrapolated inequality series, we compare it to an external source: the high-quality subsample of the Deininger and Squire (1996) database. We use the latest update of the database and extract Gini measures based on gross household income. Table A.3 below shows the relationship between our series and the Deininger and Squire data separately for the periods from 1900 to 1970 (the majority of extrapolated values occur before 1960) and 1971 to 2019. Entries are simple standardized regression coefficients and standard errors. Table A.3 reveals a reasonably close ($\approx$ 0.8) relation between Deininger and

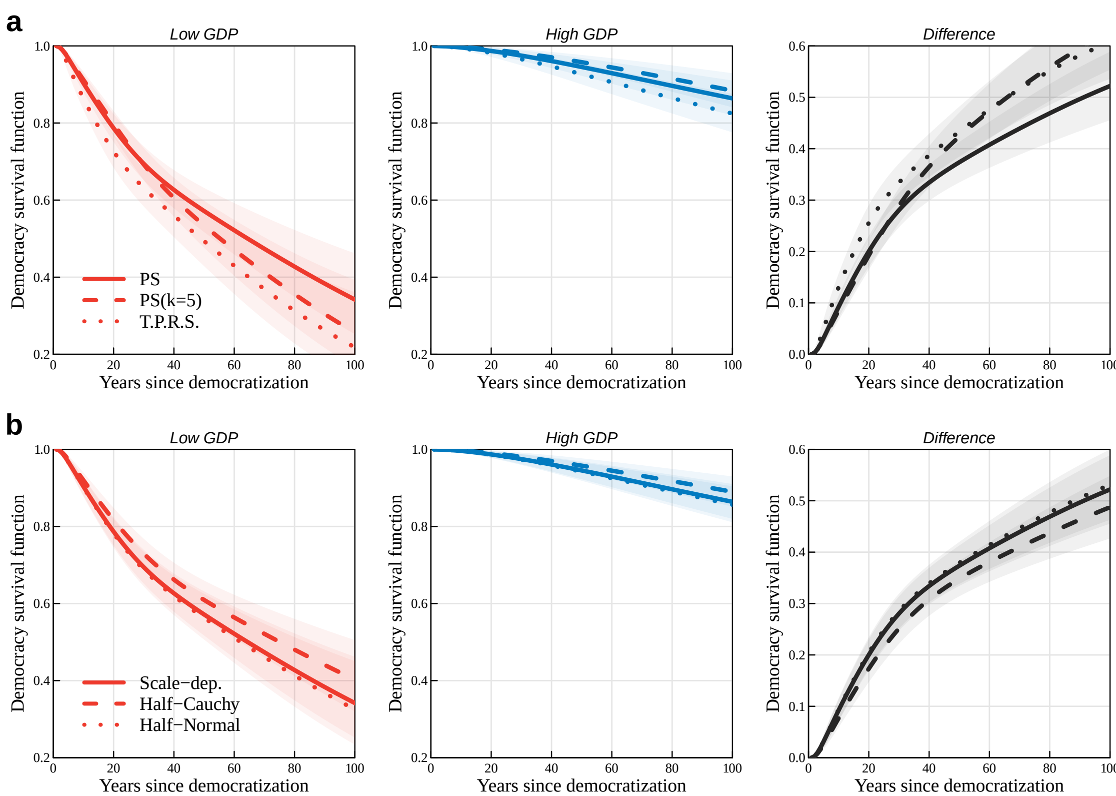

Figure A.2
Semiparametric extrapolation model sensitivity analyses

Plotted are standardized survival curves of high-inequality countries with low (50th percentile) and high (90th percentile) GDP as well as their difference with 95% credible intervals. Panel (a) compares different spline parametrizations (penalized splines, penalized splines with only 5 knots, thin-plate regression splines); panel (b) shows compares different prior choices for the spline coefficient variance parameters ω.

Squire Ginis and our series–both in the later period and the earlier period, where we required extrapolation. The difference between the two slopes is not statistically significant.

A.3.4. Assessing the impact of extrapolation

Different starting points Another strategy to guard ourselves against an undue impact of our extrapolation, is to examine its ultimate impact on survival estimates. Figure A.3 shows standardized survival curves for high-inequality countries at low (50th percentile) and high (90th percentile) of GDP as well as their difference with 95% confidence intervals. We subsequently shift forward the starting point of our analysis from 1900 in steps of 10 years, re-estimate the model and plot the corresponding survival curves. Thus, each subsequent step uses less of the inequality information that has been imputed.

Figure A.3 clearly shows that the impact of these shifts on our substantive conclusions is very limited. Our estimated survival curves do change as a function of the changing sample (which,

Table A.3
Relationship between our measure of total inequality and highest quality Gini from Deininger and Squire

	TI = $\beta\times$ Gini		
	$\hat{\beta}$	s.e.	N
Years from 1900 − 1970	0.853	(0.089)	66
Years from 1971 − 2019	0.795	(0.038)	139

Note: Entries are coefficients (and standard errors) from regression of (standardized) total inequality on (standardized) Gini from Deininger and Squire (1996) database update v2. High quality sample, gross income, household equivalence definition. Included countries (with at least 3 time-series observations): Australia, Bahamas, Bangladesh, Brazil, Canada, Colombia, Costa Rica, France, Germany, Hong Kong, Japan, Malaysia, Mexico, New Zealand, Philippines, Singapore, South Korea, Sri Lanka, Thailand, Trinidad & Tobago, United States, and Venezuela. Test of difference in slopes between 1900–1970 and 1971–2019 sample: $p = 0.550$.

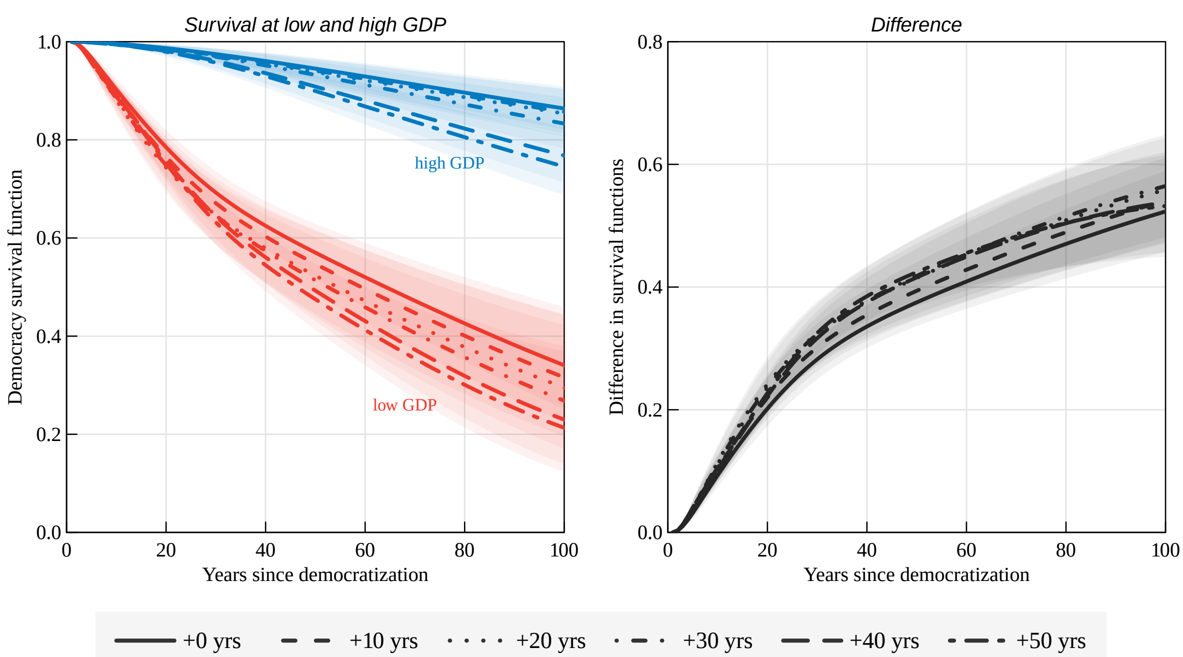

Figure A.3
Assessing the impact of extrapolation: shifted starting periods
Each line represents a 10-year shift in the starting point of the analysis (i.e., 1900, . . . , 1950). Plots standardized survival curves for high-inequality countries at low (50th percentile) and high (90th percentile) of GDP in the left panel and their difference in the right panel. Shaded areas represent 95% confidence intervals.

of course, also captures changes in time period-specific factors) indicating an elevated risk of democratic breakdown even under high levels of development (an increase of about 10 percentage points). However, this does not alter the general conclusion that low levels of development are a major risk factor. As the right panel shows, the difference in standardized survival curves between lower and high levels of development are clearly significantly different from zero no matter the chosen analysis starting point.

Restricting the number of extrapolated time points In this paragraph we explore the stability of the inequality estimates when limiting the number of extrapolated time points in our inequality time series. More specifically, we vary the maximum number of extrapolated points up to 50 time points per country and exclude from the analysis countries that require more extrapolation. Figure A.4 shows the estimated effect of a one standard deviation increase of inequality from the median on the y-axis. Smaller values on the x-axis show more *restrictive* specifications (limiting the number of interpolations), while larger values permit more extrapolated time points per country. The resulting estimates are fairly stable within a band of about 3 percentage points (note that the number of included countries changes across the x-axis). All estimates are negative and clearly statistically different from zero.

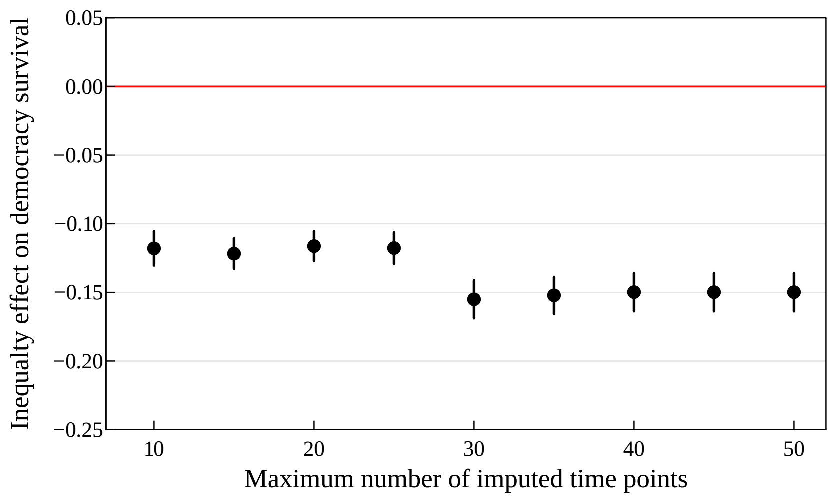

Figure A.4
Assessing the impact of extrapolation: Restricting the number of extrapolated time points
Estimated effect of standard deviation increase in inequality on the survival probability of a (60-year old) democracy when allowing for a varying number of interpolated time-points in the inequality series by country. Shown are first differences in probabilities with 95% confidence intervals.

Alternative construction of measures A further robustness analysis concerns the construction of the inequality measure itself. Figure A.5 shows results from an enhanced extrapolation model. In the main model, we impute the income inequality component as a (non-linear) function of time and assuming it moves in relation to long-run GDP per capita (Maddison 2010). In this extended model, we add additional information (where available) in the extrapolation model: the income share of the top 1% obtained from the World Inequality Database. We use top 1% shares calculated using pre-tax income of adults (equal-split adults for couples in households) in order to maximize time coverage. We include this additional covariate in both linear form—i.e., by adding $x_{t,2}$ to equation (A.1)—and as flexible function allowing for different effects at different levels of top income inequality—i.e., adding $f(x_{t,2})$ estimated as in eq. (D.2), *mutatis mutandis.* As the plotted survival curves in Figure A.5 indicate, our results are substantively very close to the ones presented in the main text.

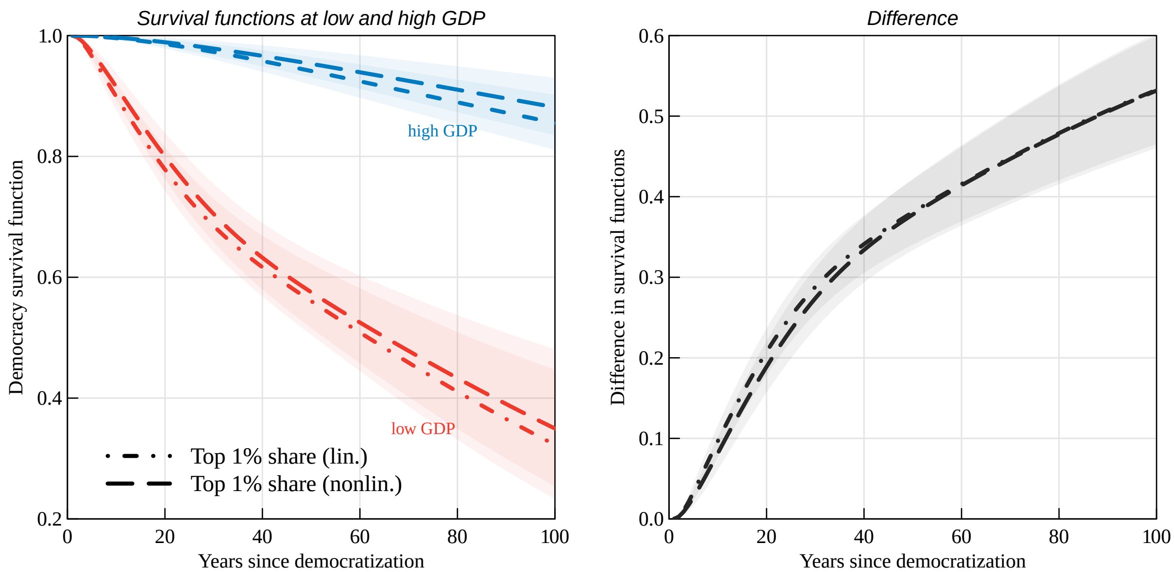

Figure A.5

Assessing the impact of extrapolation: enhanced extrapolation model adding the (pre-tax) income share of the top 1%.

Enhanced extrapolation model including top 1% percent income share in addition to GDP per capita as predictive covariate. Specifications include $x_{it,2}$ as linear term and $f(x_{it,2})$ as non-linear term estimated using a penalized B-spline basis representation. Plotted are standardized survival curves for high-inequality countries at low (50th percentile) and high (90th percentile) of GDP in the left panel and their difference in the right panel. Shaded areas represent 95% confidence intervals.

A.4. Time-series interpolation of controls

We fill in missing time-series values for controls (such as average years of education) using fitted flexible time-series models. More precisely, we proceed as follows: for each country and each time-series, y_t we estimate a set of Auto-Regressive Integrated Moving Average ($ARIMA(p, d, q)$) models:,

$$(1 - \phi_1 B - \cdots - \phi_p B^p)(1 - B)^d (y_t - \mu t^d / d!) = (1 + \theta_1 B + \cdots + \theta_q B^q) e_t \qquad \text{(A.5)}$$

where B is the backshift operator, e_t is a white noise process with estimated variance σ^2, and ϕ and θ are polynomials terms of order p and q. The order of differencing is given by d and μ represents “drift”, i.e., the mean of the differenced data (or the slope of the trend in the undifferenced data).

We estimate our model in first-differences ($d = 1$) and search over the space of plausible values for p ($p \in \{0, \ldots, 4\}$) and q ($q \in \{0, \ldots, 4\}$) and the inclusion of μ. The search proceeds by calculating the Akaike Information Criterion for all possible combinations and selecting the model with the lowest value. Then, based on the chosen best model, we forecast missing time-series observations using the Kalman filter (Hamilton 1994: 378f.).

B. Linear Fixed Effects models of backsliding indicators

B.1. Losers' consent to election results

This section provides details and estimates for models relating the extent to which losers refuse to consent to election results to total inequality and development. Denote lack of election consent in country i ($i = 1, \ldots, N$) at time t ($t = 1, \ldots, T_i$) by y_{it}. We estimate the following standard linear two-way fixed effects model (Hsiao 2003):

$$y_{it} = \beta_1 w_{it} + \beta_2 x_{it} + \beta_3 w_{it} x_{it} + z'_{it}\gamma + \mu_i + \lambda_t + \epsilon_{it} \tag{B.1}$$

where w_{it} denotes total inequality and x_{it} logged GDP per capita, z_{it} is a vector of controls and μ_i and λ_t are country and year fixed effects. Estimation proceeds by projecting out country and year fixed effects.

Table B.1 shows parameter estimates (with robust standard errors in parentheses) for a series of specifications. The first three specifications simply include GDP, total inequality, and their interaction without, with basic, and with full controls, respectively.[5] Specification (4) limits our sample to post-WW II democracies. Panel heterogeneity is a concern when pooling time series for many countries. While fixed effects capture stable country heterogeneity, ideally, more flexible specifications allow for more variation in within-country dynamics. Specification (5) uses the measure of disposable household income inequality (cf. section A.1) in the post-WW II period instead of our measure of total inequality. Specification (6) returns to specification (3) but includes interactive fixed effects (Bai 2009), allowing for country-specific heterogeneity in time shocks (as opposed to the common time shocks assumed in the standard two-way fixed effects specification). The model is implemented via a one-dimensional common factor with country-specific loadings estimating using the iterative procedure given in Bai (2009). Figure III in the main text is based on specifications (2) and (3).

[5] There are two additional controls that we considered predominantly relevant for the survival process and have thus not included it in the set of controls in the backsliding analysis: a country's involvement in armed conflict and a measure of natural resource abundance. Adding these controls to the ones already included in specification (3) yields the following results: the coefficient for GDP per capita is 0.283 (s.e.: 0.08), the coefficient for inequality is 0.828 (s.e.: 0.18). The key term, the interaction between inequality and development, is estimated as −0.087 (s.e.: 0.02). Thus, our core results remain substantively unchanged.

Table B.1
Linear Fixed Effects models for lack of losers' consent. Parameter estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
Inequality [/10]	0.766	0.882	0.852	0.606	0.701	0.827
	(0.167)	(0.178)	(0.179)	(0.224)	(0.338)	(0.144)
GDP per capita [log]	0.180	0.327	0.304	0.159	0.332	0.269
	(0.069)	(0.076)	(0.077)	(0.092)	(0.116)	(0.062)
Inequality×GDP	−0.078	−0.095	−0.089	−0.054	−0.078	−0.085
	(0.019)	(0.020)	(0.020)	(0.024)	(0.033)	(0.016)
Model	2-way FE	2-way FE	2-way FE	2-way FE	2-way FE	Int. FE[a]
Sample	full	full	full	post-1945	ineq. only	full
Controls	no	basic	all	all	all	all
F test p	—	0.000	0.000	0.000	0.000	0.000
R^2	0.571	0.609	0.614	0.628	0.609	0.560
N	1339	1315	1282	1036	1130	1282

Note: Linear two-way fixed effects model estimates with robust standard errors. Fixed effects for country and year. 1900–2018. Specification (2) adds controls for political polarization and an index of equal resource distribution, while specification (3) additionally adjusts for average years of education, the percentage of enfranchised adults, equal civil liberties and equal access to government jobs for all social groups. Specification (4) limits the sample to the post-WW2 period. Specification (5) uses income inequality instead of total inequality.

a Interactive fixed effects (Bai 2009) specification relaxing the common shocks assumption. Includes country and year fixed effects and one-dimensional country × year factor.

B.1.1. Incumbency status

In this subsection we explore the stability of our results to incumbency status. As one of our reviewer points out, one of our measures of backsliding—the extent to which losing parties and candidates accept election results—does not distinguish between unjustified refusal to accept results (i.e., after losing a free-and-fair election) and the justified refusal, for example after an incumbent uses their power to influence the electoral process. While one might argue that even if the latter case is true, the measure still captures (indirectly) a breakdown of democratic practices, it is germane to ask if our results are sensitive to this distinction. While we are of course unable to recode the V-Dem measure itself, we can differentiate elections where and incumbent ran and won from those where this is not the case. For each election we create an indicator variable equal to one if the incumbent ran and won and zero otherwise.[6]

Panel (a) of Figure B.1 shows that the incumbents' winning status does indeed affect V-Dem measured loser's consent. If the incumbent won the election, the election loser is more likely to not consent to the election results. How does this affect our results? Panel (b) shows the marginal

[6] We match elections to V-Dem measure years. In years where more than one election took place, we use the latest one. Our analysis excludes a small numbers of countries where defining an incumbent is problematic (most notably Switzerland's federal council) leading to 1,275 observations (compared to 1,339 in the main analysis).

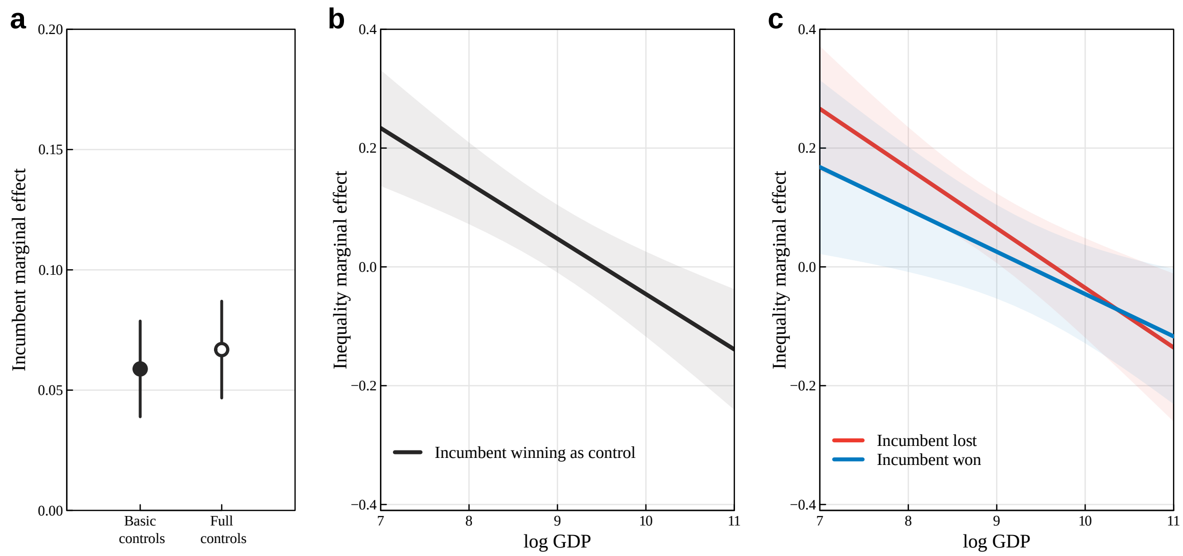

Figure B.1
The role of incumbents winning on electoral consent of election losers

This figure examines the role of the incumbent winning the election on the V-Dem loser's consent measure. Panel (a) shows the marginal effect of the incumbent winning on the loser's consent. Panel (b) shows the marginal effect of inequality on loser's consents at varying levels of GDP per capital when adjusting for the incumbent winning the race. Panel (c) uses a three-way interaction of incumbent win status, inequality, and development and plots the marginal effect of inequality over GDP when the incumbent won or lost. Based on linear two-way fixed effects models with robust standard errors.

effect of inequality at increasing levels of GDP while including incumbent win-status as a control. The results confirm the finding reported in the main text. In panel (c) we probe the issue further, by estimated a three-way interaction between inequality, development, and incumbent win-status. The plot shows marginal effects of inequality by GDP for elections where the incumbent won and where the incumbent lost or did not run. We find that in both settings, the moderating role of development is confirmed. Furthermore, the difference between the two marginal effects slopes is small and not statistically distinguishable from zero.

B.2. Further indicators of democratic backsliding

In this section we analyze further indicators of democratic backsliding using the same model setup as in the previous analysis of losers' consent. The analyses are also summarized in panel (c) of Figure III in the main text. Table B.2 on page 15 displays four measures of backsliding at different levels of granularity. We have adjusted their orientation such that larger values indicate more negative outcomes. The first outcome is V-Dem's electoral democracy index. It is a broad ("high-level" in V-dem parlance) measure and captures to which extent the "ideal of electoral democracy in its fullest sense is achieved" (Coppedge et al. 2021). The next two measures are sub-components of this index and focus on more specific aspects of potential democratic backsliding: the conduct of free and fair elections and freedom of expression and information.

The latter captures to what extent the government respects press and media freedom, the freedom of ordinary people to discuss political matters at home and in the public sphere, as well as the freedom of academic and cultural expression.

The final outcome is the V-Dem 'Judicial constraints on the executive index'. It captures the degree of independence of the judiciary (or lack thereof) and the extent to which government respects court rulings. In line with expectations raised by the literature on democratic backsliding, all four indicators are significantly related to the hazard of democratic failure.[7]

We now explore the (conditional) effect of inequality and development on these four measures of backsliding. While panel A of Table B.2 lists the estimated parameters of the inequality × GDP interaction, their substantive magnitude is not straightforward to interpret. To ease interpretation, panel B displays the difference between the average marginal effect of inequality evaluated at two levels of GDP per capita (at the median and 90th percentile). This difference (and its standard error) captures how increasing development moderates the impact of inequality on backsliding. We find that in each and every case higher levels of GDP are associated with a lowering of the marginal effect of inequality on backsliding outcomes. The difference in inequality marginal effects due to increasing GDP is always negative and statistically significant.

C. Survival models

We begin by defining some key parameters and notation (for a detailed introduction see Lancaster 1990). We omit country subscripts for ease of notation. Consider the spells of democracy experience by any given country (i.e., from the time of democratization or sample entry up to the event of a democratic breakdown). The duration of that spell is a continuous random variable and is denoted by T with probability density function $f(t) = Pr(T = t)$. The cumulative distribution function $F(t)$ is given by

$$
\begin{aligned}
F(t) &= Pr(T \leq t) && \text{(C.1)} \\
&= \int_{s=0}^{t} f(s)ds && \text{(C.2)}
\end{aligned}
$$

and represents the probability of democratic breakdown by time t. One key quantity of our analysis is the probability of survival of a democracy up to at least time t, i.e., the probability $Pr(T \geq t)$. Denote this time-specific survival probability as $S(t)$. It can be calculated making use

[7]Evaluating the hazard of democratic failure when the electoral democracy index is at its mean and at one standard deviation (SD) above the mean leads to a ratio of hazards of 4.26 ± 0.35, i.e., democracies are about four times more likely to experience breakdowns when electoral democracy declines (remember that we have oriented all measures such that larger values indicate more backsliding). The hazard ratio related to our measure of free and fair elections is 3.37 ± 0.22, while for freedom of expression it is 1.96 ± 0.09. Finally, the hazard ratio associated with judicial constraints is 2.69 ± 0.18.

Table B.2
Further indicators of democratic backsliding

	Electoral Democracy[a]		Free elections[b]		Media freedom[c]		Judicial constraints[d]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: coefficient estimates								
Inequality	1.050	1.082	1.726	1.746	0.988	1.047	0.916	0.985
	(0.105)	(0.106)	(0.126)	(0.125)	(0.127)	(0.132)	(0.104)	(0.100)
GDP	0.405	0.498	0.682	0.774	0.394	0.628	0.171	0.232
	(0.053)	(0.057)	(0.064)	(0.067)	(0.064)	(0.063)	(0.040)	(0.044)
Inequality × GDP	−0.116	−0.120	−0.198	−0.201	−0.106	−0.118	−0.100	−0.107
	(0.012)	(0.012)	(0.015)	(0.014)	(0.015)	(0.015)	(0.012)	(0.012)
B: Difference of inequality marginal effect at median vs. high GDP								
Difference	−0.135	−0.140	−0.232	−0.235	−0.124	−0.137	−0.117	−0.126
	(0.015)	(0.014)	(0.017)	(0.017)	(0.017)	(0.018)	(0.015)	(0.014)
Country FE	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Controls	basic	full	basic	full	basic	full	basic	full
F-test p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.845	0.859	0.823	0.835	0.762	0.792	0.892	0.896
N	4168	4077	4168	4077	4168	4077	4168	4077

Note: Entries in panel B are the difference of two marginal effects of inequality $\partial E[\,y|\,w_{it}, x_{it}\,]\,/\,\partial w_{it}$ evaluated with x_{it} (GDP) set to the 50th and 90th percentile, respectively. Controls are held at observed values. Calculated from linear two-way fixed effects model estimates with robust standard errors. Fixed effects for country and year. 1900–2018. Basic controls include the degree of political polarization and an index of equal resource distribution, full controls add average years of education, equal civil liberties and equal access to government jobs for all social groups.

a V-Dem index coding to what extent the ideal of electoral democracy in its fullest sense is achieved. Reversed (so that larger values represent backsliding) and re-scaled to mean zero unit standard deviation.

b V-Dem clean elections index coding to what extent elections are free and fair. Reversed and re-scaled.

c V-Dem Freedom of Expression and Alternative Sources of Information index. Codes to what extent government respect press and media freedom, the freedom of ordinary people to discuss political matters at home and in the public sphere, as well as the freedom of academic and cultural expression. Reversed and re-scaled.

d V-Dem Judicial constraints on the executive index. Codes to what extent the executive respects the constitution and complies with court rulings, and to what extent the judiciary is able to act in an independent fashion. Reversed and re-scaled.

of the following relationship:

$$\begin{aligned} S(t) &= Pr(T \geq t) && \text{(C.3)} \\ &= 1 - F(t) && \text{(C.4)} \\ &= 1 - Pr(T \leq t) && \text{(C.5)} \end{aligned}$$

When obtaining this probability via models, the survival probability calculation will generally be conditional on covariates.

To arrive at the statistical model used in our analyses, we need to define a function, $h(t)$, that represents the instantaneous rate of exit from one state (democracy) to another (failed democracy) at time t. This is commonly referred to as hazard function or hazard rate. To see the role of the hazard rate, consider the probability that a country who has remained a democracy up to time t suffers a breakdown of democracy in a small time interval dt following time t: $Pr(t \leq T \leq t + dt | T \geq t)/dt$. Making this time interval arbitrarily small leads us to the hazard rate

$$h(t) = \lim_{dt \to 0} \frac{Pr(t \leq T \leq t + dt | T \geq t}{dt} \tag{C.6}$$

Note that the hazard rate is simply the ratio of the duration density to the survival function at time t:

$$h(t) = \frac{f(t)}{S(t)} \tag{C.7}$$

An important aspect of a survival model is the shape of duration dependence. If the probability of democratic breakdown increases over time, then the hazard rate increases over time, i.e.,

$$\frac{dh(t)}{dt} > 0 \tag{C.8}$$

Similarly, if the probability of democratic breakdown decreases over time the hazard rate decreases in t.

In standard parametric survival models, choosing a distribution amounts to making an a priori statement about the form of duration dependence. For example, using an exponential distribution for the duration density implies constant duration dependence, $h(t) = h_0$. More flexible densities, such as the Weibull distribution allow positive or negative duration dependence, but still require a monotonic hazard rate. The survival function for the Weibull model is

$$S(t) = \exp(-\lambda t^{\gamma}) \tag{C.9}$$

which expressed on the log cumulative hazard scale (denoted by $\ln[H(t)]$)[8] is

$$\ln[H(t)] = \ln[-\ln(S(t))] = \ln(\lambda) + \gamma \ln(t) \tag{C.10}$$

[8]The cumulative hazard function of T is defined as $H(t) = \int_0^T h(t)dt$.

and shows that we get a linear function of log-time. The specification of the baseline hazard is important, because its misspecification will also bias the parameter estimates of explanatory variables (Ridder 1987). It is thus attractive to eschew strong distributional assumptions for the log-baseline hazard. Two popular alternatives are either (i) to treat the hazard function as a nuisance not to be estimated (as in the partial likelihood approach of Cox , cf. Cox 1972) or (ii) to relax the linear form of time by estimating it in a flexible fashion (Rutherford et al. 2015). The latter allows for non-monotonic time dependence (while still providing useful information about the functional form of time-dependence, which might be of interest in its own right). In this paper we follow the latter strategy (and show that our results are close when using the Cox approach).

C.1. Semiparametric survival model

A proportional hazard model for democratic failure for country i ($i = 1, \ldots, 210$) expressed on the log *cumulative* hazard scale is given by

$$\ln\left[H(t)|w_i(t), x_i(t), z_i\right] = \ln\left[H_0(t)\right] + w_i(t)\beta_1 + x_i(t)\beta_2 + z_i'\gamma \tag{C.11}$$

where $w_i(t)$ is our measure of total inequality, $x_i(t)$ is logged GDP per capita, z_i is a vector of controls including political world region fixed effects. Note that there are good reasons to assume that the hazard is affected by current values of explanatory variable (as opposed to, say, only their start-of-spell values). Thus, we specify our explanatory covariates as time-varying (Hosmer and Lemeshow 2008: 213f.). Finally, $\ln[H_0(t)]$ is a general log-cumulative baseline hazard function. Royston and Parmar (2002) propose to approximate $\ln[H_0(t)]$ by a restricted cubic spline (see also Rutherford et al. 2015). Employing a restricted cubic spline allows for the estimation of a continuous function (instead of a step function) of the baseline hazard. A cubic regression spline of a variable z with K knots is defined as follows (e.g., de Boor 1978):

$$s(z) = \eta_0 + \eta_1 z + \sum_{j=2}^{K-1} \eta_j s_j \tag{C.12}$$

It includes an intercept and a linear term of the original variable z as well as a number of spline terms s_j with associated spline coefficients η_j. The spline terms are constructed as follows:

$$s_j = (z - k_j)^3 - \phi_j(z - k_1)_+^3 - (1 - \phi_j)(z - k_j)_+^3 \qquad j = 2, \ldots K - 1 \tag{C.13}$$

with knot locations k and $\phi_j = (k_K - k_j)/(k_K - k_1)$.

Using this spline to estimate the baseline log cumulative hazard yields the following model:

$$\ln\left[H(t)|w_i(t), x_i(t), z_i\right] = s(\ln(t)|\eta, K) + w_i(t)\beta_1 + x_i(t)\beta_2 + z_i'\gamma \tag{C.14}$$

Here $s()$ is the restricted cubic spline of log time with K knots and associated coefficients η. The vector of model parameters to be estimated is $(\eta', \gamma', \beta_1, \beta_2)'$. K is chosen a priori. All model parameters are estimated by maximum likelihood. This specification permits flexible estimation of the baseline hazard (allowing, for example, patterns of decreasing and then increasing risk of democratic breakdowns over time) and allows for the straightforward calculation of smooth survival functions (or 'curves') conditional on covariates. The impact of time-varying inequality and development on the log cumulative hazard is captured by β_1 and β_2, respectively. The impact of covariates is captured by γ. When creating plots and other derived quantities of interest, we transform from the log cumulative hazard scale to the survival and hazard scale. Let $\nu_i = s(\ln(t)|\eta, K) + w_i(t)\beta_1 + x_i(t)\beta_2 + z_i'\gamma$. Then the survival function (at time t and conditional on covariates) is obtained by

$$S(t|w_i(t), x_i(t), z_i) = \exp[-\exp(\nu_i)] \tag{C.15}$$

while the hazard is

$$h(t, w_i(t), x_i(t), z_i) = \frac{ds(\ln(t)|\eta, K)}{dt}\exp(\nu_i) \tag{C.16}$$

It is important to note that since the survival probabilities are a function of time, it is best to calculate and plot quantities of interest as a function of time as well (Hosmer and Lemeshow 2008). Therefore, we calculate and plot conditional adjusted survival curves (conditioned on model covariates) in the main text and relegate parameter estimates to this appendix (see below).

C.2. Conditional survival curves

Conditional survival curves (often referred to as "regression standardized" curves in epidemiology) plot expected values of $S(t)$ at relevant (counterfactual) values of explanatory variables while adjusting for (modelled) confounders. For notational brevity, denote by X a key explanatory variable and by x_0 and x_1 two specific values of interest (e.g., low and high inequality). Denote the set of confounders by C. We are interested in the survival difference produced by changes in X while accounting for confounders, which is given by:

$$E(S(t|X = x_1, C)) - E(S(t|X = x_0, C)) \tag{C.17}$$

Note that the expectation is taken over the population distribution of C. We obtain this quantity of interest by estimating

$$N^{-1}\sum_{i=1}^{N}\hat{S}(t|X_i = x_1, C_i) - N^{-1}\sum_{i=1}^{N}\hat{S}(t|X_i = x_0, C_i) \tag{C.18}$$

that is, we predict $\hat{S}(\cdot)$ from our estimated survival model first forcing all countries to be exposed to x_1 and then to x_0 while using each country's observed covariate pattern C_i. In our application with N countries, this amounts to predicting N survival curves over a 100-year time-grid and then taking the average of these curves. The variance of this quantity can be obtained using the delta method. Panel (e) of Figure IV in the main text shows the resulting conditional survival difference curves. We also calculate and display survival curves at specific explanatory variable values (thus showing levels instead of differences), that is, $E(S(t|X = x_1, C))$, which is calculated analogously as $N^{-1} \sum_{i=1}^{N} \hat{S}(t|X_i = x_1, C_i)$. Panels (b) to (d) of Figure IV show this kind of curve.

C.3. Survival model parameter estimates

Table C.1 shows parameter estimates for models of democratic breakdowns.[9] Specifications (1) and (2) estimate the model just described, with (1) including inequality, GDP, previous failures, and political region fixed effects, while (2) adding a set of controls. In specification (3) we instead estimate the popular Cox proportional hazard model where the baseline hazard is treated as a nuisance parameter. We find that its results are quite close to the semi-parametric estimates. This does not change the fundamental results of our model, but it does increase the standard error of our parameter estimates.

In specifications (4) and (5) we relax the assumption of proportional hazards. In (4) we allow for a non-proportional impact of inequality by specifying it as a cubic regression spline as shown in (C.12). In specification (5) we additionally allow GDP to impact the hazard of democratic breakdown non-proportionally.

A key issue in our analysis is the existence of recurrent events—the fact that some countries experience more than one instance of democratic breakdown. The reason for the recurrence of democratic failures can be due to unobserved heterogeneity and/or event dependence (Box-Steffensmeier and De Boef 2006). Event dependence occurs when the experience of a previous breakdown shapes the future likelihood of a breakdown. Past failures might weaken the state of democracy, making future failures more likely, or they might strengthen the state of democracy thus decreasing the likelihood of future failures. All our survival analyses include the number of previous failures as a time-varying covariate in order to capture such event dependence. However, another reason for repeated breakdowns is a country's susceptibility (or 'frailty'). Countries differ in a variety of unobserved characteristics (e.g., political culture, or historical institutional legacies) which influence the probability that democracy will fail but are not included in the model (either because they cannot be easily measured or because they are unknown). Countries experiencing a breakdown of democracy do so because they have been more susceptible to them all along. In extended model specifications we thus add country-specific frailty terms. In the context of survival models, this amounts to specifying a unit-level random effects term that multiplicatively acts on the hazard of democratic breakdown (Hosmer and Lemeshow 2008: 296f.).[10] Specifications (6) and (7) display estimates for a mixed Cox proportional hazard models where country-level frailties are introduced via Gaussian random effects (with mean zero and estimated variance). Parameters of the model are estimated using restricted maximum likelihood (Therneau and Grambsch 2014: ch.9).

[9] Specifications (1), (2), and (4) are used to calculate standardized survival curves displayed in the main text.

[10] Accounting for country unobservables is especially important in the type of non-linear model considered here, where omitted unobservables lead to biased estimates—even when these unobservables are uncorrelated with inequality and development (Gail et al. 1984).

Table C.1
Survival models for inequality and democratic breakdowns.

	Basic models			Nonprop. Haz.		Frailties	
	(1)[a]	(2)[a]	(3)[b]	(4)[c]	(5)[d]	(6)[e]	(7)[e]
Inequality [/10]	0.057	0.036	0.034	0.052	0.038	0.147	0.038
	(0.012)	(0.013)	(0.013)	(0.018)	(0.019)	(0.027)	(0.021)
GDP [log]	−2.176	−1.603	−1.501	−1.590	−1.868	−3.879	−1.244
	(0.232)	(0.425)	(0.405)	(0.417)	(0.486)	(0.375)	(0.443)
Failures	1.734	1.774	1.703	1.763	1.839	2.678	2.195
	(0.125)	(0.147)	(0.128)	(0.148)	(0.150)	(0.216)	(0.176)
Add. controls	no	yes	yes	yes	yes	no	yes
Wald test p	—	0.000	0.000	0.000	0.000	—	0.000
Region effects	yes	yes	yes	yes	yes	no	no
Wald test p	0.000	0.000	0.000	0.000	0.000	—	—
Frailty std.dev.						3.000	1.389
BIC	584.0	539.3	888.4	542.2	548.3	453.3	493.9
N	4252	4113	4113	4113	4113	4252	4113
Estimator	SP-PH	SP-PH	Cox-PH	SP-PH	SP-PH	Cox-MPH	Cox-MPH

Note: Robust standard errors in parentheses.

a Maximum likelihood estimates of proportional hazard models with baseline hazard rates estimated using cubic regression splines with 3 degrees of freedom. For list of controls see text.

b Estimates from standard Cox Proportional Hazard model.

c Relaxes proportional hazards assumption by allowing for time-varying effect of inequality. Non-proportional effect estimates via cubic regression spline with 3 degrees of freedom.

d Adds time-varying effect of GDP (spline df. set to 2 to minimize convergence issues).

e Mixed Cox Proportional Hazard models with Gaussian frailties/random effects estimated using restricted maximum likelihood. BIC calculated from integrated partial likelihood (integrating out the random effects).

C.4. Post-World War II results

Figure C.1 shows results of our survival model for democracies when the analysis period is limited to the post-WW II period. Panel (a) plots the effect of a standard deviation increase from median levels of total inequality and GDP, respectively, on the predicted survival of a mature democracy (here defined as a democracy of 40 years without a previous breakdown). Panel (b) examines the impact of high inequality (90th percentile) on the over-time survival of democracies. It plots conditional survival curves (see Appendix C.2 for their definition and calculation) and their corresponding 95% confidence intervals with GDP fixed at the 50th and 90th percentile, respectively. The inset of panel (b) uses the full set of controls discussed in the main text. We find that our results are substantively similar.

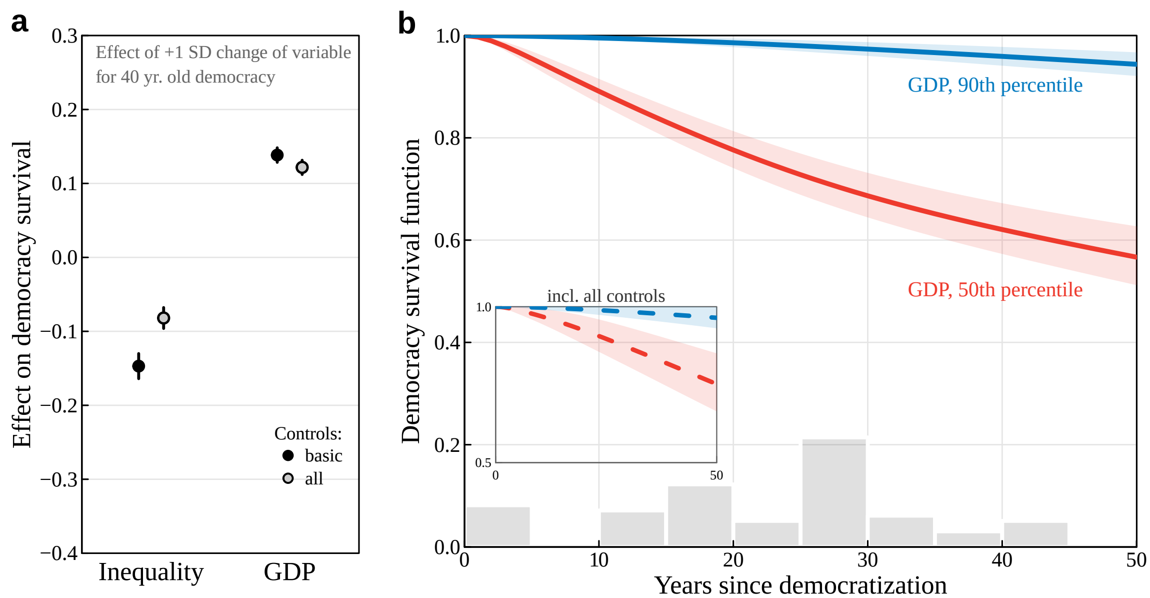

Figure C.1
Inequality, Development, and survival of Democracy. Post-1945 sample.

C.5. Survival curves at varying levels of inequality and development

In our main plots, we hold the level of inequality at the 90th percentile of the inequality distribution and contrast GDP at the median and the 90th percentile. While this presentation focuses on the main contrasts we are interested in—the impact of development under high inequality—it is germane to ask for a presentation of patterns at different levels of inequality and development. Figure V in the main text does this by estimating a survival model with a full semi-parametric interaction of inequality and development. Here, we present an alternative based on the simpler survival regression. Figure C.2 plots survival curves (the probability of a democracy staying a democracy across time) at varying levels of inequality and development. The five panels of Figure Figure C.2 hold inequality at the median, the 60th, 70th, 80th and 90th percentile. The lines in each panel hold GDP per capital at the 40th to the 90th percentile.

Our results illustrate the interaction between inequality and development. Scanning Figure C.2 from left to right reveals two important patterns. First, as inequality increases, the probability of the survival of democracy becomes increasingly lower, as evidenced by the steeper declining survival curves across the panels. Second, while development matters regardless of the level of inequality (higher development always limits the decline in survival), it matters especially when inequality is high, as evidenced by the "fanning out" of the development-specific survival curves across the different inequality panels. These results also confirm that our key insight regarding the buffering role of development are not driven by the specific inequality and development percentiles displayed in the main text.

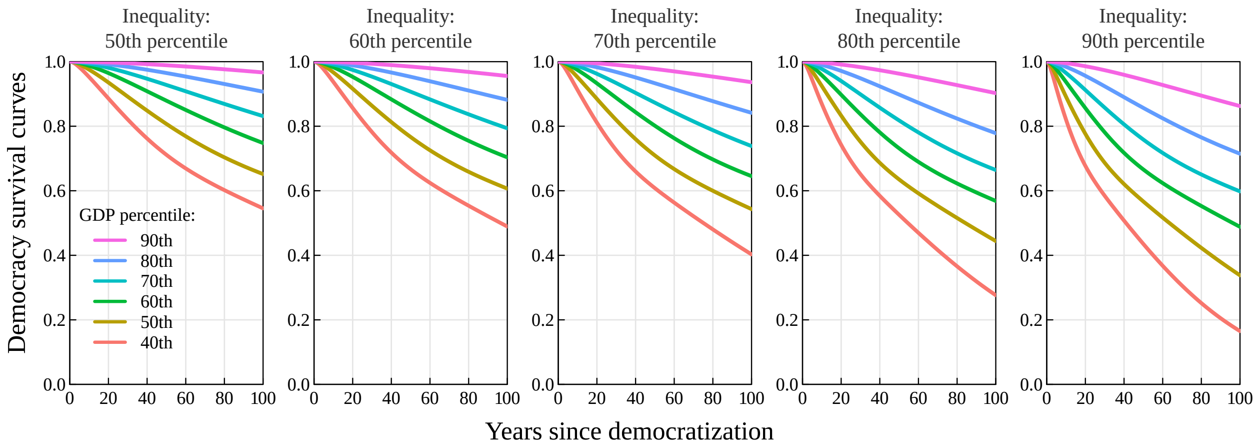

Figure C.2
Democratic survival curves at varying levels of inequality and development.

Plotted are regression-standardized survival curves (see C.2 for details on their calculation) at different levels of GDP (colored lines within each panel) and inequality (different panels). Based on a survival regression with region effects and adjusting for previous democratic breakdowns.

C.6. Results when using only income inequality

While total inequality (combining land and income inequality) is our preferred measure to capture the long-run evolution of inequality in a society, we also conducted analyses using a only a measure of income inequality. As described in section A.1, we use the Gini index of disposable household income from the SWIID database (Solt 2016) (Solt 2016) with missing observations imputed using the Bayesian semi-parametric time-series imputation approach discussed in section A.3.1. Figure C.3 shows survival curves for societies with high levels of income inequality (defined as either the 90th or 70th percentile of the income inequality distribution) and lower and high levels of development.

We find the basic pattern of our results confirmed. Compared to our main results, the decline in survival is less marked. But the damaging effect of income inequality on the survival of democracies is still much more marked at low levels of development (represented by the red lines in Figure C.3 depicting median levels of GDP per capita). As the inset of Figure C.3 shows, the difference between the two survival curves is statistically different from zero. This is true no matter if we use the 90th of the 70th percentile of the inequality distribution.

C.7. Baseline hazard robustness to choice of K

The flexibility of our estimated baseline hazard function is directly influenced by the choice of the number and location of knots. In practice, between 2 and 4 knots are often sufficient. We provide sensitivity analyses that show that our estimated quantities of interest are not substantively affected by our choice of K. Figure C.4 plots differences in standardized survival curves for different degree of freedom choices. It shows that our results are rather insensitive to specific choices

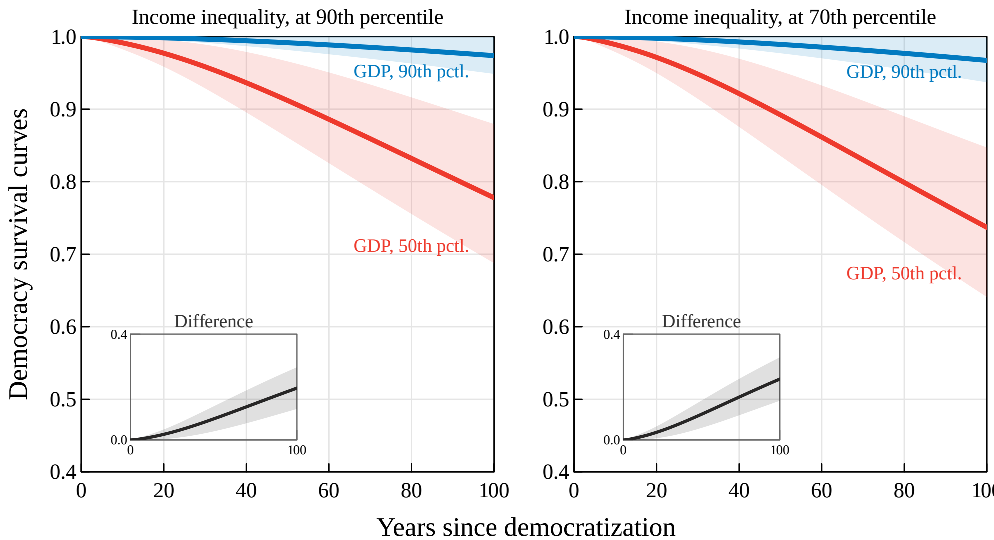

Figure C.3
Results when using income inequality instead of total inequality.
Analyses with disposable household income inequality (SWIID database) instead of total inequality. Plotted are survival functions (with 95% confidence intervals) at low (50th percentile) and high (90th percentile) levels of GDP. The left panel holds income inequality at the 90th percentile (as in the main text), the right panel at the 70th percentile. Inset shows differences in survival curves with 95% confidence intervals.

(specifying 'too many' degrees of freedom simply leads to some spline coefficients being nearly identical).

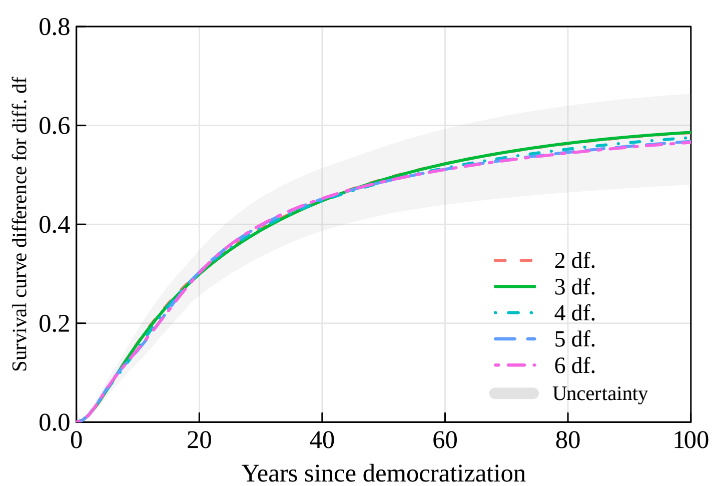

Figure C.4
Impact of baseline hazard spline degree of freedom choices.
This figure plots differences in conditional survival curves contrasting survival under high inequality at low vs. high GDP (cf. equation C.18) with $df = (2, 3, 4, 5, 6)$ for restricted cubic spline baseline hazards.

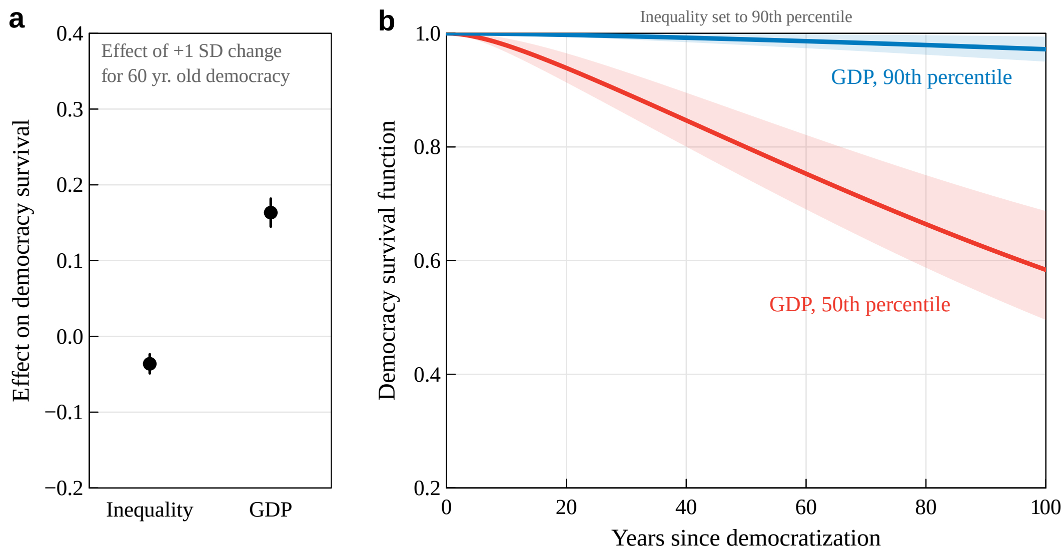

Figure C.5
Accounting for regional number of democracies and democratic breakdowns.

Note: This figure plots results from analyses accounting for the number of democracies in the region of country i at time t as well as the number of breakdowns of democracies in the region. Panel (a) shows the effect of a standard deviation increase in inequality or GDP on the probability of democractic survival; panel (b) shows standardized survival curves for high-inequality democracies at low (50th percentile) and high (90th percentile) levels of GDP.

C.8. Regional democracy

In this subsection we examine the stability of our core results when accounting for the regional prevalence of democracy as well as the incidence of democratic breakdowns. We estimate a model that includes for each country at each point in time: (i) the number of countries in the region that are currently classified as democratic, (ii) the number of democratic breakdowns.[11] Panel (a) of Figure C.5 shows the effect of a standard deviation increase in development and inequality on the probability of democratic survival, while panel (b) plots standardized survival curves. When accounting for regional democracy, the model predicts that democracies are somewhat more stable over time. This is noticeable under high development, where the probability of survival stays close to one, and under median levels of development, where the survival probability over time is between 10 and 20 percentage points higher (compared to the results reported in the main text). But these results also confirm our core finding: the negative impact of inequality on democratic survival is significantly less pronounced in societies characterized by high levels of development.

[11]See section A.1 for details on the regional classification of countries used.

D. Bayesian survival model with nonlinear interaction surface of inequality and GDP

In our main duration model we have investigated the survival of democracies under high equality at medium and high levels of development. To gain a fuller picture of the interaction between total inequality and GDP in shaping the hazard of democratic breakdowns, we estimate a model that includes a two-dimensional smooth surface of the two variables. We model the hazard of country i experiencing a breakdown event at time t as follows:

$$h_i(t) = \exp\left\{f_\eta(t) + f_{\mu 1}(w_i(t)) + f_{\mu 2}(x_i(t)) + f_{\mu 3}(w_i(t), x_i(t)) + r_i'\rho + z_i'\gamma\right\} \tag{D.1}$$

where $f_\eta(t)$ is a flexible log-baseline hazard function, $f_{\mu 1}(w_i(t))$ is a smooth function of (time-varying) total inequality and $f_{\mu 2}(x_i(t))$ is a smooth function of (time-varying) GDP per capita. The smooth two-dimensional interaction surface of the two variables is captured by $f_{\mu 3}(w_i(t), x_i(t))$. Additional covariates, such as the number of previous democratic breakdowns, enter the model linearly and are collected in z_i. The r-th element of indicator vector r_i is equal to one if country i belongs to region r ($r = 1, \ldots, R$) and zero otherwise. The corresponding coefficients ρ_r have a random effects structure and are distributed $\rho_r \sim N(0, \sigma_\rho^2)$.

To estimate the shape of the log-baseline hazard function flexibly, we approximate f_η in terms of basis function expansions:

$$f_\eta(t) \approx \sum_{m=1}^{M} \zeta_m B_m(t) = \boldsymbol{X}_\eta(t)\boldsymbol{\beta}_\eta \tag{D.2}$$

where $B_m(t)$ are basis functions with corresponding basis coefficients ζ_m. We use cubic B-splines with 8 knots. The constructed $n \times M$ design matrix is given by $\boldsymbol{X}_\eta(t)$ and $\boldsymbol{\beta}_\eta$ is the associated length-M coefficient vector to be estimated—subject to a quadratic penalty which penalizes for too abrupt function jumps (Wood 2017: 205). We implement penalization using a hierarchical prior (e.g., Ruppert et al. 2003; Wood 2004):

$$\boldsymbol{\beta}_\eta \sim N\left(0, \left[\frac{1}{\omega_\eta^2}\boldsymbol{K}_\eta\right]^g\right) \tag{D.3}$$

Here A^g denotes the generalized inverse of A and $\boldsymbol{K}_\eta$ is a penalty matrix specified as $\boldsymbol{K} = \boldsymbol{D}_r'\boldsymbol{D}_r$. $\boldsymbol{D}_r$ is a difference matrix of order r (Eilers and Marx 1996). In our analyses we specify $r = 2$, i.e., second order differences. See Stegmueller (2014) for an illustration of second order difference penalties. The smoothness of the function is thus governed by the penalty term $\lambda_\eta = \omega_\eta^{-2}$, which we learn from the data. Note that in the limit, $\lambda_\eta \longrightarrow 0$ one obtains a linear fit. The prior we put on the variance ω_η^2 is parametrized such that it prefers linear effects over "wiggly" ones unless demanded by the data (more details below).

Interaction surface We now turn to the approximation of the non-linear smooth interaction surface of inequality and development. We specify the interaction surface in three parts: splines for the main effects of inequality and GDP and a tensor product of these two splines (Wood 2017: 227ff). Beginning with inequality, the function $f_{\mu 1}(t)$ is specified as a penalized spline:

$$\boldsymbol{f}_{\mu 1}(t) = \boldsymbol{X}_{\mu 1}\boldsymbol{\beta}_{\mu 1}, \qquad \boldsymbol{\beta}_{\mu 1} \sim N\left(0, \left[\frac{1}{\omega^2_{\beta_{\mu 1}}}\boldsymbol{K}_{\mu 1}\right]^{g}\right), \tag{D.4}$$

where, $\boldsymbol{X}_{\mu 1}$ is a design matrix of B-spline bases with 5 knots and $\boldsymbol{\beta}_{\mu 1}$ are the corresponding amplitudes (coefficients) with a second-differences regularization prior as discussed above. For GDP, the function $f_{\mu 2}(t)$ is specified as:

$$\boldsymbol{f}_{\mu 2}(t) = \boldsymbol{X}_{\mu 2}\boldsymbol{\beta}_{\mu 2}, \qquad \boldsymbol{\beta}_{\mu 2} \sim N\left(0, \left[\frac{1}{\omega^2_{\beta_{\mu 2}}}\boldsymbol{K}_{\mu 2}\right]^{g}\right), \tag{D.5}$$

with design matrix $\boldsymbol{X}_{\mu 2}$ of B-spline bases with 5 knots and spline coefficients $\boldsymbol{\beta}_{\mu 2}$. The smooth interaction surface of inequality and development can now be constructed using the marginal bases for the two terms (denoting inequality terms by w and GDP terms by x and dropping country and time information for notational parsimony):

$$\boldsymbol{f}_{\mu 3}(w, x) = (\boldsymbol{X}_{\mu 3w} \odot \boldsymbol{X}_{\mu 3x})\boldsymbol{\beta}_{\mu 3} \tag{D.6}$$

where $\odot$ denotes the tensor product[12], $X_{\mu 3w}$ is an $N \times D$ matrix of evaluations of a marginal spline basis at w, while $X_{\mu 3x}$ is an $N \times D$ matrix of evaluations of a marginal spline basis at x. We penalize the corresponding spline coefficients (or amplitudes) to discourage too abrupt function jumps:

$$\boldsymbol{\beta}_{\mu 3} \sim N\left(0, \left[\frac{1}{\omega^2_{\mu 3w}}\boldsymbol{K}_{\mu 3w} \otimes \boldsymbol{I}_x + \frac{1}{\omega^2_{\mu 3x}}\boldsymbol{I}_w \otimes \boldsymbol{K}_{\mu 3x}\right]^{g}\right) \tag{D.7}$$

where $\otimes$ denotes the Kronecker product, $\boldsymbol{K}_{\mu 3x}$ is the penalty matrix for the GDP splines, which we specify as second order differences, and $\boldsymbol{K}_{\mu 3w}$ is the penalty matrix for the inequality splines, also specified in terms of second order differences. This hierarchical setup implies two penalty terms, $\lambda_1 = \omega^{-2}_{\mu 3w}$ and $\lambda_2 = \omega^{-2}_{\mu 3x}$. Using second order difference penalty matrices implies that in the limit, $\lambda_1 \longrightarrow 0$ and $\lambda_2 \longrightarrow 0$ a linear fit of the function is obtained.

Country frailties As discussed before in this appendix, a key issue in a survival analysis of democracy is the presence of unobserved heterogeneity. That is, some countries might have a higher or lower chance of breakdowns due to unknown (unmeasured or unmeasurable) characteristics. In the extended specification of this model, we account for (time-constant) unobserved country heterogeneity by adding country frailties/random effects that act multiplicatively on the hazard of

[12]Note: for a $p * a$ matrix A and a $p * b$ matrix B, the row tensor product $\odot$ is given by: $A \odot B = (A \otimes 1'_b) \cdot (1'_a \otimes B)$

democratic breakdown. The extended model has the following form:

$$h_i(t) = \exp\left\{f_\eta(t) + f_{\mu 1}(w_i(t)) + f_{\mu 2}(x_i(t)) + f_{\mu 3}(w_i(t), x_i(t)) + r_i'\rho + z_i'\gamma + \xi_i\right\} \tag{D.8}$$

where ξ_i are country random effects specified as arising from a common normal distribution, $\xi_i \sim N(0, \sigma_\xi^2)$.

Priors and estimation Identification of the model requires centering the functions $f_{\mu 1}$ and $f_{\mu 2}$, which is implemented by suitably transforming the relevant design matrices (Wood 2017: 211). We estimate the model in a Hierarchical Bayesian framework. To complete the model we assign (hyper-) priors to all remaining model parameters. The most important choice concerns the hyperpriors for the smoothing variances, $\left\{\omega_\eta^2, \omega_{\beta_{\mu 1}}^2, \omega_{\beta_{\mu 2}}^2, \omega_{\mu 3w}^2, \omega_{\mu 3x}^2\right\}$. We follow Klein et al. (2016) who propose a prior that prefers a simple linear functional form unless a deviation is indicated by the data. It follows the principles for function priors outlined in Simpson et al. (2017):

$$\omega_p \sim \frac{1}{2\theta}\left(\frac{\omega^2}{\theta}\right)^{-\frac{1}{2}} \exp\left[-\left(\frac{\omega^2}{\theta}\right)^{\frac{1}{2}}\right] \tag{D.9}$$

The free parameter θ relates to the rate of decay of the distance to a parsimonious linear functional form. We set it to 0.0088 (cf. Klein et al. 2016: Appendix B, esp. Table B1 and Figure B1). For a more detailed discussion in a political science context see Becher et al. (2021). Finally, covariate effects γ are assigned "flat" normal priors with mean zero and standard deviation 1000. Priors for random effect variances (e.g, for region random effects) are assigned inverse gamma priors with shape and scale set to 0.001. We estimate the model in two stages. First, the log-posterior mode of the model is maximized using a Newton-Raphson algorithm. The resulting estimates serve as starting values for the MCMC sampler. Second, sampling from the posterior distribution of the model is done using Metropolis-Hastings sampling (integrals in the survival function are integrated numerically using the trapezoid rule). We run two chains for 25,000 MCMC iterations thinned by a factor of two, and we discard the first 5,000 samples in each chain as transient phase.

D.1. Accounting for spatial correlation / heterogeneity

In this extension, we allow for spatial correlation in country unobservables/frailties. Decompose country unobservables into an idiosyncratic and a spatially correlated component (Besag et al. 1991):

$$\xi_i = \xi_i^{(u)} + \xi_i^{(s)} \tag{D.10}$$

The idiosyncratic term is modelled as before, $\xi_i^{(u)} \sim N(0, \sigma_\xi^2)$, whereas the spatial term $\xi_i^{(s)}$ is modelled as a spatial (intrinsically) conditional autoregressive structure (Besag and Kooperberg 1995) via a Gaussian Markov Random Field prior (Fahrmeir and Lang 2001; Rue and Held 2005;

Banerjee et al. 2015):

$$\xi_i^{(s)} | \xi_j^{(s)}, i \neq j, \phi^2 \sim N\left(\frac{1}{S_i} \sum_{j \in \mathcal{A}_i} \xi_j^{(s)}, \frac{\phi^2}{S_i}\right) \tag{D.11}$$

where S_i is the number of neighboring countries, and $j \in \mathcal{A}_i$ denotes that country j is a neighbor of country i (the set $\mathcal{A}_i$ contains the indices of the neighbors of i). Thus, each spatial country random effect has a conditional mean equal to the average of the neighboring countries. It can be shown that the conditional normal distribution given in (D.11) corresponds to a multivariate normal distribution with mean zero and precision matrix equal to the adjacency matrix induced by the neighborhood structure (Banerjee et al. 2015). We implement this prior in its equivalent penalization form (Wood 2017):

$$\boldsymbol{\xi}^{(s)} | \phi^2 \propto \exp\left(-\frac{1}{2\phi^2} \boldsymbol{\xi}^{(s)\prime} \boldsymbol{K}^{(s)} \boldsymbol{\xi}^{(s)}\right) \tag{D.12}$$

where the elements of the penalty matrix $\boldsymbol{K}^{(s)}$ are $k_{ii} = S_i$ and

$$k_{ij} = \begin{cases} -1 & \text{if } j \in \mathcal{A}_i \\ 0 & \text{otherwise} \end{cases} \tag{D.13}$$

We define "neighbors" in $\boldsymbol{K}^{(s)}$ based on their spatial closeness (the distance between centroids of the country polygons) and select the closest country as neighbor.[13] We explored other neighborhood choices (such as using the two closest neighbors) with similar substantive results. With the penalty matrix in hand, the only remaining free parameter is the penalty term $\lambda = \phi^{-2}$. Estimating the variance ϕ^2 from the data (using Gibbs updates at every step of the MCMC sampler) allows us to learn the degree of spatial smoothing. Its hyperprior is inverse Gamma with small shape and scale ($\phi^2 \sim IG(a = b = 0.001)$), but we ensured that alternative choices, such as a half-Normal prior, leads to substantively equivalent results.

Figure D.1 plots the results from our semi-parametric survival model when accounting for spatial interdependencies. As before, our specification adjusts for previous democratic breakdowns and includes political region effects (cf. equation D.1.) The z axis reports the probability of a breakdown (in the full range from 0 to 1) for combinations of semi-deciles of development and democracy, reported on the x and y axes, respectively.

The overall pattern revealed in Figure D.1 is quite similar to the one we report in the main text. As inequality increases, the collapse of a democracy becomes increasingly likely everywhere. However, for wealthy countries, the negative impact of inequality is considerably more limited compared to poorer countries. In comparison to Figure V in the main text, this analysis yields a somewhat higher probability of democratic breakdowns as inequality increases even at high

[13] This is preferable over the common definition of neighbors as units sharing a common border, because it allows close countries separated by water to still be defined as neighbors.

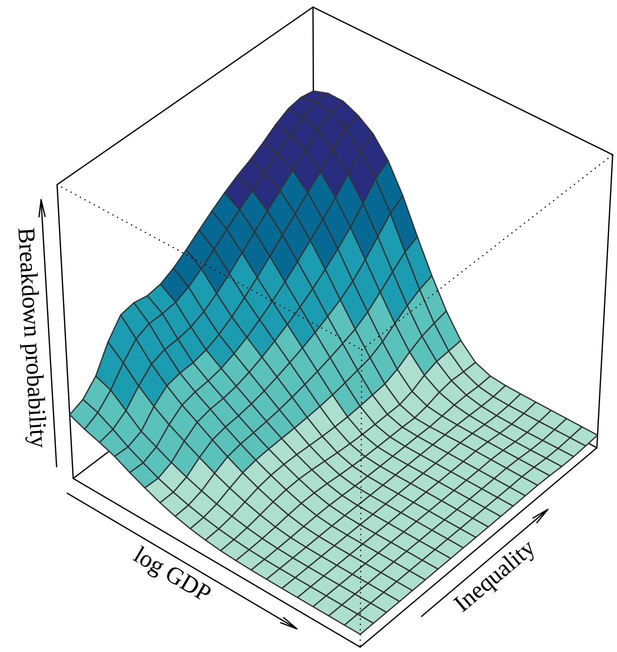

Figure D.1
Probability of democratic breakdown for semi-deciles of inequality and GDP when allowing for spatial dependency in country unobservables.

This figure plots the interaction surface of the probability of a breakdown ($1 - P(T > t)$) for a democracy of median age (that has not previously failed). Both the GDP and inequality axis are subdivided into semi-deciles yielding predicted non-survival rates in 400 GDP–inequality cells shown on the z-axis (ranging from 0 to 1). Calculated from a semi-parametric model using a tensor product of cubic penalized splines of inequality and GDP and with intrinsic conditional autoregressive spatial effects.

levels of development – a finding that is in line with a model where a highly developed country's risk of democratic failure can be influenced by that of a potentially less developed close neighbor.

At very low levels of development (the lowest decile) Figure D.1 also shows a slightly lower probability of breakdown under high inequality compared to Figure V. This pattern is likely the result of a few countries that display the unusual combination of very low (log) GDP, high inequality and a spell of democracy (e.g., Sierra Leone and Nigeria in the early 1960s), which lower the breakdown probability of close, spatially correlated at-risk democracies.[14]

E. Bayesian simultaneous model of backsliding and survival

In this section we discuss our simultaneous model of democratic survival and indicators of backsliding (such as losers' non-consent to electoral results). The aim of the model is to

[14]Note that the 3D plot necessarily only shows the posterior expectation of the predictions and not their uncertainty. Thus, small differences between the figures should probably not be over-emphasized.

simultaneously estimate two processes—the evolution of the backsliding indicator(s) and the survival process—while allowing for the fact that the latter is influenced by the former. This setup mirrors joint models of time-to-event and time-varying bio-markers employed in medical research on cancer, diabetes onset, and HIV progression (e.g., Tsiatis and Davidian 2001, 2004; Lawrence Gould et al. 2015; Köhler et al. 2017). Below, we first discuss the survival process and how we model its dependence on systematic changes in backsliding. We discuss an extension where the association between the dynamics of backsliding and democratic survival is not constant, but itself a (possibly non-linear) function of development. Next, we discuss how we model country-specific backsliding dynamics using a flexible semiparametric functional random effects model. The model is implemented in the Bayesian framework. A discussion of prior choices and estimation concludes this section.

The survival process: semi-parametric hazard model

Denote by T_i the time of democratic breakdown for country i ($i = 1, \ldots, n$), which is possibly right-censored. The corresponding event indicator δ_i is equal to 1 if a country experienced the event and 0 if it is censored (i.e., still a democracy at the end of our observation period). We model the hazard of a breakdown at time t as:

$$h_i(t) = \exp\left\{f_\eta(t) + \kappa \cdot s_i(t) + \xi_i + f_\alpha(x_i(t)) \cdot \mu_i(t)\right\} \tag{E.1}$$

Here, $f_\eta(t)$ is the possibly non-linear log-baseline hazard function; κ is a scalar parameter capturing the impact of the time-varying count of previous breakdowns, $s_i(t)$; ξ_i are political region random effects, which we model as arising from a zero-mean normal distribution with freely estimated variance: $\xi_i \sim N(0, \upsilon^2)$. Our core quantity of interest is $f_\alpha(\cdot)$, which captures the (possibly non-linear) association between the outcome of the longitudinal measurement submodel of backsliding indicators, $\mu_i(t)$, and the log-hazard of democratic breakdown. We allow this association (i) to have a flexible functional form, and (ii) to possibly depend on the level of development, $x_i(t)$, measured by logged GDP per capita at time t. We estimate the association parameter $\boldsymbol{f}_\alpha$ via a penalized B-spline:

$$\boldsymbol{f}_\alpha = \boldsymbol{X}_\alpha(x_{it})\boldsymbol{\beta}_\alpha, \quad \boldsymbol{\beta}_\alpha \sim N\left(0, \left[\frac{1}{\omega_\alpha^2}\boldsymbol{K}_\alpha\right]^g\right) \tag{E.2}$$

where A^g denotes the generalized inverse of A, $\boldsymbol{K}$ is a second-difference penalty matrix ($\boldsymbol{K} = \boldsymbol{D}_2'\boldsymbol{D}_2$), and the variance ω_α^2 controls the smoothness of the estimated function. Finally, to estimate the shape of the log-baseline hazard function flexibly, we approximate $f_\eta(t)$ in terms of basis function expansions as in equation (D.2) above and the same prior as in equation (D.3). The amount of non-smoothness penalization is governed by the variance ω_η^2, which can be learned from the data.

The backsliding process: functional mixed effects model

We now turn to our measurement model for the dynamics of backsliding. Denote by $y_{ik}(t_{ij})$ the longitudinal backsliding indicator k ($k = 1, \ldots, K$) for country i at (potentially country-specific) time points t_{ij} ($j = 1, \ldots, n_i$). Here, n_i denotes the number of time points observed for country i. The total number of country observations in the longitudinal submodel is given by $N = \sum_{i=1}^{n} n_i$. In the analysis in the main text we present results when using a single poignant indicator of backsliding (losers' consent to election results) and when using multiple indicators. Below, we discuss the setup with multiple indicators (the losers' consent model emerges as a special case).

More compactly, we write $y_{ik}(t)$ for the outcome at time t. A key point to understanding the role of this longitudinal submodel is the measurement model structure, which decomposes measurements of backsliding indicators into (i) a time-varying semi-parametric variable, $\mu_i(t)$, which captures true changes in the extent of backsliding in a country; and (ii) error components that capture stochastic deviations for each indicator, (for example due to non-systematic measurement error in the V-Dem expert raters):

$$y_{ik}(t) = \mu_i(t) + \epsilon_{ik}(t), \quad \epsilon_k \sim N(0, \sigma_k^2). \tag{E.3}$$

It is $\mu_i(t)$ that enters the survival outcome model. We thus need to specify a model for it that captures changes in backsliding in a flexible fashion.[15] Two issues are important. First, we need to allow for the possibility that the time trend in consent is more complex than what would be captured by simple linear or quadratic trend specifications. Second, we need to account for the fact that the dynamics of backsliding are country-specific.

Thus, we specify a functional random effects model (see, e.g., Guo 2002; Zhang et al. 1998) of the form:

$$\mu_i(t) = f_{\mu 1}(t) + f_{\mu 2}(i) + f_{\mu 3}(t, i) \tag{E.4}$$

where $f_{\mu 1}(t)$ is a smooth non-linear time effect, $f_{\mu 2}(i)$ are country-specific random intercepts, and $f_{\mu 3}(t, i)$ captures smooth non-linear country-specific deviations from the overall time effect. Identification of the model requires $\int f_{\mu 1}(t) dt = 0$ and $\int f_{\mu 3}(t, i) dt = 0$, which can be implemented by suitably transforming the relevant design matrices discussed below.

The function $f_{\mu 1}(t)$ is specified as a penalized spline

$$\boldsymbol{f}_{\mu 1}(t) = \boldsymbol{X}_{\mu 1} \boldsymbol{\beta}_{\mu 1}, \qquad \boldsymbol{\beta}_{\mu 1} \sim N\left(0, \left[\frac{1}{\omega^2_{\beta_{\mu 1}}} \boldsymbol{K}_{\mu 1}\right]^{g}\right), \tag{E.5}$$

where, as discussed above, $\boldsymbol{X}_{\mu 1}$ is a design matrix of B-spline bases with 10 knots and $\boldsymbol{\beta}_{\mu 1}$ are the corresponding amplitudes (coefficients) with a second-differences regularization prior. Random

[15] Popular social science models of this form include the well-known class of growth curve models (with a single or multiple indicators) which usually include unit-specific linear or quadratic time trends (in addition to unit-specific effects). We assume that $\epsilon_j \perp \epsilon_k | \mu_i(t)$ for $j \neq k$, i.e., that conditional on the latent variable the measurement items are independent (Jackman 2008).

intercepts $f_{\mu 2}(i)$ are constructed via an $N \times n$ indicator matrix $\boldsymbol{X}_{\mu 2}$ where the columns indicate which longitudinal symptom measurements belong to country i.

$$\boldsymbol{f}_{\mu 2}(i) = \boldsymbol{X}_{\mu 2}\boldsymbol{\beta}_{\mu 2}, \qquad \boldsymbol{\beta}_{\mu 2} \sim N\left(0, \left[\frac{1}{\omega^2_{\beta_{\mu 2}}}\boldsymbol{I}_n\right]^g\right), \tag{E.6}$$

where $\boldsymbol{I}_n$ is an $n \times n$ identity matrix. Thus, random intercepts are distributed normal with mean zero and variance $\omega^2_{\beta_{\mu 2}}$. Country-specific function deviations $f_{\mu 3}(t, i)$ can now be constructed using the marginal bases for the random intercepts (denoted by s) and time (denoted by t):

$$f_{\mu 3}(t, i) = (\boldsymbol{X}_{\mu 3s} \odot \boldsymbol{X}_{\mu 3t})\boldsymbol{\beta}_{\mu 3} \tag{E.7}$$

where $\odot$ denotes the tensor product, $X_{\mu 3s}$ is an indicator matrix for random intercepts and $X_{\mu 3t}$ is an $N \times D$ matrix of evaluations of a marginal spline basis at t. Again, we penalize the corresponding spline coefficients (or amplitudes) to discourage too abrupt function jumps:

$$\boldsymbol{\beta}_{\mu 3} \sim N\left(0, \left[\frac{1}{\omega^2_{\mu 3s}}\boldsymbol{K}_{\mu 3s} \otimes \boldsymbol{I}_t + \frac{1}{\omega^2_{\mu 3t}}\boldsymbol{I}_s \otimes \boldsymbol{K}_{\mu 3t}\right]^g\right) \tag{E.8}$$

where $\otimes$ denotes the Kronecker product, $\boldsymbol{K}_{\mu 3t}$ is the penalty matrix for the splines, which we specify as second order differences, and $\boldsymbol{K}_{\mu 3s} = \boldsymbol{I}_n$ is the penalty matrix for the random effects. This yields a random effects structure with smoothness penalties *across time* for each country. Including two variance terms above allows for smoothing penalties to differ between time and units.

Priors and estimation

To complete the Bayesian specification of the model, we assign (hyper-) priors to all remaining model parameters. The most important choice concerns the hyperpriors for the smoothing variances, $\omega_p,\ p \in \left\{\omega^2_\lambda, \omega^2_\alpha, \omega^2_{\beta_{\mu 1}}, \omega^2_{\beta_{\mu 2}}, \omega^2_{\mu 3s}, \omega^2_{\mu 3t}\right\}$. As before, we use a prior that prefers a simple linear functional form unless a deviation is indicated by the data.

$$\omega^p \sim \frac{1}{2\theta}\left(\frac{\omega^2}{\theta}\right)^{-\frac{1}{2}} \exp\left[-\left(\frac{\omega^2}{\theta}\right)^{\frac{1}{2}}\right] \tag{E.9}$$

The free parameter θ relates to the rate of decay of the distance to a parsimonious linear functional form. We set it to 0.0088 (cf. Klein et al. 2016: Appendix B, esp. Table B1 and Figure B1). For the regression-type parameter κ we use a simple mean-zero normal prior with variance 100. For the variance of observation-level residuals σ^2 and the variance of the political region effects υ^2 we use an inverse gamma prior with shape and scale set to 0.001. We estimate the model in two stages. First, the log-posterior mode of the model is maximized using a Newton-Raphson algorithm (with a limit of 200 iterations) and optimum smoothing variances are selected using a stepwise approach

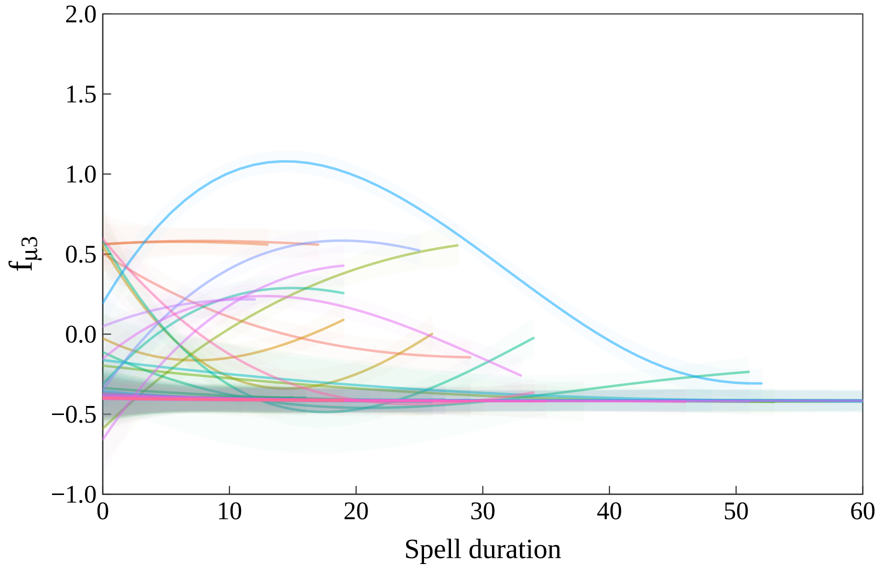

Figure E.1

The dynamics of losers' electoral consent. Estimated functional random intercepts, $f_{\mu 3}(t, i)$, for 50 randomly selected countries

Calculated from semiparametric hierarchical model with functional random country-time intercepts. Main effect of time modeled via penalized B-splines (10 knots); time-constant country random effects modeled via hierarchical IG prior, functional (time-varying) random intercepts modeled via B-spline–country indicator matrix tensor product. Penalization on splines via hierarchical scale-dependent priors. Based on 5,000 MCMC samples.

(using the *AICc* criterion). The resulting estimates serve as starting values for the MCMC sampler. Second, sampling from the posterior distribution of the model is done using Metropolis-Hastings sampling. We run two chains for 14,000 MCMC iterations thinned by a factor of two, and we discard the first 2,000 samples in each chain as transient phase.

Figure E.1 on the previous page plots posterior means of $f_{\mu 3}(t, i)$ for the first 60 years of 50 randomly chosen democracies.[16] It reveals considerable heterogeneity of within-country dynamics of losers' electoral consent in terms of levels, inflection points, and rate of change. This complexity is unlikely to be captured by standard panel data models, underscoring the importance of our flexible functional random effects model specification.

The expected value of losers' consent at time t, $\mu_i(t)$, enters the hazard of democratic breakdown through the (non-linear) term $f_\alpha(x_i(t)) \cdot \mu_i(t)$. We display its estimated functional form (on the hazard ratio scale) in the main text and repeat it as Figure E.2 for convenience. We find that as $\mu_i(t)$ increases the hazard of democratic breakdown does indeed shift upwards. However, this relationship is clearly moderated by development. As log GDP per capita (x_{it}) increases, lack of losers' consent shifts the hazard by a decreasing amount. At very high levels of development, the relationship between the backsliding indicator and the ultimate failure of democracy is greatly reduced.

[16]For purposes of visualization, we chose among democracies who survived for more than 10 years.

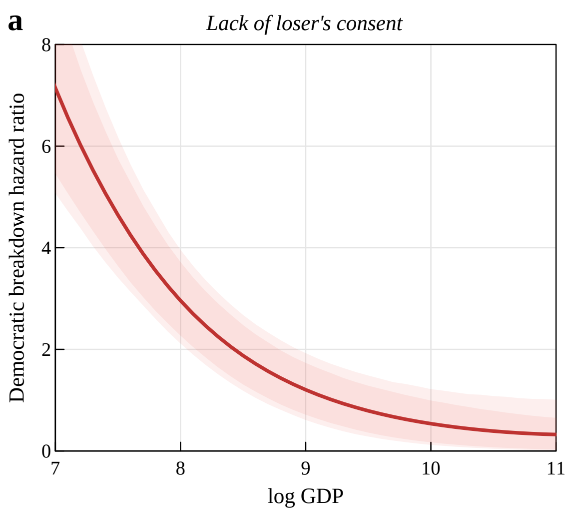

Figure E.2

Association between lack of losers' consent and democratic failure as function of development. This figure plots $f_\alpha(x_i(t))$ – the relationship between the expected value of a longitudinal marker $\mu_i(t)$ (lack of losers' consent to election results) and the hazard ratio of democratic breakdown as a function of logged GDP per capita.

F. Female suffrage definition of democracy

The definition of democracy used in the main text is based on three conditions: (i) election of a legislature in free multi-party elections; (ii) an executive that is (directly or indirectly) elected in popular elections and is responsible to either voters directly or to a legislature elected according to (i); and (iii) a majority of the population holding the right to vote. Since our analyses reach back to 1900, we define 'majority' as at least 50% of adult men in the main text. When defining majority as including at least 50% of adult women as well, we alter the analysis in fundamental ways. While for some countries, this change simply pushes back the *onset* of democracy (e.g, in Denmark from 1901 to 1915), for others it removes complete *spells* of democracy. For example, the Guatemalan Revolution from 1944 to 1954 is only classified as a spell of democracy when using the male suffrage definition. Thus, employing the female suffrage definition removes an instance of democratic breakdown from the analysis.

Figure F.1 show survival curves of democracies under high inequality at median and high levels of development when using this alternative definition. In panel (a), we find very similar results for both definitions when estimating models that account for past failures and political world region effects. When adding a set of covariates in panel (b), the difference between the two definitions becomes somewhat larger, especially for the high GDP setting. Note that the distribution of covariates changes between both definitions (because they change the population of democratic country-years). In addition, we find that the confidence bounds of the survival curves using the female suffrage definitions are wider compared to the analysis presented in the main text. However, the difference between the median and high GDP survival curves is still statistically different from zero, as shown in panel (c) of Figure F.1.

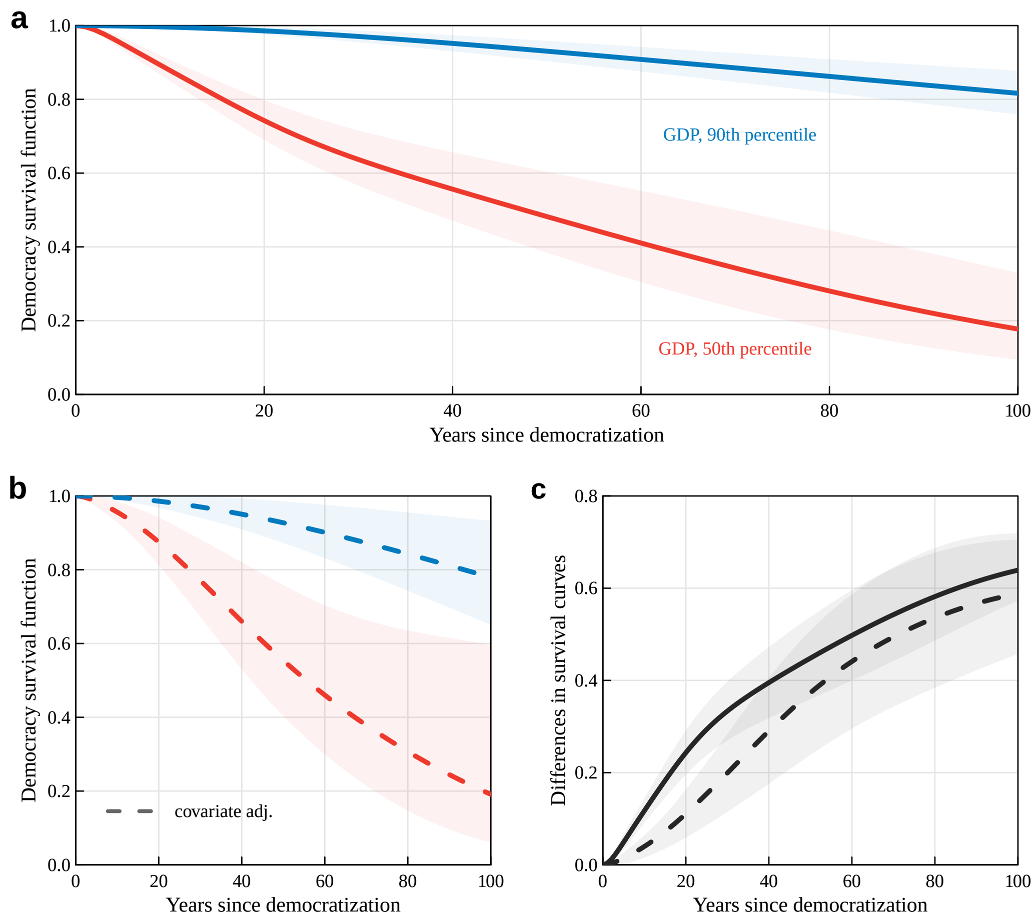

Figure F.1
Democratic survival as function of inequality and development when definition of democracy includes female suffrage.

G. Alternative measure of democracy

In this section, we repeat our survival analysis using an alternative measure of democracy based on the Polity5 database. We classify a country-year as being a democracy if its value is equal or greater than six on the polity scale.

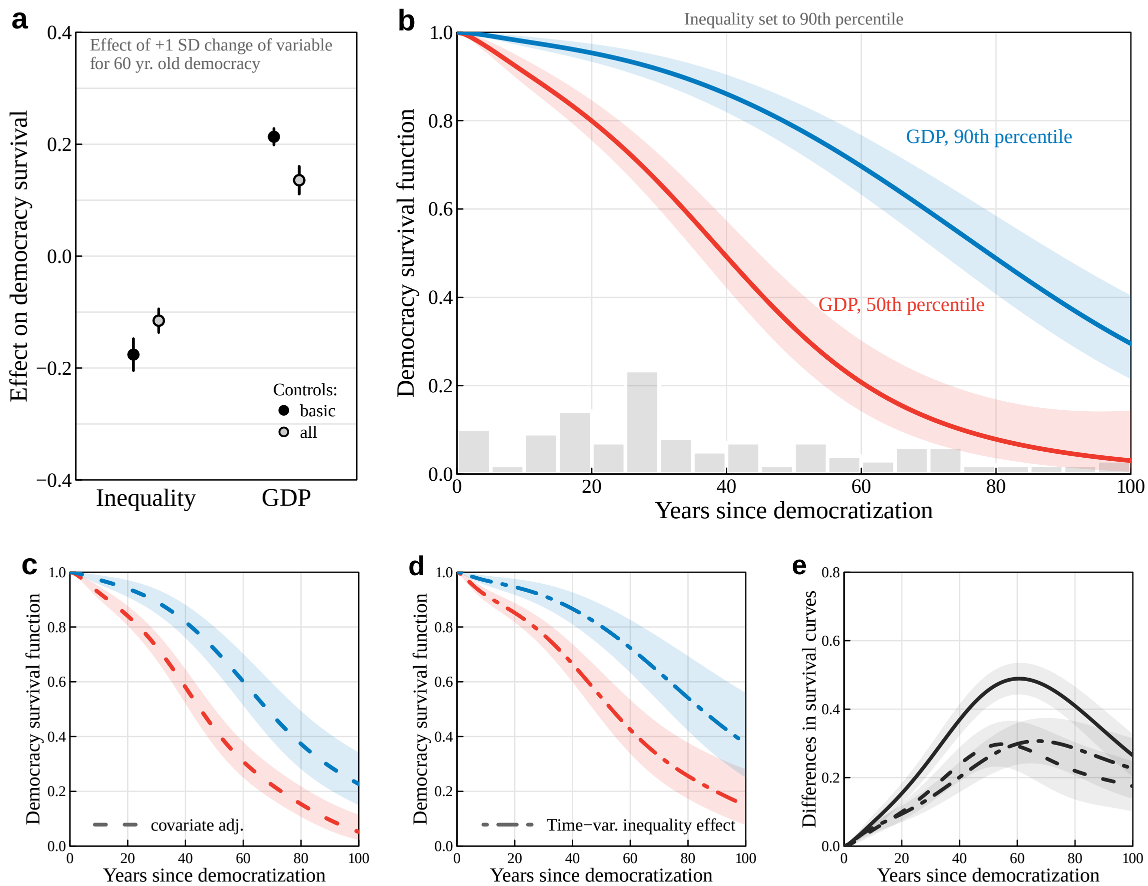

Figure G.1
Results when classifying democracies based on Polity5.

Survival predictions as in Figure IV in the main text but using Polity5 to defined democracy (a score of 6 or higher on the polity scale). Survival predictions from flexible proportional hazard model with baseline hazard rate estimated via cubic regression splines (*df=3*). Panel (a) plots the effect of a standard deviation increase from median levels of total inequality and GDP, respectively, on the predicted survival of a mature democracy (a democracy of 60 years without a previous breakdown). Panel (b) examines the impact of high inequality (90th percentile) on the over-time survival of democracies via conditional survival curves (see Appendix C.2 for their definition and calculation) and corresponding 95% confidence intervals with GDP fixed at the 50th and 90th percentile, respectively. Panel (c) adds a larger set of controls (see text). Panel (d) relaxes the proportional hazard assumption by allowing for time-varying effects of inequality. Panel (e) plots differences (with 95% confidence intervals) of conditional survival curves, i.e., the change in survival probability when moving GDP from the 50th to the 90th percentile conditional on high inequality.

Figure G.1 mirrors Figure IV in the main text and broadly confirms our key finding: while exposure to high levels of inequality over time puts democracies at higher risk of failure, development buffers this impact. As shown in panel (b) of Figure G.1, the probability of survival of a democracy with GDP at the 90th percentile compared to the median is considerably higher. Across a sizable span of the age distribution of democracies, this difference is larger than 40 percentage points. Panel (c) adds a set of covariates, while panel (d) allows for a time-varying effect of inequality (relaxing the proportional hazard assumption). Both confirm the basic pattern. Finally panel (e) shows, that the difference between survival curves at median and 90th percentile GDP at high inequality are statistically different from zero.

Figure G.2 shows the corresponding results from our joint backsliding and democratic survival model. It again confirms our core finding: there is a strong association between backsliding—whether measured using lack of loser's consent or the measurement model of five V-Dem indicators. But the strength of the relationship is moderated by development. For relatively rich societies, the association between backsliding and the risk of democratic breakdown is much more muted. Compared to the results when using the Boix et al. (2013) classification of democracy, we find that the relationship between lack of loser's consent and the risk of breakdown at very low levels of development (log GDP per capita below 7.5) is even higher.

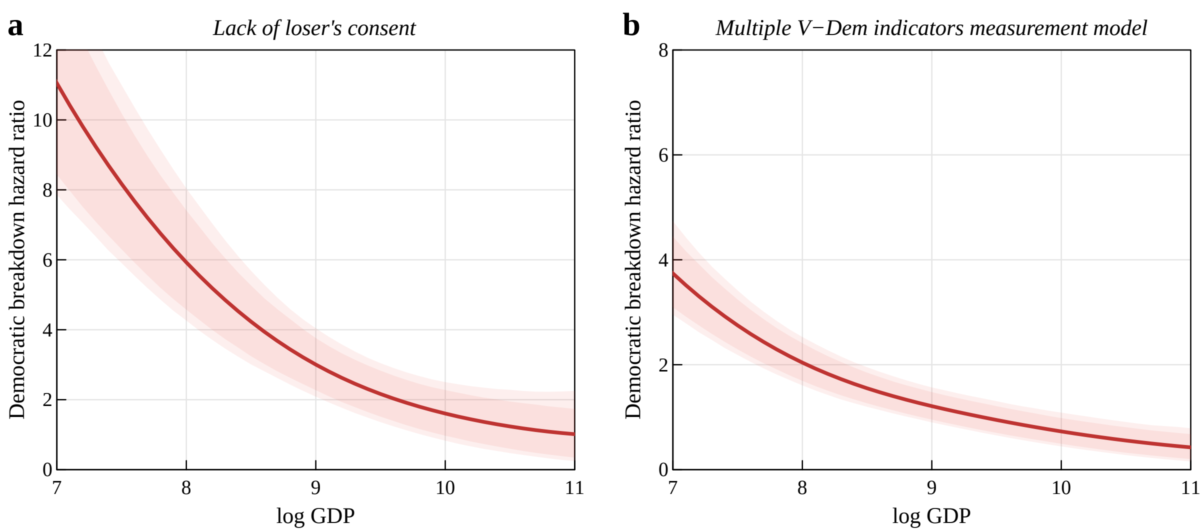

Figure G.2
Results when measuring democracy via Polity 5.

This figure plots the relationship between indicators of democratic backsliding and the hazard ratio of democratic breakdown as a function of logged GDP per capita estimated via a joint Bayesian model of a semiparametric longitudinal process and survival outcomes. See Appendix E for details. Democracies are classified using Polity5 (a score of 6 or higher on the polity scale). Panel (a) uses a single indicator, lack of losers' consent to election results. Panel (b) combines four backsliding indicators via a dynamic semiparametric measurement model. Shaded areas represent 95% credible intervals.

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