Resilient Democracies*

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What makes democracy survive, particularly in countries beset by high economic inequality and political polarization? In this paper, we analyze the drivers of democratic stability in the long run. We show that while on average inequality and polarization foster social strife and jeopardize democratic life, their ultimate institutional consequences vary with each country's level of development. Democratic institutions in developed countries remain by and large resilient despite the corrosive impact of inequality and polarization. Democracies in poor countries do not. To test our theory, we compile a data set covering sovereign states over more than a century and include a novel measurement approach appropriate for capturing the long-term evolution of income inequality. We employ semiparametric duration models that capture the complex interplay between inequality and development in shaping the probability of democratic survival over time while allowing for unobserved heterogeneity and state dependence.

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1 Introduction

The latest decades since the invention of the internet and the acceleration of globalization pose an intriguing puzzle to the student of democratic politics. In most advanced democracies, low incomes have stagnated and economic inequality has risen substantially, accompanied by increasing ideological and partisan polarization. Yet, in spite of a growing number of voices forecasting an inevitable process of democratic backsliding, representative institutions have proved to be quite resilient across the board. Inequality and polarization may well be affecting how democracies work. Yet they are not causing a wave of democratic breakdowns: governments continue to be chosen in competitive elections, competing on valence and policy to obtain the support of the majority, and remain accountable, even if imperfectly, to voters.

In this paper, we revisit existing theoretical and empirical work in the democratization literature to explain the current compatibility of economic and political polarization with democratic survival across countries. In a nutshell, we claim that, while on average inequality may foster social strife and jeopardize democratic institutions, its political consequences vary with each country's level of development. At low and intermediate levels of development, higher levels of inequality exacerbate distributive conflicts to the point of endangering democracy. There elites may coordinate to protect their economic assets and social status—either by blocking the introduction of representative institutions or by preventing their consolidation. By contrast, at advanced levels of development, the structure of income (and its impact on welfare) increases the tolerance for democracy among high earners (and wealth holders), attenuating the negative effects of inequality, and stabilizing representative democracies.

In developing our claims, we make four contributions. First, while we still rely upon standard theories characterizing democracy as an equilibrium, we refine and extend them to make the relationship between development and inequality and their (temporally varying) effects on democracy more precise. This allows us to put current discussions on democratic backsliding and survival in context. While symptoms of backsliding may be accumulating across democracies around the world, we study the conditions under which those symptoms actually jeopardize the regime itself. We show that, even though high development does not prevent the emergence of attempts to capture political institutions by elites, as the recent experience in the USA exemplifies, it does constrain the extent to which such attempts translate into the collapse of the regime.

Second, we unpack the economic and technological transformations that have shaped the nature of industrial capitalism since its emergence about two centuries ago (from pre-Fordist factories through mass production to the recent rise of information technologies) and that lie behind our two main variables of interest: development and equality. Understanding those dynamics enables us to overcome a generalized (and, at the same time, often criticized) acceptance of modernization theory as a linear process consisting of ever rising incomes and the accumulation of wealth. By showing how the forces of economic growth have shaped the distribution of assets and income, we are able to clarify how, when and why economic change has aided to the rise of democracy while pointing to its limits also.

Third, we pay particular attention to the connection between inequality and polarization, one of the main threats to democracy today, and integrate into the analysis the implications of recent contributions on democratic backsliding. We show that our findings hold even when one replaces binary measures of democracy (and its breakdown) with indicators more focused on actual elite behavior.

Finally, we advance the empirical testing of democratization theory in two ways. On the one hand, we propose a new approach to measure 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.[1] We employ 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. Furthermore, we introduce a novel modeling approach that 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, allowing us the study the conditional relationship between backsliding and democratic survival.

Our paper is organized as follows. Section 2 describes the main trends of democratization and democratic backsliding with the aid of data for the whole world starting in the early nineteenth century. Section 3 presents our theory. Section 4 presents a succinct historical analysis of the transformation of the economy in the last two centuries to shed light on the specific mechanisms through which development and equality contribute to democratic transitions and consolidation. Section 5 puts our theory to a systematic statistical test by focusing on the (separate and conditional) effects of economic growth and inequality on regime type. Section 6 discusses in detail the implications of our findings for the existing literature on both democratization and democratic backsliding. Finally, section 7 summarizes our core insights and points to complementary lines of work.

2 Empirical trends

Before we lay down our theory, consider the overall performance of democracies across the world for the last two centuries. Figure I represents the annual proportion of democratic countries from 1800 to 2015. A country is coded as a democracy if it meets three conditions: the legislature is elected in free multi-party elections; the executive is directly or indirectly

[1] Previous scholarship on the direction of the effect of inequality on democracy is highly dependent on the choice of inequality indicator: measures of land inequality yield a negative association whereas measures of income inequality point to a positive one (Ansell and Samuels 2014) .

elected in popular elections and is responsible either directly to voters or to a legislature elected according to the first condition; and, a majority of the population has the right to vote.[2]

The majority is defined in two ways. The dashed line represents the proportion of democracies if the country granted the right to vote to at least 50 percent of adult men. The solid line represents the proportion of countries where more than 50 percent of adult women also have the right to vote. After the 1970s, the two lines coincide fully, while they did not before. As is well known, in the majority of countries men were granted the vote earlier than women. If women's franchise is excluded from the definition of democracy, democratization took off in the second half of the nineteenth century. If it is included, then democratization happened after World War I.

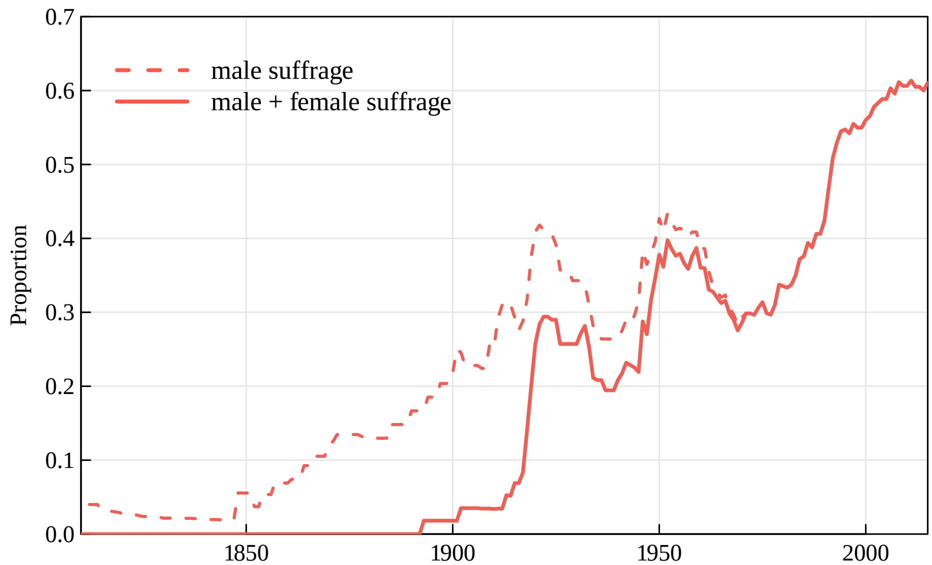

Figure I
Proportion of democracies, 1800-2015

Figure I confirms in a crisp manner Huntington's characterization of the history of democratization as a process played out through three (growing) waves so far. Following the revolutionary uprisings of 1848, the number of democracies rose from three countries or less than 6 percent of all independent states that year, to 18 nations, that is, about one third of all countries, in 1914, and to 28 countries, or 42 percent of all states, in 1921. After peaking in the early 1920s, the number of democracies declined to 13 cases and 18 percent of sovereign nations by 1940. A second and fast-paced democratization wave took place right after World War II, leading to 34 democracies or 40 percent of independent states by 1950. A third and even more dramatic democratization wave started in Southern Europe in the mid-1970s, crossed the

[2]The first two conditions follow Przeworski's definition and coding of democracy (Przeworski et al. 2000). The third one comes from Boix et al. (2013).

Atlantic to Latin America in the following decade, and then, back again in Europe, crested with the fall of the Soviet Union in the early 1990. By the early 2000s, the share of democracies peaked at 60 percent of all sovereign countries. Despite rising concerns about democratic backsliding or, to use Huntington's terms, the ebbing of democratic fortunes, Figure I shows no sign that the number and proportion of democratic regimes have declined in the last two decades.

Because reporting the aggregate number of democracies may conceal considerable volatility at the individual or country level, Figure II plots the number of democratic breakdowns and democratic transitions by decade in already sovereign states. Two things stand out. The number of breakdowns in the 2010s dropped to 1 from 11 in the previous decade— the lowest value since 1920. Already democratic countries appear to be rather robust—a far cry from the impending "crisis of democracy" portrayed by a growing number of publicists and scholars (Foa and Mounk 2016; Levitsky and Ziblatt 2018). At the same time, however, the number of democratic transitions has also dwindled to 1—a figure lower than in the late 1960s, when the ebb of the second democratization wave bottomed out. We turn to the next section to explain these two patterns while also trying to make sense of the (spasmodic) diffusion of democracy over the last two hundred years.

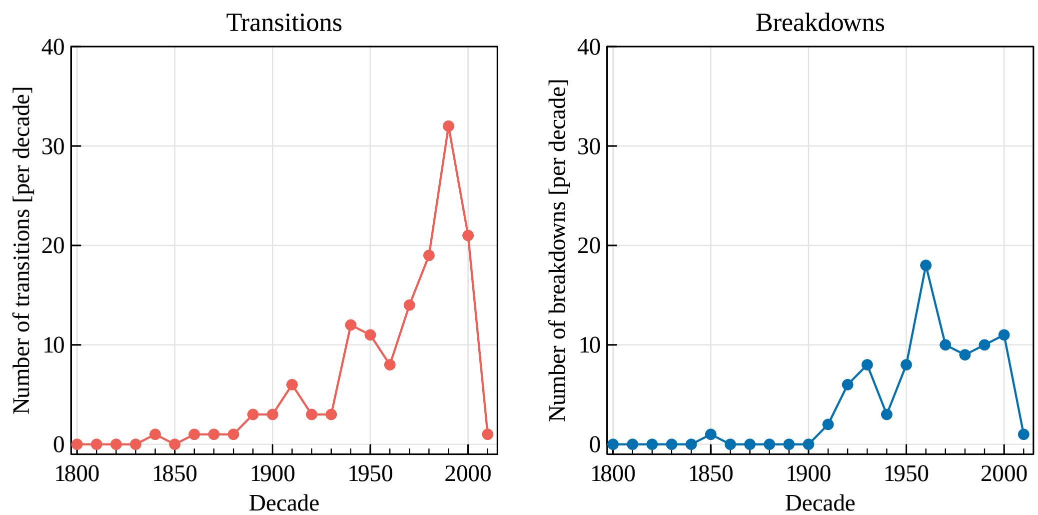

Figure II
Democratic transitions and breakdowns, 1800-2015

3 Theory

In line with the literature that portrays democracy as a political equilibrium, we model its survival as the result of the calculations that political actors make about the net benefits of maintaining it relative to reverting to a nondemocratic outcome. Democracy prevails when the "costs of repression" incurred to establish authoritarian institutions are higher than the expected policy losses from having democracy and losing control over government with some non-negative probability (losses that Dahl (1971) referred to as "costs of toleration") for all the parties in the political game (Przeworski 1991; Weingast 1997; Boix 2003).

Also in line with standard practice in the literature, a simple way to develop that general insight would be as follows. In a democracy, voters (the decisive voter or, more narrowly, the median voter) determine their policy-maker, the tax rate and the level of redistribution. In an authoritarian regime, instead, a fraction of the electorate sets taxes. Authoritarianism is not cost-free: the authoritarian elite incurs a cost to exclude the rest of the population.

Following the existing formal democratization literature, let us then characterize a polity where there are two types of agents, h or high-income individuals and l or low-income individuals. While the former have a per capita income y_h, the latter enjoy a per capita income y_l, with $y_h > y_l$. Low-income individuals constitute a majority of the population. The polity's average income, y_a, is determined by the level of y_h and y_l and the proportion of each type of individual.

Under democracy, the median voter, who is a type-l individual, sets the tax rate to maximize her final income: $\hat{y}_l = (1-\tau)y_l + \tau y_a - y_a\tau^2/2$. The low-income voter will then choose $\tau^* = 1 - y_l/y_a$. With τ^*, the post-tax post-transfer income of a high-income individual will be $\hat{y}_h$. By contrast, under authoritarian rule, taxes are 0. For low-income individuals, the final income is y_l. For high-income individuals, it is $[1-c^{1/\log y_l}]y_h$. The parameter c, $0 \geq c \leq 1$, is the cost that high-income agents pay to exclude low-income citizens from voting. That exclusion cost is a convex function of l's income: the cost c accelerates as the income of low-income agents rises.

For the sake of simplicity, all agents have full information about all the parameters, including the structure of the exclusion cost function. The latter, which again gives the cost of repression, reveals the extent to which high-income individuals are able to impose an authoritarian regime. If they pay the full cost c, they establish an authoritarian regime and low-income citizens cannot contest it successfully (and, as a result, they do not). Hence, in this set-up, the regime choice amounts to the high-income agents choosing between the utility derived from an authoritarian regime $U([1-c^{1/\log y_a}]y_h)$ and the utility derived from a democratic regime $U(\hat{y}_h)$. They will subvert democracy if:

$$U([1-c^{1/\log y_a}]y_h) > U(\hat{y}_h). \tag{1}$$

The marginal utility of additional income declines with income.[3] Hence, the disutility a transfer imposes on high-income individuals declines as their per capita income increases. In 2011, Warren Buffett called for higher taxes on $1-million incomes or higher with even a more

[3]For low incomes, below or barely above the threshold of subsistence, each additional unit of income increases individual utility almost proportionally. As income increases, utility increases at a slower pace. At very high income levels, the marginal utility of additional income approaches zero. Formally, $U(y_i) = y_i^\alpha$ for $0 < \alpha < 1$.

severe tax code on those making \$10 million or more. As Buffet put is, "I know well many of the mega-rich and, by and large, they are very decent people. They love America and appreciate the opportunity this country has given them (....) Most wouldn't mind being told to pay more in taxes as well, particularly when so many of their fellow citizens are truly suffering."[4] Likewise, in the December 2019, Bill Gates wrote, in his blog, that "I'm for a tax system in which, if you have more money, you pay a higher percentage in taxes. And I think the rich should pay more than they currently do, and that includes Melinda and me." Rising taxes on them would not distort working and investment incentives at all: "Americans in the top 1 percent can afford to pay a lot more before they stop going to work or creating jobs."[5] More generally, 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).

Four key results follow from the model:

1. First, the incentives of high-income individuals to overturn democracy fall with income equality (denoted as y_l/y_a) since the higher l's income relative to h's income, the lower the tax rate under democracy and the loss of h's income under that regime. Formally, keeping $c^{1/\log y_a}$ constant, inequality (1) is less likely to hold.

2. Second, h's incentives to establish an authoritarian regime decline with a growing income y_h. Higher taxes (imposed by a democratic regime) will have a declining marginal impact on h's welfare to a point that establishing an authoritarian regime will generate more disutility than the welfare losses resulting from majority voting.

3. Third, when average per capita income is low, economic shocks will be particularly dangerous for the survival of democracy for two reasons: (1) they will imply strong welfare effects for all parties involved; (2) at low income levels, it will be harder to finance social policies to absorb the distributive effects of those shocks because the utility loss of higher taxes is high for net taxpayers.

4. Fourth, the exclusion cost function affects the stability of democracy through two mechanisms. On the one hand, the costs of exclusion rise with income (in a convex manner), making democracy more stable as economies grow. On the other hand, the type of political regime will be directly affected, at each income level, by the size of c. This state will depend on the existing technologies of both political mobilization and repression. For example, some have hailed the internet as a "liberation technology" that would enable "citizens to report news, expose wrongdoing, express opinions, mobilize protest (...) and

[4]Warren Buffett, 'Stop Coddling the Super-Rich,' New York Times, August 14, 2011.
[5]Bill Gates, 'What I'm thinking about this New Years Eve,' Gates' Notes, December 30, 2019.

expand the horizons of freedom" ((Diamond 2010), p.70) while others have cautioned that AI technologies in general empower political incumbents (Xu 2021; Nyst 2018). The parameter c will also change with international conditions: the regional diffusion of democracy and the hegemony of liberal great powers, by increasing the costs of authoritarian politics, has been behind Huntington's democratic waves (cf. Boix 2011; Gunitsky 2014).

4 Development, Industrialization, and Democratic Institutions

In this section, we flesh out the mechanisms of the theory sketched in the previous section by looking at the joint evolution of growth, inequality and political institutions over the last two centuries. As pointed earlier, authoritarian rule was the almost universal point of departure at the turn of the nineteenth century. There were no representative democracies anywhere, except for a few North American states—and even there, the franchise was limited to property owners. Political participation was extremely limited—ranging from countries in the hands of a very small clique (Tsarist Russia or imperial China) to polities run by political elites elected by a narrow stratum of citizens (between 5 and 7 percent of the adult population in Britain before 1832). In addition, and without hardly any exceptions, ruling elites tended to correspond to the wealthy strata of society.

Such a political structure corresponded to rather specific economic and social conditions. An overwhelming majority of humankind lived at the margin of subsistence. Around 1820 about 95 per cent of the world population earned less than the equivalent of two dollars (of 1990) per day. More than four fifths had to survive with just one dollar per day. Inequality was rampant. Right before the French Revolution, the French top decile received 55 per cent of all income (Morrisson and Snyder 2000). Employing income distribution data for 28 pre-industrial 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. By contrast, they compute the level of 'rent extraction' in today's advanced economies to range from one third to two fifths. To sustain the system of privileges, personal favors and side-payments that generated those outcomes, *ancien regime* elites could not in any way acquiesce to the liberalization of political institutions.

Starting in the nineteenth century, industrialization resulted in explosive economic growth. In the north Atlantic region, per capita incomes of 1820—slightly above $1,700 in Britain and around $1,200 in other northwestern European economies and the United States—doubled over the following sixty years. By the eve of the Second World War they had more than doubled again. In 2008, per capita incomes in advanced countries were about twenty times larger than in the early nineteenth century (Maddison 2010). Nevertheless, the impact of the industrial revolution or, more precisely, of several sequential industrial revolutions on economic and social institutions was not linear. While making the deployment and use of input factors more efficient, successive waves of technological change transformed the system of production and, more crucially, the kind of labor that was most useful (i.e., most complementary) to capital. Broadly speaking, while nineteenth-century firms employed unskilled labor, twentieth-century companies relied on semi-skilled labor located in factories organized around assembly lines. In turn, today's information technologies favor high-skilled labor while making semi-skilled labor routine tasks redundant.

The evolving nature of those capital-labor "complementarities" shaped wages, the distribution of income, capital's incentives to invest in public goods, and social agents' preferences toward political institutions. The first industrial revolution, which entailed the substitution of unskilled workers employed in the modern factory for artisans working in small workshops, resulted, at least until the last decades of the nineteenth century, in both low wages and rising profits (Allen 2009; Feinstein 1998). Full democracy remained out of the question—opposed by both pre-industrial elites and the new industrial capitalists. The extension of voting rights, when it happened, was circumscribed, at most, to well-to-do town dwellers. Political oligarchies accepted, at most, a regime of limited democracy that integrated well-to-do urban strata holding moderate distributive demands.

A second industrial revolution, sparked by the use of electricity and electric motors and by the invention of the assembly line and mass production techniques, eventually attenuated the economic inequalities and social tensions of nineteenth-century capitalism. As semi-skilled and skilled employees replaced unskilled workers as the main type of labor complementary to capital, wages grew across the board, particularly among middle social strata, making the distribution of earnings more equal. 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. In the wake of higher salaries and a more equal income distribution, political conflict lost its past intensity. As the American sociologist Daniel Bell wrote in "America as a Mass Society" in 1955, "in the advanced industrial countries, principally the United States, Britain, and northwestern Europe, where national income has been rising, where mass expectations of an equitable share in that increase are relatively fulfilled, and where social mobility affects ever greater numbers (...) extremist politics have the least hold" (Bell 1988). Representative democracy had found the right soil to grow.

In the last three decades of the twentieth century, the invention of the personal computer and, later on, the creation of internet, email, and mobile phones transformed again the structure of the production process and, with it, the economy in general. Automation, while intensifying in manufacturing, now reached routine non-manual jobs. A host of software programs could reproduce and replace a growing set of routine administrative tasks, transforming employment conditions in a wide range of traditional white-collar jobs, from accounting and banking to travel agencies. Routine occupations employed almost forty-five percent of the working-age population in the United States until the mid-1980s. By 2014, that share had declined to around thirty-one percent (Cortes et al. 2017). In the meantime, the number of professional and managerial jobs, which are low in routinized tasks and highly reliant in abstract, relatively creative thought processes, rose steadily. In the United States, the share of high-skill occupations (managers and professionals) over total employment grew from almost twenty-eight percent of all civilian employment in 1980 to thirty-nine percent in 2010 (Katz and Margo 2014).[6]

A changing labor market came hand in hand with a shifting wage and income distribution. Labor productivity and median earnings, which had trended together until 1975, diverged afterwards. While US labor productivity continued to grow at a similar rate than during the postwar period, doubling between 1975 and 2016, median earnings remained flat throughout the whole period. In the United Stated as well as those economies that had regulatory structures closer to the American model of flexible labor markets, wage and income distribution broadened. 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 highly regulated economies, low wages rose and earnings inequality remained unchanged—but the cost was negligible employment growth or even a fall in jobs in the private sector in net terms.

To recap, incomes have risen, except for major depressions, almost continuously over the last hundred years. At the same time, however, they grew faster for bottom earners from the last decades of the nineteenth century until the last quarter of the twentieth century. Trends reversed then—with growth picking up among top earners. Starting from considerable levels of inequality, the distribution of income narrowed down and then widened again. Yet, the nature of political institutions did not change in a mechanical change following those distributional shifts. At the beginning of the period, high-income earners had strong incentives to oppose the expansion of the franchise. At the end of the period under analysis, growing inequality may generate (and in fact has generated) considerable political (and economic) turmoil. However, in light of the welfare calculations discussed previously, existing predictions about the death of current representative democracies (cf. Levitsky and Ziblatt 2018) are difficult to defend.[7] In principle, the level of economic development and accumulated wealth make it feasible to compensate losers—without generating uncompromising opposition from net taxpayers—and even to intensify the level of interpersonal redistribution.

[6] The direct effects of ITs on employment were compounded by growing globalization due to the emergence of newly industrialized countries, such as the East Asian Tigers, and the decision of an increasing number of American, European and Japanese companies, from toy- and other consumer-good-makers in the 1970s to electronics in the 2000s, to unbundle their production operations across the world and move low-wage jobs to developing countries. The latter' strategies were arguably the result of a sharp fall in transportation costs and the impact of the on-going information and communication revolution.

[7] For a critical position similar to ours, see Treisman (2018).

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

We turn to examine more systematically, through a battery of econometric tests employing a data set that covers the lifetime of political regimes from 1900 to 2019, our theory and the intuitions developed in the previous section.[8] Appendix A.2 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.1 illustrates the resulting data structure. All our survival analyses account for the fact that countries can experience more than one spell of democracy.

5.1 Democratic Survival

Our first analysis relates the survival of democracy over time to changes in 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 adjusting for both time-constant and time-varying confounders. For presentational reasons, we focus on graphical presentation of key quantities of interest. Appendix B provides model details and maximum likelihood parameter estimates (see Table B.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 B 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.2 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). We also 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.

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

[8]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.

(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 2021), as well as, in recent decades, the rise of the digital economy and the spatial reallocation of manufactures around the world.

This has direct implications for how we measured inequality, which, over the long run is a function of the relative importance of factors (land, capital, labor), the distribution of assets, and the distribution of income derived from each of these assets. Unfortunately, we lack precise information to fully compute a measure capturing these three things with sufficient temporal and spatial coverage. However, we can still approximate it as follows. Conceptually, we compute total inequality (TI) as a weighted sum of income inequality (II) and rural inequality (RI), where the weights capture the changing importance of the agricultural sector (AES) over time.[9]

$$TI = RI \times AES + II \times (1 - AES).$$

For rural inequality (RI), which is a measure of the distribution of land property, we employ the country-year index of rural inequality developed by Ansell and Samuels (2014: 116). For income inequality (II), which describes the distribution of income from all sources, we use data from the Standardized World Income Inequality Database (SWIID), which covers 1960 to 2020. (Solt 2016). 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.3. There we also conduct a range of sensitivity and specification tests to ensure that our substantive results do not depend on this particular methodological choice. To capture the changing relative importance of land versus capital in the domestic structure of the economy, we weight both terms with the Agricultural Employment Share (AES) for each country-year (Wingender 2014).

==> See Appendix B.6 only income inequality

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 III.[10] Panel (a) plots the effect of a one standard deviation increase from median levels of total inequality and real 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

[9] The formula captures the insights of Smith, Ricardo, and to a large extent Marx, for whom inequality was mostly a problem between factors of production, under the assumption that land, capital and labor were internally homogeneous. With modernization, however, this assumption needed relaxing and the distribution of wealth (land property, capital) and income (mostly within labor, but also returns to capital income). Accordingly, we strive to capture their internal dispersion as well.

[10] 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).

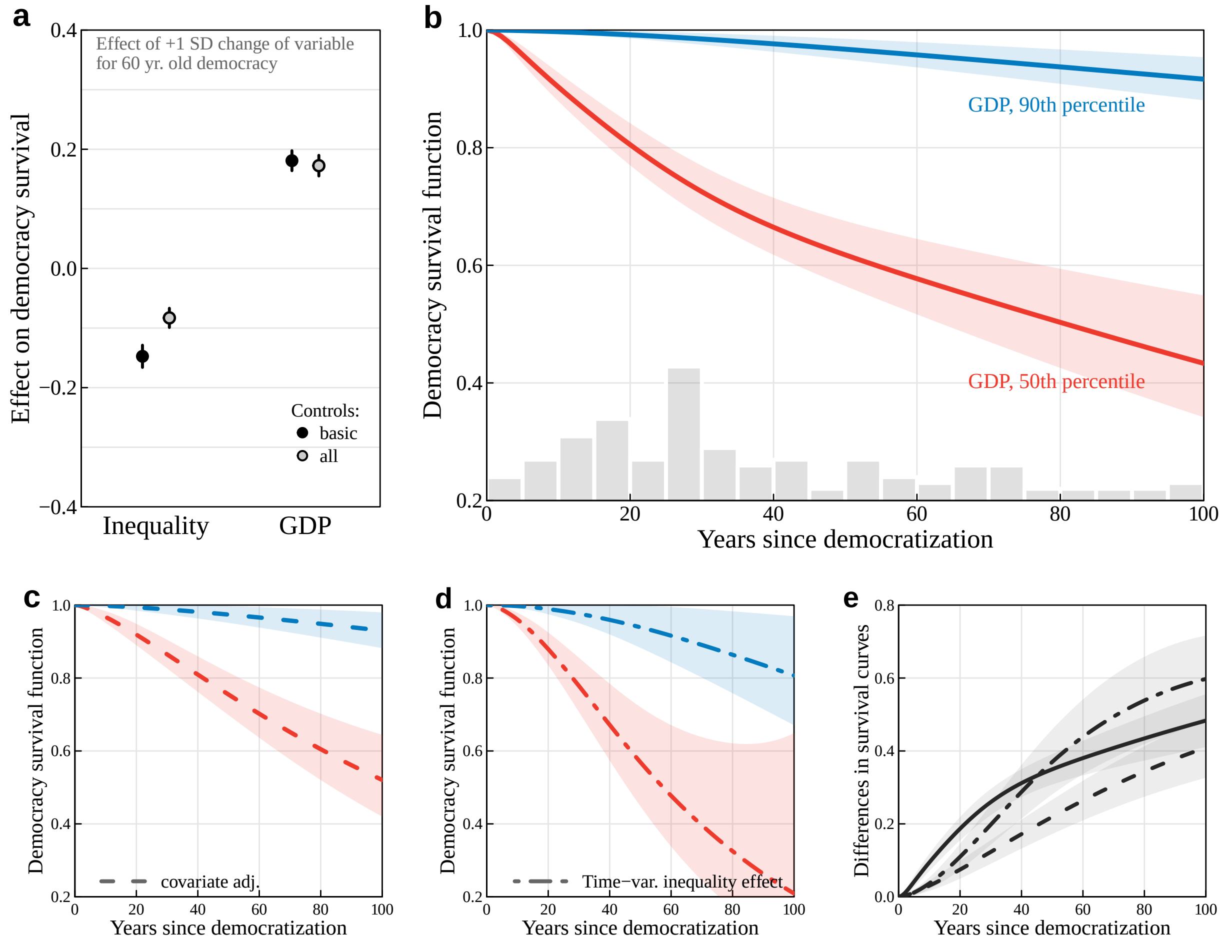

Figure III
Inequality, Development, and Survival of Democracy.

Survival predictions based on a 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 (specified as 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. It plots conditional survival curves (see Appendix B.2 for their definition and calculation) and their corresponding 95% confidence intervals with GDP fixed at the 50th and 90th percentile, respectively. Panel (c) adds a set of controls (see text for details). Panel (d) relaxes the proportional hazard assumption by allowing for time-varying effects of inequality. Panel (e) plots the differences of the two conditional survival curves, i.e., the change in survival probability when moving GDP from the 50th to the 90th percentile conditional on high inequality (with 95% confidence intervals). Distribution of democracy spell durations (in 2018) shown as gray histogram.

country with inequality at the 90th percentile in the world distribution and a real per capital 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) and societal polarization (see Appendix A.2 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 for all previous models and the corresponding 95% confidence intervals. In all cases, we find that development acts as a statistically significant moderator of the inequality effect, making the corrosive effect of inequality on the survival rate of high income democracies highly marginal.

Figure IV 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. The penalization avoids too abrupt function jumps (which enables more meaningful interpretation of the plot) and is estimated from the data. Appendix D presents the model in detail. The z axes of Figure IV 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 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 unmodelled 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 per capita 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 rathe low in both societies with low and high levels of total inequality.

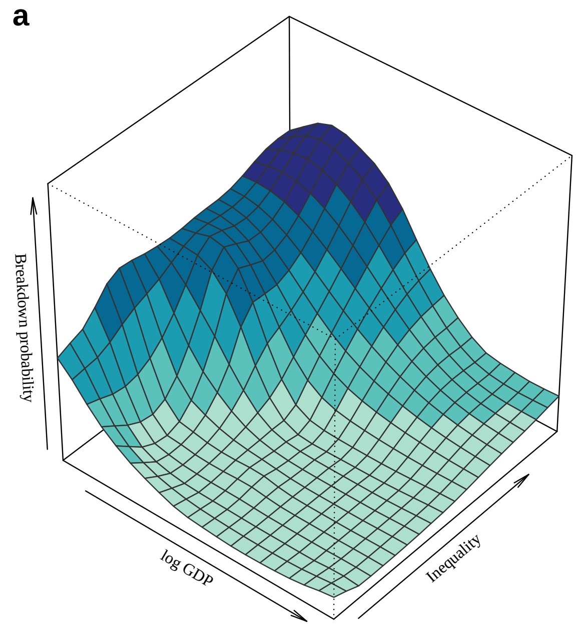

Figure IV
Probability of democratic breakdown for semi-deciles of inequality and GDP.
This figure plots the interaction surface of the probability of a breakdown ($1 - P(T > t)$) for a democracy of median age (that has not previously failed) both without (a) and with (b) country frailties. Both the GDP 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.)

Thus, our survival analyses show evidence consistent with the claim that democracy is safer under higher levels of economic development even at very high levels of inequality. Analyzed in the context of current debates, these findings are subject to two possible criticisms. The first one concerns the nature of the outcome variable. The second concerns the nature of the threat to democracy. In the next two subsections, we address each one of these objections.

5.2 Lack of losers' consent

Admittedly, our previous models assume a binary concept of democracy (or absence thereof), a conceptual prior that has come under criticism by recent scholarly work on the various ways democracies may collapse. Of particular interest recently is the notion that 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 (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 analyze an alternative dependent variable generally understood to be a *symptom* of potential democratic breakdown: the refusal of losing parties or candidates to accept their electoral defeat. As emphasized in the Theory section, 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 estimate a series of models relating the extent of lacking losers' consent to levels of inequality, development, and their interaction. 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 and estimates are available in appendix C. Here we present graphically the results of three specifications, all of which are linear panel data models with two-way fixed effects (for country and year) with robust standard errors. Panel (a) of Figure V 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 areas 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.

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. Finally, panel (c) limits the analysis to the most recent period (1946-2018). It is possible that the engines behind the current crisis of democracy have little to do with the reasons why they collapsed in the past. More generally, there is little reason to believe ex ante that the role of structural factors on regime survival is constant across space or over time. The focus on the recent period allows us to model the role of inequality and development in shaping more recent dynamics directly. This analysis

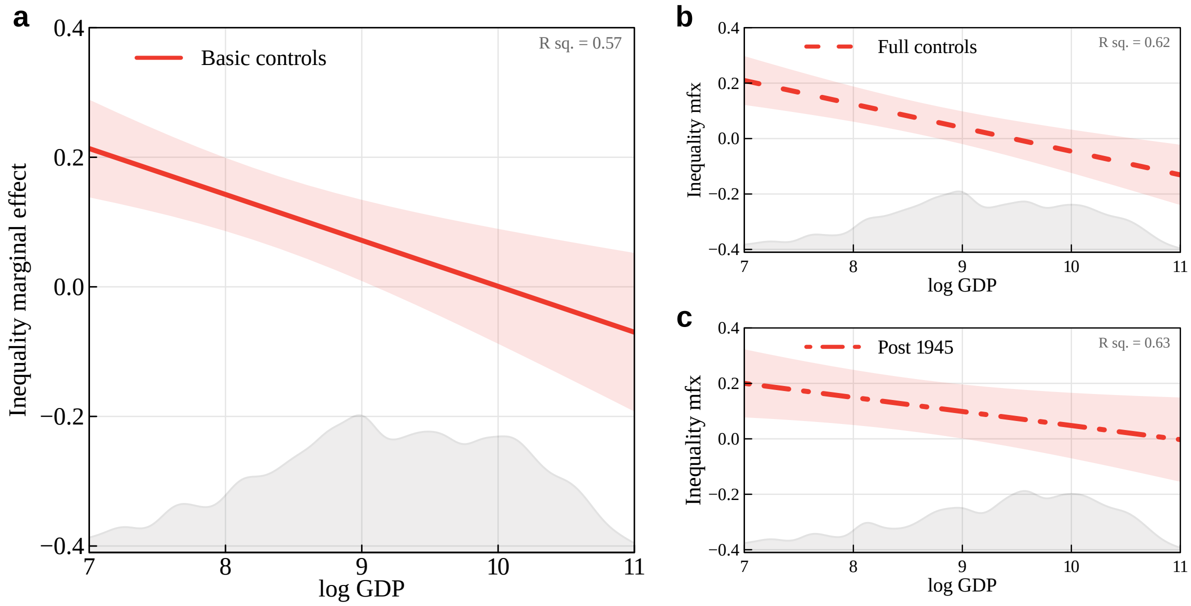

Figure V

Marginal effect of inequality on lack of losers' consent 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.

yields a weaker relationship, but nonetheless suggests that higher levels of development mute the negative impact of inequality.

Our findings reveal that there is a good deal of consistency across analyses centered around a major symptoms of democratic crisis (*lack of losers' consent*) and the systemic collapse of the regime as defined by a full democratic breakdown. Our logic, however, points to an additional logical step worthy of exploration. A clear implication from our analysis is that the extent to which instances of lack of losers' consent actually translate in democratic collapses may itself be a function of development.

Evaluating the connection between a symptom and its potential outcome over the range of third variable, in this case development, within a duration framework is hardly an automatic exercise. Figure VI reports the finding of a Bayesian joint longitudinal survival model, which models both the survival of democracy and the evolution of loosers' consent, as well as the connection between the two. In our analysis, we allow the latter to be a function of development. A full description of the statistical model can be found in Appendix E.

The analysis reveals a clear pattern: the refusal by incumbents to concede defeat constitutes a very real threat to democracy as a regime. The intensity of threat, however, declines in income. Very poor democracies are extremely frail to incumbents' decisions not to accept election results,

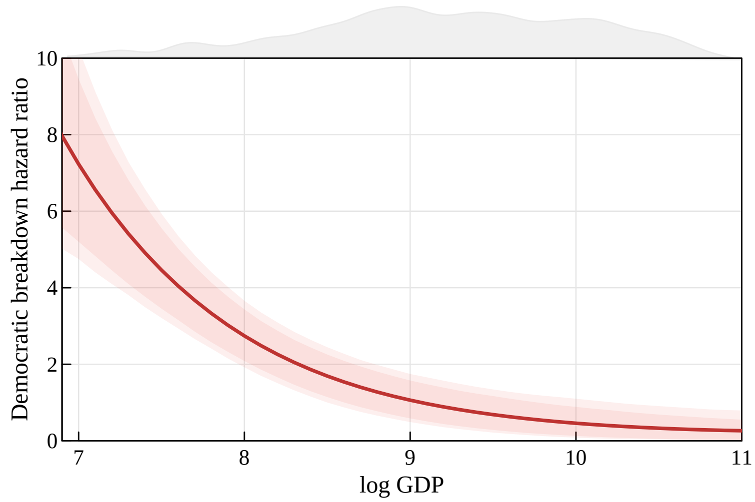

Figure VI

Association between lack of losers' consent and democratic failure as function of development.

This figure plots the relationship between the expected value of a longitudinal marker (lack of losers' consent to election results) and the the hazard ratio of democratic breakdown as a function of logged GDP per capita (whose density is shown on top). Based on a Bayesian joint longitudinal survival model. Survival equation specified semiparametrically. Longitudinal model specified as functional random effects model. See Appendix E for details.

though our sample includes very few of them. Middle income democracies, up until a GDP per capita of about US$ 18,000, experience these episodes as real threats to their stability (with hazard ratios between 2 and 4), whereas for democracies with a GDP per capita above US$ 30,000 the potential impact of the incumbents' refusal to accept defeat becomes negligible.

5.3 Societal Polarization and Democratic Survival

We turn now to the second potential objection to our results, namely the claim that the fundamental threat to democratic stability today does not derive from the distributive tensions triggered by inequality but from the institutional tensions fueled by polarization. If that was the case we should see that polarization undermines democratic stability beyond inequality and in a way that is not conditional on development. To evaluate this claim more systematically, Figure VII shows the relationship between societal polarization, development, and democratic survival. We use the same indicator of societal polarization (based on V-Dem (Coppedge et al. 2021), further details in Appendix A) introduced simply as a control in previous analyses.[11] We implement the same semiparametric duration model as in subsection 5.1.

[11]Like many of the long run variables included in V-Dem, the polarization variable relies on experts' responses. There are good reasons to question the validity of such an exercise when analyzing long historical periods. Latent variables may be capturing experts' biases rather than actual processes. To ameliorate this concern, we present a validation analysis of the V-Dem polarization variable in Appendix A.4, in which we show that the

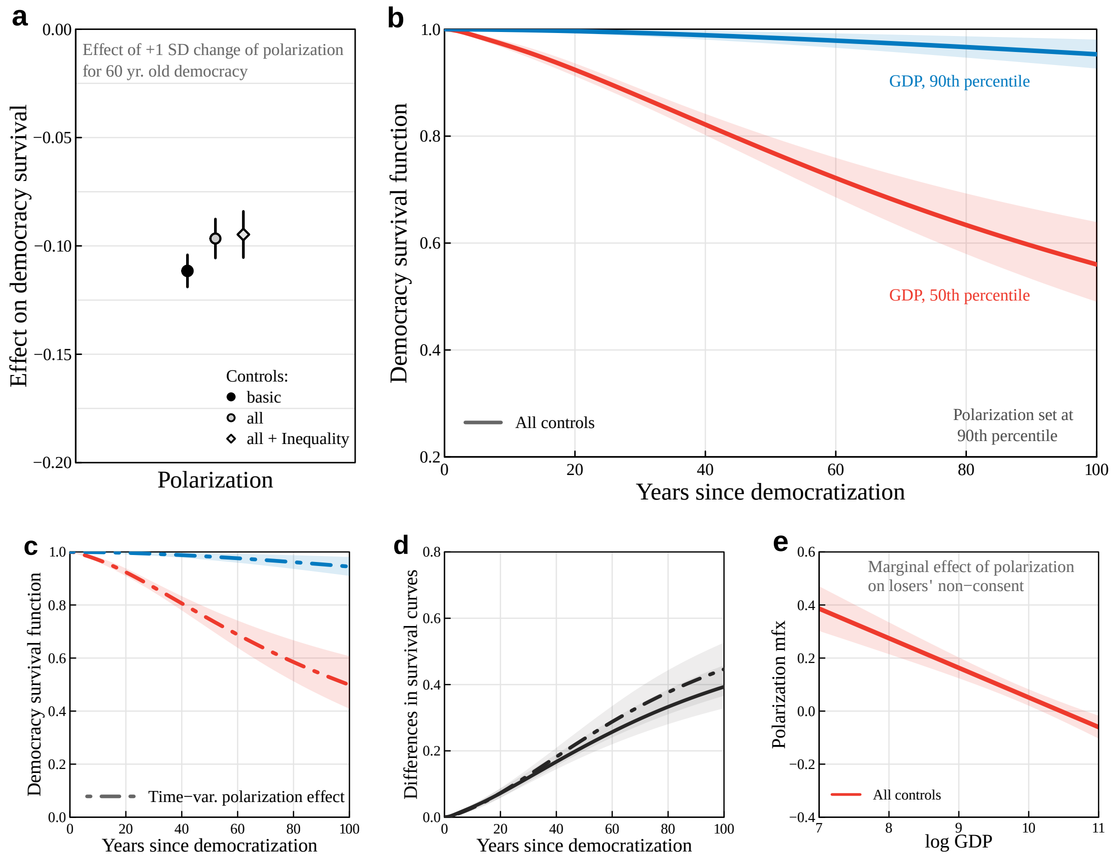

Figure VII
Societal Polarization and Democratic Survival

Survival predictions based on a 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 polarization on the predicted survival of a mature democracy (specified as a democracy of 60 years without a previous breakdown). Panel (b) examines the survival impact of high polarization (90th percentile of the sample polarization distribution) plotting conditional survival curves (cf. Appendix B.2) with GDP fixed at the 50th and 90th percentile, respectively. Panel (c) relaxes the proportional hazard assumption by allowing for time-varying effects of polarization. Panel (d) plots the differences of the two conditional survival curves, i.e., the change in survival probability when moving GDP from the 50th to the 90th percentile conditional on high inequality. Panel (e) shows the relationship between polarization and losers not consenting to election results as moderated by development. It plots the marginal effect of polarization conditional on logged GDP from a two-way fixed effects model of losers' non-consent.

Our results show that, on average, polarization shortens the life of democracies. Panel (a) shows that a one standard deviation increase in polarization carries a sizeable reduction in democratic survival. The magnitude of the effect is marginally smaller after our measure of

V-Dem indicator is significantly related to the number of actual assassinations of major political leaders in a country as measured by Jones and Olken (2009).

inequality is included in the full set of controls, which might suggest polarization itself could be channeling some of the effect of inequality on democratic survival, but the independent negative effect of polarization remains negative and substantively meaningful.[12] More importantly, we also show that the negative effect of polarization on survival is concentrated at low/intermediate levels of development. Given high levels of development, polarization is as mild a threat to the actual survival of democracies as high inequality is. The pattern is consistent across specifications and model assumptions (panels b and c) and, reassuringly, when the outcome variable the (lack of) loser's consent (panel e). It is also broadly consistent with the fact that the frequency, incidence, and gravity of attempts at power grabbing in polarized contexts, whether through inter-branch capture (Helmke 2017) or the erosion of the democratic process (Nalepa 2021), tend to be significantly higher in low (Africa) and middle income regions (Latin America, Eastern Europe).

6 Backsliding in Context

In his landmark study on the breakdown of democratic regimes, Linz (1978) highlighted the political effects of elite polarization at similar levels of development. Given comparable levels of prosperity, Linz claimed, democracies were prone to break down 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. Linz's tale turned out to tell, however, only half of the story about the relationship between democracy, development and polarization. His study focused on relatively developed polities. Yet, when looked at from our vantage point, they were, at most, middle-income countries. Today, fully developed economies are five to six times richer, in per capita terms, than they were in the interwar period. Exploiting the rather extraordinary growth that followed World War Two, which has generated a much longer left tail in the contemporary distribution of cases in terms of income per capita, we have shown that democracies functioning at high levels of development are more likely to survive even at high levels of inequality or polarization. These findings stand whether we model societal tensions with inequality or with polarization and whether we approximate democracy's troubles with discrete indicators of survival or more nuanced indicators of elite behavior. In establishing this fact, we also provide a mechanism to explain why, as originally established by Przeworski et al. (2000), no democracy above a certain level of development reverts back to autocracy. This central idea relies on a simple point: context matters to the point of conditioning the extent to which strategic interactions among elites can threaten the functioning and survival of democracy as a regime.

[12] A full analysis of the causal structure of the relation between inequality and polarization is beyond the scope of this paper.

This insight bears important implications for two main debates currently taking place among democracy scholars: the first one, between redistributive and contractarian models of democratization; the second one, on democratic backsliding. The first debate concerns the nature of the conflict that revolves around the transition to democracy. Redistributive models of democratization see conflict as happening between an authoritarian/proto-democratic minority and a non-enfranchised (generally poorer) majority (Boix 2003; Acemoglu and Robinson 2006). Contractarian models of democratization focus on intra-elite conflict, specifically between an agrarian elite and an emerging industrial bourgeoisie, and emphasize the role that democratic institutions play in guaranteeing property rights (Ansell and Samuels 2014). In redistributive theories, economic inequality plays a key role in politics: unequal societies are, generally speaking, less likely to democratize.[13] For contractarians, land inequality undermines democracy, but income inequality does not. Indeed, they argue, early democratization goes along with increasing income inequality, pointing to the extension of the franchise in nineteenth-century Britain.[14]

Interestingly, despite all their contrasting predictions, both arguments share two features. First, the theoretical models on which they build are similarly distributive in their assumptions. Actors evaluate expected distributional outcomes over different policy tools: tax and spending in redistributive models; a given level of public goods in the contractarian approach. Second, their empirical tests are often partial in nature, in that they do not take changes in the structural composition of inequality over time into full consideration. Most redistributive models employ measures of land inequality primarily—in line with the insight that inequality bites mostly in asset specific economies—but then project that data onto periods where agricultural production accounts for a smaller share of distributive conflicts. In turn, the contractarian perspective on income inequality de-couples the two measures and evaluates the marginal impact of each of them at a time where industrialization was reducing the relative importance of land and fiscal redistribution was extremely limited. Our proposed approach to inequality integrates both sources of distributive tensions (assets and income) and takes into account their changing relative importance over time. When adopting this integrated approach, our findings do lend support to the idea that inequality undermines democracy by virtue of exacerbating distributive tensions (the correlation between inequality and polarization is rather striking), although it does so only at low and intermediate levels of development.

[13] The exact role of inequality varies within that general approach. In Boix (2003, 2011), inequality is, first, negatively related to democracy and, second, conditional on the specificity of assets held by the authoritarian minority. In Acemoglu and Robinson (2006), inequality and democracy are related through a convex function.

[14] Contractarians also point to two empirical patterns that challenge the central distributivist premises: first, at the micro-level, inequality does not lead to higher levels of support for redistribution (Ansell and Samuels 2014); second, empirically, it is not obvious that democracies necessarily lead to higher levels of redistribution. This is disputed empirical terrain, particularly the latter (cf. Mulligan et al. 2004; but see Ferwerda 2020). But even if one was to take these patterns as given, the fact that the fears of elites do not materialize does not invalidate them as modeling assumptions.

This brings us to a second debate on the relation between polarization and democratic backsliding. For backsliding theorists, as elites begin to perceive adversaries as enemies, control over the rules of the game becomes the object of political competition. Political elites question the shared norms or codes of conduct that sustain democracy – mainly, toleration for rivals as well as respect for the principles of fair elections and the peaceful transition of power. As a result, their common institutional ground erodes and politics turns around the manipulation of norms and the capture of institutions, from electoral rules to the judiciary. Slowly, democracies degenerate and death creeps up silently, until it is too late to prevent it.[15]

In this tale of de-democratization, backsliding and polarization are deeply intertwined. Yet the relationship is stated in very imprecise terms. In some instances, (political or economic) polarization apparently precedes the behavior of elites, pushing the latter to act in a pro-authoritarian manner. For most of the literature, however, elites seem to be the agents that sow the seeds of polarization and backsliding: they act in a polarizing (or, as it were, a Schmittian way) toward each other, and they embrace electoral tactics (such as populist appeals and strategies) that polarize public opinion.

This narrative, however attractive to public punditry, remains trapped in an unfalsifiable "post hoc, ergo propter hoc" logic. Descriptions of elite behavior substitute for theoretical models and are only presented as causes after the crisis occurs. The fundamental source of this problem is the following: backsliding theorists pay little attention to the incentives or motives of political actors (elites and non-elites) or, in other words, to the factors that trigger their backsliding strategies. The latter cannot simply derive from politicians' will to power. Most, if not all, 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 an important theorist of democracy, "the dream of all politicians is to conquer power and to hold on to it forever" (Przeworski 2019: 19). Now, if that were the original cause of treating rivals as foes, questioning civic norms of engagement, and corrupting institutions, we should see backsliding everywhere and at all times. Yet, 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 context that facilitates the success of authoritarian practices.[16]

Our paper provides that context. Economic inequality, polarization and lack of losers' consent, which tend to be well correlated, do not occur everywhere. Still, when they happen, their certainly deleterious consequences for the normal operation of representative democracies

[15] For a systematic elaboration of these connections, see, among others, Bermeo (2016); Levitsky and Ziblatt (2018); Haggard and Kaufman (2021).

[16] Backsliding theorists' theory problem is compounded by an empirical one: they tend to ignore cases in which similar behavior leads to no democratic decline and that they do not offer a systematic account of the origins of such variation.

only translate in actual regime collapse at low levels of development. In the 1930s, young democracies were challenged by both communism and fascism. Overwhelmed by a massive economic crisis and still in their path to full development, many collapsed. By contrast, the effects of polarization appear to be rather subdued in very developed economies. 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. The challenge may come, at most, from (some part of the) political and economic elites attempting to protect their privileged position within the system and striving to capture the inner workings of the political system through gerrymandering, the abuse of judicial politics and so on. Still, it is unclear that this may result in the dismantling of democratic institutions. The opportunity cost for elites of foregoing democracy is far too high: Trump's putative attempt to subvert the 2020 election is, according to our results, both an exception (loser's consent behaves very similarly to other indicators of democracy) and an illustration of our logic. For such kind of attempts to succeed, coordination between economic and political elites is a sine qua non: economic elites showed their back to Trump in January 2020 in a way that German economic elites did not do with Hitler in the early 1930s. To put it in more general terms, elites' attempts to capture branches of power are a constant in the history of democracy. Yet, assessing the actual risk of these attempts for democracy itself unconditionally is both inaccurate and misleading. Considering the conditions on the ground allows us, instead, to sort out those countries where democracies are in peril from those where democratic institutions simply muddle through.

Finally, let us cap this section tackling a related issue concerns. The very conceptualization of democracy. Relying on Polity scores, for instance, makes the United States a full democracy since 1864. Similarly, Ansell and Samuels (2014) include as democracies cases in which franchise was very limited by income and property. The problem with such an extensive use of the term democracy is the conflation of situations in which the nature of political conflict and the policies over which conflict takes place are very different. For instance, fiscal redistribution was not the key dimension of conflict in nineteenth-century England. Rather, political conflicts about constitutional development, regulation and infrastructure were much more salient. That historical period does indeed question some of the key assumptions among distributive theories of democracy, but its relevance for the debate depends on stretching the concept itself.

Likewise, such an approach leads some backsliding theorists to consider the United States as "democracy" during the institutionally stable period between the end of reconstruction and the civil rights movement. Yet that stability rested on the federal acquiescence to the tampering of voting rights in the South. Polarization followed, in large measure, the intra-elite split triggered by the realignment of the Southern states. Tensions exacerbated only after the full democratic incorporation of racial minorities in what is, de facto, a very young full democracy, and after certain social sectors felt their status threatened. If the price for elite coordination and forbearance is the effective exclusion of a significant part of the demos along racial lines, it is unclear how polarization undermines a democracy that was not actually full. A better understanding of the conditions under which democracies deteriorate requires careful conceptualization and attention to historical dynamics.

7 Conclusions

This paper has addressed a central question in the political economy of democracy: why, contrary to what extant models would lead to expect, ever increasing levels of inequality have resulted in no democratic collapses, at least in advanced countries? We respond to this puzzle both theoretically and empirically. First, we explore analytically the conditional relationship between average income and the dispersion around it in different periods. Contrary to some naive understandings of economic development, technological change and economic growth are not linearly related to the distribution of income and wealth. Current information technologies have raised inequality – at least within countries. However, that growing inequality may not necessarily imperil democracy. The negative impact of a widening income distribution on democracy varies with the level of development – mainly declining for high income levels.

Second, we refine prior efforts to analyze democratic stability in a number of ways: we develop a new approach to measure inequality in the long run and to explore conditional relationships; we adjust duration models to account for prior crises; and we show our core findings to be robust to region and period effects. In addition, we model systematically the role of polarization and alternative definitions of what constitutes a democratic crisis, in particular lack of loser's consent. Our findings are clear and robust: the negative consequences of inequality and polarization on democratic survival take place only in low and middle income democracies. At high levels of development, democracies survive: there is neither demand by low income citizens to establish authoritarian institutions nor incentives by elites to coordinate and overthrow a democratic regime.[17]

When engaging with the backsliding literature, we have focused primarily on the fundamental aspect of electoral competition of democratic crises: losers' consent. However, other aspects of democratic backsliding, such as encroachments on the separation of power, trying to increase the political control of media, or undermining the opposition, might be just as pertinent. To assess whether our logic also speaks to these other dimensions of the decline of democracy, Appendix C.2 replicates our analyses focusing on a broader range of indicators. We include a bread measure of electoral democracy, indices of free and fair elections, judicial independence, and media freedom. Reassuringly, it is the case that the damaging effect of inequality and the moderating effect of development apply to these other dimensions as well. But an in depth

[17] Carey et al. (2020) provide evidence on the heterogeneity of donors' responses to candidates who advocate the transgression of democratic norms.

analysis of the specific ways these forms of institutional deterioration undermine democracy is outside of the scope of this paper and requires additional scholarly efforts.

We close with a general reflection on the so called "crisis of democracy" – an expression that has come and gone from the academic scene several times in the last decades.[18] According to backsliding theorists, although the capture of institutions by undemocratic elites may be taking place slowly and almost by stealth, it points toward an inevitable outcome. Their logic places us, however, in a terrain in which ambiguities about predictions and outcomes replace analytical thinking. It avoids explaining which are the incentives that motivate naturally self-seeking elites to behave well in some instances yet corruptly in others. It assumes implicitly that outcomes can only worsen and rules out other potential paths. As an example, polarization may be self-correcting. Asymmetric polarization implies that the right moves to the extreme much more than the left and that, under those circumstances, the left may reap important electoral gains (provided some kind of spatial logic of competition prevails). In equilibrium, significant fractions of conservatives would have an incentive to moderate themselves. Finally, it disregards the possibility that policy-makers may establish mechanisms to address the sources of that 'crisis': curtailing globalization, if that is what generates most anxiety among voters, or employing the massive wealth of today's advanced countries to compensate the losers of economic change. Initial signs may not be not encouraging but it remains as early to rule this outcome out as any other. Our results reinforce the view that the deck is structurally stacked against those attempting a regime change. Still, we grant that there is much to learn about how elites adjust their behavior to electoral outcomes in contexts of high inequality and high polarization.

[18] For one of its first incarnations, see Crozier, Huntington and Watanuki (1975).

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(Online) Appendix to "Resilient Democracies"

Contents

A. Data details

A.1. 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.1 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.

Table A.1
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	⋮	⋮	⋮	⋮	⋮	⋮
1	1910	Dem	1	11	1	yes
1	1911	Aut	–	–	–	no
1	1912	Aut	–	–	–	no
1	1913	Aut	–	–	–	no
1	⋮	⋮	–	–	–	⋮
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	⋮	⋮	⋮	⋮	⋮	⋮
1	2019	Dem	2	40	0	yes

A.2. Data sources

Our base data set is created as a balanced panel of countries and years spanning 1800 to 2019 to which we then merge several data sets. From this we create the datasets used in our survival analyses (as described above; spanning 1900 to 2019) and the dataset used in our analysis of losers' consent. 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.

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.3 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 backwards-extrapolate missing observations time-series observations using a flexible semiparametric model (with model terms tailored to each specific country) described in more detail in subsection A.3 below.

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).

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).

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,
- 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.[1]. 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.2 provides descriptive statistics for key covariates in our sample of democracies at risk of breakdown.

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

Table A.2
Descriptive statistics

	Mean	SD	N
GDP per capita [log]	9.123	0.970	4975
Inequality [/10]	35.610	9.932	4344
Political polarization	−0.594	1.305	5261
Equal distribution of ressources	0.672	0.266	5447
Civil liberties social groups	1.087	1.184	5448
Engaged in internat. conflict [0, 1]	0.064	0.244	5443
Average education [years]	7.581	3.092	4870
Natural res. abundance [real $ pc /100]	4.200	18.274	5046
Enfranchised adults	0.936	0.184	5445

Note: Data are for country spells at risk (democracies and autocracies, respectively). 1900-2019.

A.3. Inter-/extrapolation of missing time series information

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 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 trends.[2] 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).[3] The inverse of the variance parameter ω_ζ^2 thus controls the abruptness of function jumps (the "non-linearity" of the estimated relationship between

[2]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.

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

the covariate and time) and we can estimate it from the time-series data. Similarly, we estimate the flexible time-varying 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).

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:,

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

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.).

A.3.2. Sensitivity analyses

We ensure that our substantive results are not sensitive to specific modeling choices. Panel (a) Figure A.1 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 (thin plate regression splines). Panel (b) Figure A.1 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).

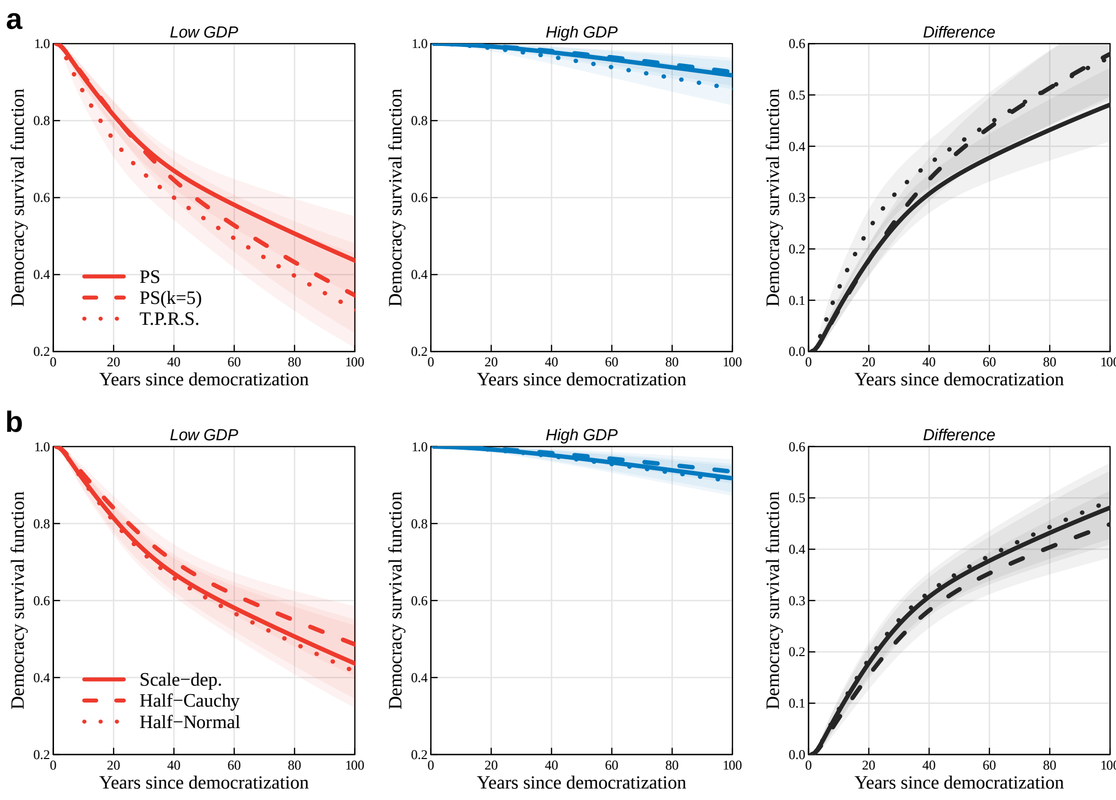

Figure A.1
Semiparametric extrapolation model sensitivity analyses

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.

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 (≈ 0.8) relation between Deininger and 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.

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: $p = 0.550$.

A.3.4. Assessing the impact of extrapolation

Different starting points Another strategy to guard ourselves against an unduly impact of our extrapolation, is to examine its ultimate impact on survival estimates. Figure A.2 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.

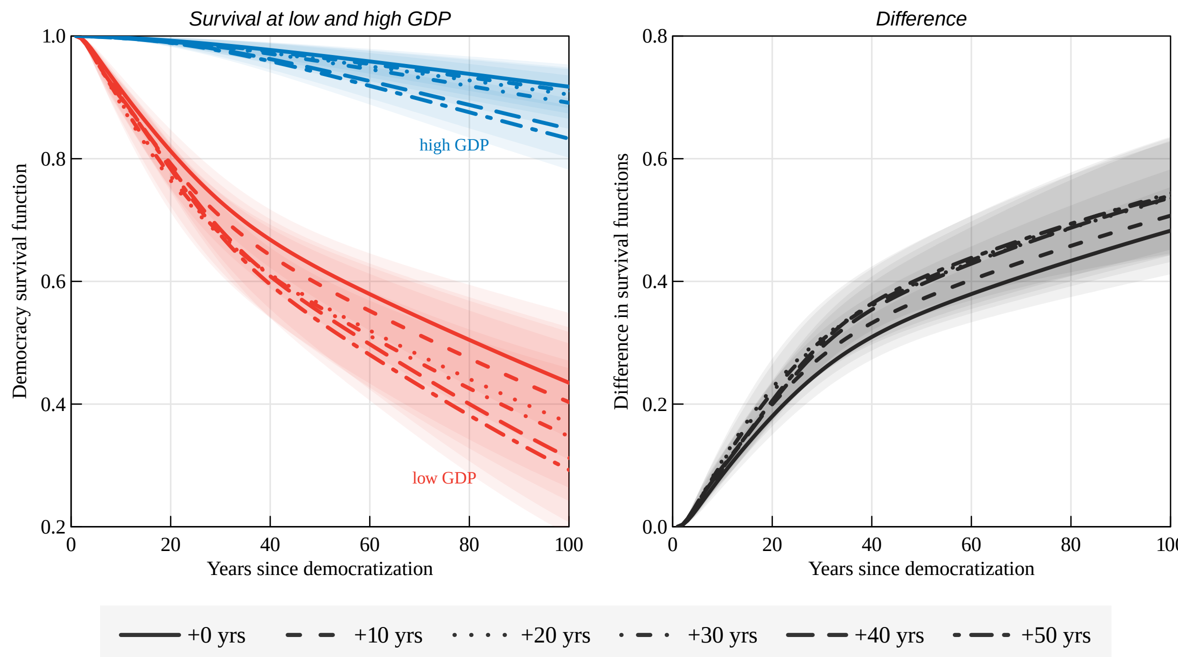

Figure A.2
Assessing the impact of extrapolation I: shifted starting periods
Each line represents a 10-year shift in the starting point of the analysis (i.e., 1900, ..., 1950). Plots standardized survival curves for high-inequality countries at low (50th percentile) and high (90th percentile) of GDP in the left panel and their difference in the right panel. Shaded areas represent 95% confidence intervals.

Figure A.2 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, 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.

Alternative construction of measures A further robustness analysis concerns the construction of the inequality measure itself. Figure A.3 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.3 indicate, our results are substantively very close to the ones presented in the main text.

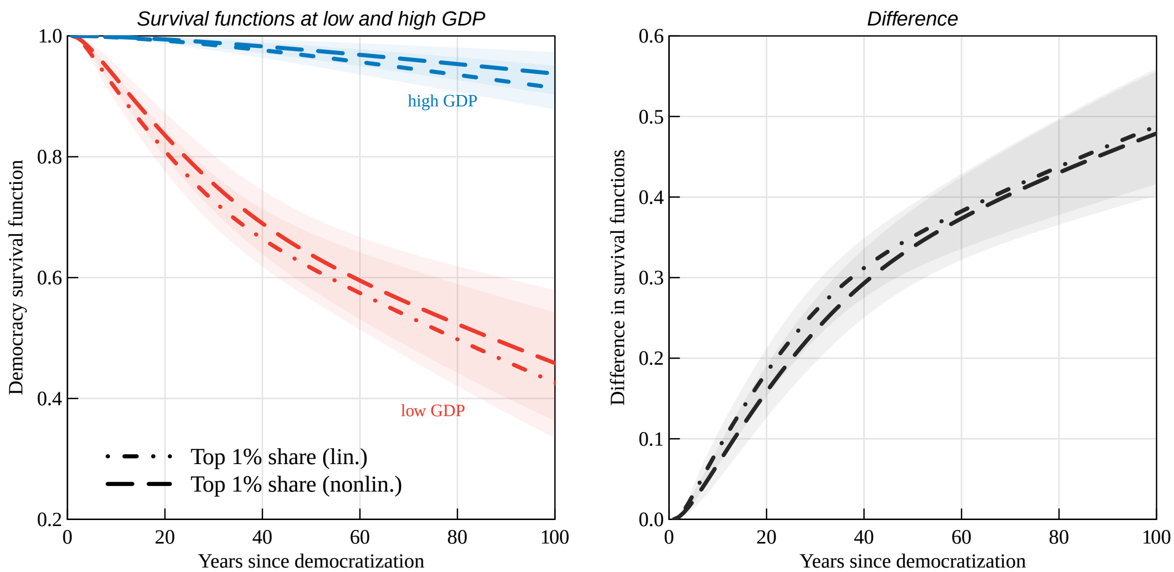

Figure A.3
Assessing the impact of extrapolation II: enhanced extrapolation model adding the (pre-tax) income share of the top 1%.

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. Exploring the validity of the polarization measure

In this section we explore the validity of the V-Dem polarization measure by judging it against an external yardstick of political events: assassination attempts of major political leaders.

Jones and Olken (2009) compile data on assassinations or assassination attempts of a nation's most important political leader (usually the president or prime minister) between 1875 and 2004.[4] We match their database to our data including the V-Dem measure of polarization for the years 1875 to 2004. For our purposes, we define an indicator variable equal to 1 if there was at least one (successful or unsuccessful) assassination attempt in a country-year and 0 otherwise. Using this definition, our sample covers 234 country-year assassination attempts between 1875 and 2004.

A first look at the data lends credence to the V-Dem measure: in country-years where assassination attempts occur, polarization is significantly higher (mean = 0.53, 95% CI = $[0.35, 0.70]$) than in country-years without attempts (mean = −0.16, 95% CI = $[-0.18, -0.14]$). We explore this relationship further by specifying a biased-reduced logit model linking the probability of an assassination attempt to levels of polarization measured by V-Dem while adjusting for political world regions. Estimation is carried out using the penalized maximum likelihood estimator of Firth (1993). Panel (a) of Figure A.4 shows that an increase in V-Dem measured polarization does indeed correspond to an increasing probability of assassination attempts. At comparatively low levels of polarization (say, below −1) the probability of assassination attempts in a given country year is less than one percent. Higher levels of polarization show a substantially increased probability of assassination attempts. For example, increasing V-Dem polarization from a value of 1 to 3 increases the probability of assassinations by 2.7(±0.6) percentage points (to a probability of almost 5 percent). Panel (b) repeats this calculation splitting the sample into democracies and autocracies. While assassinations are more frequent during autocratic spells (175 out of the 234 country-year assassination attempts), we still find the same relationship confirmed in a sample of democracies (with 59 recorded assassination attempts). Panel (b) also signifies that the basic positive relationship between V-Dem polarization and assassination attempts holds in both democracies and autocracies (statistically, the difference in the marginal effects of polarization in democracies versus autocracies is not significantly different from zero).

Table A.4 shows estimates for a range of model specifications. Column (1) shows coefficient estimates from a biased reduced logit model fit to the full sample, while columns (2) and (3) show estimates for a sample of democracies and autocracies, respectively. These specifications produce the plots presented above. We find that a standard deviation increase in V-Dem-measured polarization increases the probability of experiencing at least one assassination

[4] The baseline list of primary political leaders follows the Archigos database (Goemans et al. 2009)

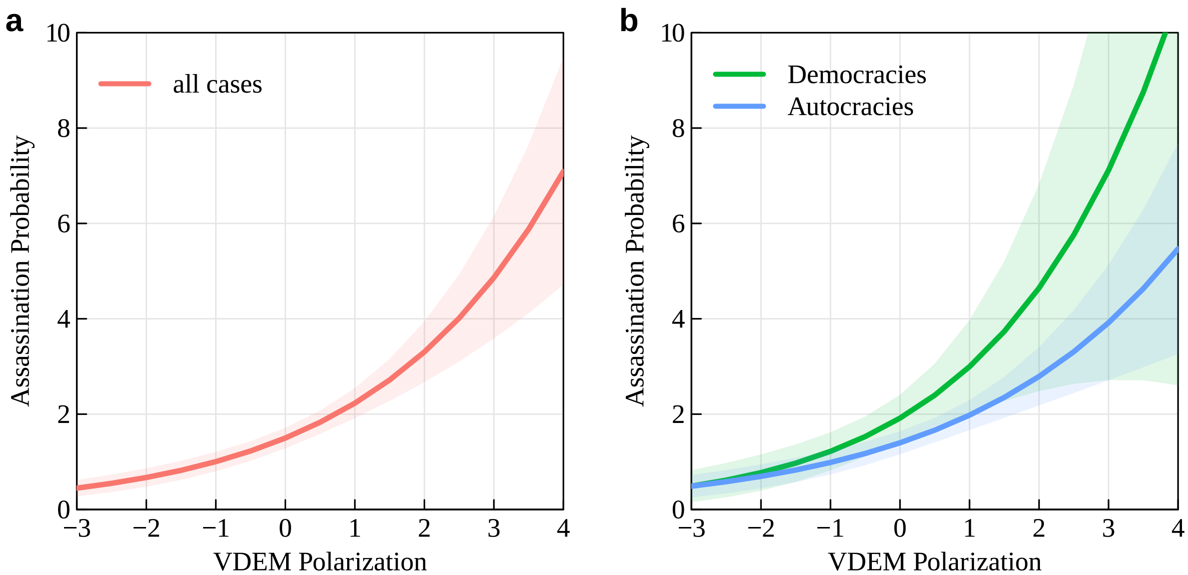

Figure A.4
Relationship between polarization and political assassinations, 1875–2004.

Table A.4
Model estimates linking political assassinations to V-Dem polarization.

	Logit models			Lin. prob. mod.	
	(1)	(2)	(3)	(4)	(5)
V-Dem Polarization	0.557	0.631	0.485	0.871	1.545
	(0.068)	(0.145)	(0.084)	(0.119)	(0.219)
Sample	full	dem.	aut.	full	full
Pol.region FE	yes	yes	yes	yes	no
Country & year FE	no	no	no	no	yes
Estimator	PML	PML	PML	OLS	FE-OLS
N assassinations	234	59	175	234	234

Note: Probability of experiencing at least one assassination attempt on a major political leader in a country-year as function of (z-standardized) V-Dem polarization scores. Data on assassination attempts between 1875–2004 compiled by Jones and Olken (2009). Columns (1) to (3) are logit models estimated using the penalized score maximum likelihood estimator of Firth (1993). Column (4) is a linear probability models (LPM) with heteroscedasticty-robust standard errors. Column (5) is a two-way fixed effects LMP (with country and year fixed effects). All models include indicators for major political world regions.

attempt in a country-year by about 0.6 percentage points, on average. In columns (4) and (5) we specify simple linear probability models. Column (4) replicates specification (1), while column (5) focuses on within-country changes by projecting out country and year fixed effects. With these specifications we find that a standard deviation increase in polarization leads to an increase in assassination probability of about 1 percentage point. However, due to the relatively rare nature of these event, the linear probability models produce predicted values outside the unit interval. Our preferred specification is thus the logit model with finite sample bias correction (cf. Firth 1993) shown in the first three columns.

B. 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

$$F(t) = Pr(T \leq t) \tag{B.1}$$

$$= \int_{s=0}^{t} f(s)ds \tag{B.2}$$

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 of the following relationship:

$$S(t) = Pr(T \geq t) \tag{B.3}$$

$$= 1 - F(t) \tag{B.4}$$

$$= 1 - Pr(T \leq t) \tag{B.5}$$

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 an 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

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

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

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

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.,

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

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

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

which expressed on the log cumulative hazard scale (denoted by $\ln[H(t)]$)[5] is

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

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).

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

B.1. Semiparametric survival model

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

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

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):

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

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:

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

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:

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

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 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

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

while the hazard is

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

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).

B.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:

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

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

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

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 III 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 III show this kind of curve.

B.3. Survival model parameter estimates

Table B.1 shows parameter estimates for models of democratic breakdowns.[6] 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 semiparametric 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 (B.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 past experiences of a breakdown may shape the future likelihood of a breakdowns. 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.).[7] Specifications (6) and (7) display estimates for a mixed Cox

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

[7] 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 B.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]	0.055	0.034	0.032	0.051	0.038	0.145	0.051
	(0.013)	(0.013)	(0.013)	(0.019)	(0.019)	(0.026)	(0.034)
GDP [log]	−2.379	−1.830	−1.773	−1.783	−1.919	−3.991	−1.798
	(0.252)	(0.459)	(0.442)	(0.454)	(0.547)	(0.392)	(0.713)
Failures	1.762	1.758	1.695	1.744	1.802	2.529	2.533
	(0.148)	(0.145)	(0.132)	(0.148)	(0.162)	(0.251)	(0.287)
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	0.012	0.018	0.017	0.013	—	—
Frailty std.dev.						3.051	3.052
BIC	550.7	514.9	808.9	517.6	524.7	387.5	433.5
N	4263	4124	4124	4124	4124	4263	4124
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).

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).

B.4. Post-World War II results

Figure B.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 B.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.

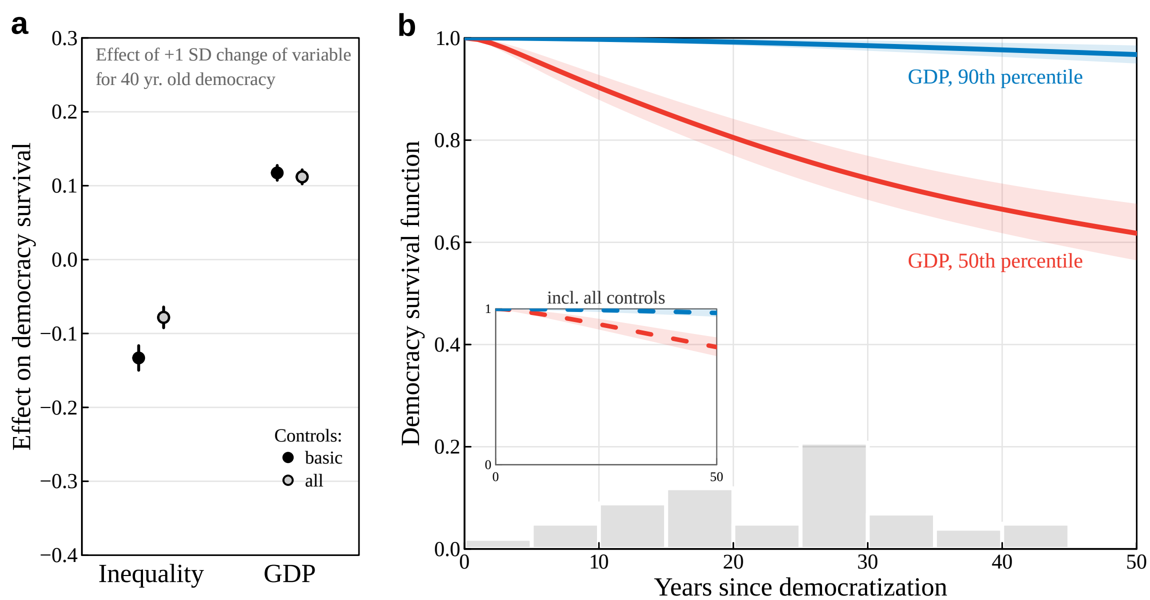

Figure B.1
Inequality, Development, and survival of Democracy. Post-1945 sample.

B.5. Survival functions at alternative levels of inequality

In our main plots we hold the level of inequality at the 90th percentile of the inequality distribution. Naturally, one might ask to what degree our substantive conclusions depend on selecting a rather high level of inequality. Figure IV in the main text already provides information about the interaction between levels of inequality and GDP. Here, in Figure B.2, we reproduce the survival curves plotted in Figure III while setting total inequality to the 80th and the 70th percentile, respectively.

Our results, shown in Figure B.2 indicate that our substantive conclusions change little when using alternative levels of inequality. Setting inequality to the 70th percentile reveals a survival curve of low income democracies that is less steep (the probability of survival for a 50 year old democracy is about 10 percentage points higher compared to the results shown in Figure III). Nonetheless, the survival gap between lower and high levels of development remains seizable. As the inset of Figure B.2 shows, the difference between the two survival curves is increasingly large as democracies age and it is statistically different from zero.

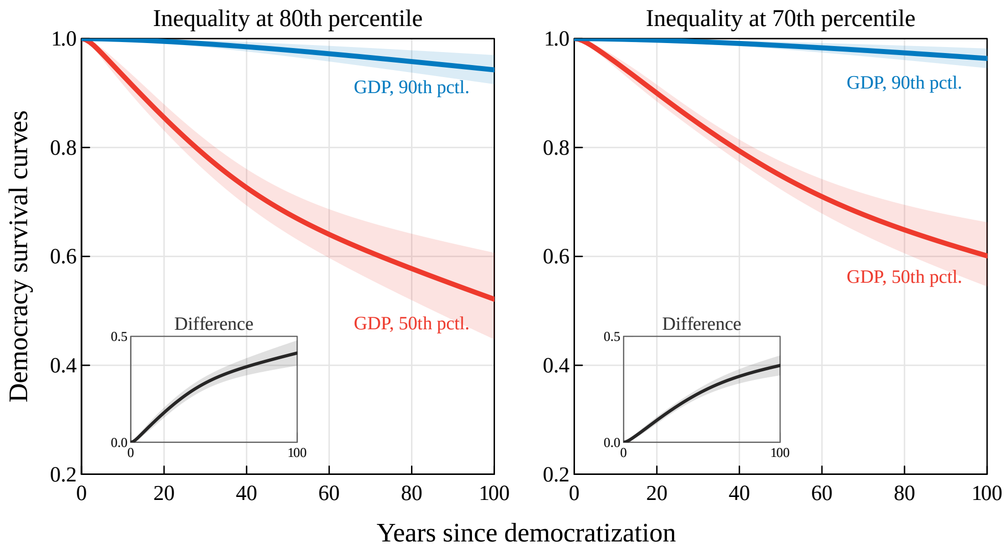

Figure B.2
Democratic survival function at alternative levels of inequality.
Plotted are survival functions at low (50th percentile) and high (90th percentile) levels of GDP with 95% confidence intervals. Based on the same specification as used for Figure III panel (b). The left panel sets total inequality at the 80th percentile, the right panel sets total inequality at the 70th percentile. Insets show differences in survival curves with 95% confidence intervals.

B.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 'traditional' measure if income inequality only. Figure B.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 B.3 depicting median levels of GDP per capita). As the inset of Figure B.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.

B.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.

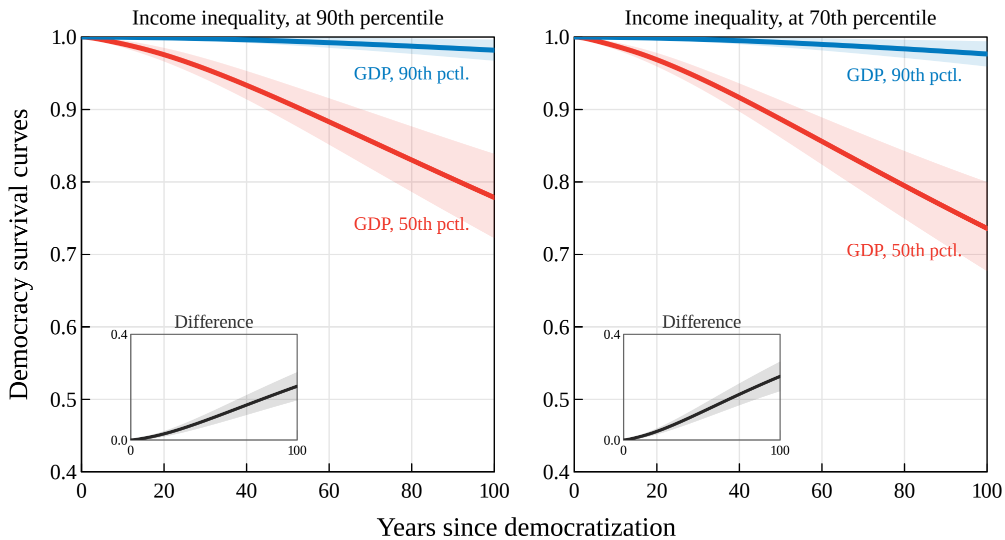

Figure B.3
Results when using income inequality instead of total inequality.
Analyses with income inequality instead of total inequality. Plotted are survival functions (with 95% confidence intervals) at low (50th percentile) and high (90th percentile) levels of GDP. The left panel holds income inequality 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.

We provide sensitivity analyses that show that our estimated quantities of interest are not substantively affected by our choice of K. Figure B.4 plots differences in standardized survival curves for different degree of freedom choices. It shows that our results are rather insensitive to specific choices (specifying 'too many' degrees of freedom simply leads to some spline coefficients being nearly identical).

B.8. Polarization and democratic survival estimates

Table B.2 shows estimates of our survival model using (V-Dem) societal polarization in place of total inequality. Specifications follow Table B.1.

C. Linear Fixed Effects models of backsliding indicators

C.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

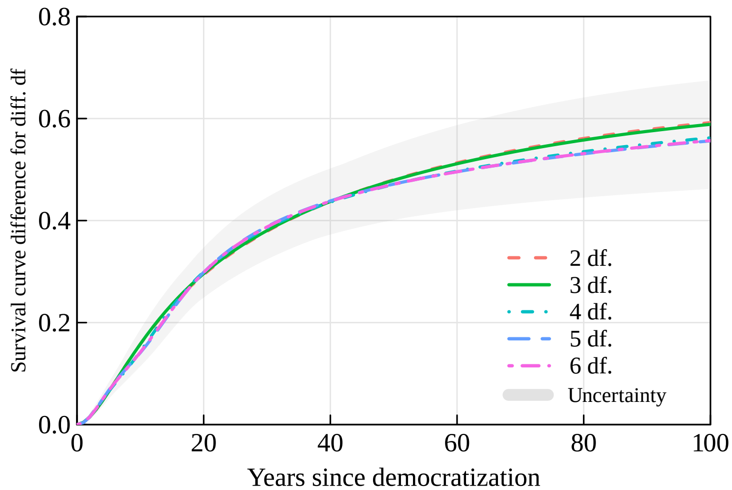

Figure B.4
Impact of baseline hazard spline degree of freedom choices.
This figure plots differences in conditional survival curves (cf. equation B.18) with $df = (2,3,4,5,6)$ for restricted cubic spline baseline hazards. Panel (a) shows differences in conditional survival curves (contrasting low vs. high GDP) for democracies; panel (b) shows differences in conditional survival curves (contrasting low and high internet coverage) for autocratic regimes.

standard linear two-way fixed effects model (Hsiao 2003):

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

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 C.1 shows parameter estimated (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. Specification (4) limits our sample to post-WW II democracies. Finally, specification (5) returns to specification (3) but includes interactive fixed effects (Bai 2009), allowing for (unit-specific) heterogeneity in time-shocks (as opposed to the common time shocks assumed in the standard two-way fixed effects specification). Figure V in the main text is based on specifications (2) to (4).

C.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. In Table C.2 we analyze four measures of

Table B.2
Duration models for societal polarization and democratic breakdowns.

	Basic models			Nonprop. Haz.		Frailties	
	(1)[a]	(2)[a]	(3)[b]	(4)[c]	(5)[d]	(6)[e]	(7)[e]
Polarization	0.684	0.573	0.566	0.684	0.687	1.238	1.179
	(0.097)	(0.114)	(0.111)	(0.147)	(0.153)	(0.204)	(0.283)
GDP [log]	−3.119	−2.162	−2.098	−2.205	−2.261	−4.682	−1.729
	(0.261)	(0.425)	(0.409)	(0.432)	(0.536)	(0.373)	(0.724)
Failures	1.869	1.785	1.723	1.762	1.807	1.923	2.679
	(0.135)	(0.135)	(0.124)	(0.136)	(0.147)	(0.243)	(0.304)
Add. controls	no	yes	yes	yes	yes	no	yes
Wald test p	—	0.001	0.000	0.007	0.001	—	0.000
Region effects	yes	yes	yes	yes	yes	no	no
Wald test p	0.000	0.001	0.001	0.003	0.004	—	—
Frailty std.dev.						3.015	3.891
BIC	554.6	545.0	859.5	551.4	555.8	416.2	455.2
N	4820	4461	4461	4461	4461	4820	4461
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 polarization. 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).

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

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

	(1)	(2)	(3)	(4)	(5)
Inequality [/10]	0.710	0.817	0.805	0.555	0.829
	(0.171)	(0.177)	(0.176)	(0.218)	(0.160)
GDP per capita [log]	0.195	0.354	0.354	0.236	0.270
	(0.075)	(0.079)	(0.080)	(0.099)	(0.065)
Inequality×GDP	−0.071	−0.088	−0.085	−0.051	−0.086
	(0.020)	(0.020)	(0.020)	(0.025)	(0.017)
Model	2-way FE	2-way FE	2-way FE	2-way FE	Int. FE[a]
Sample	full	full	full	post-1945	full
Controls	no	basic	all	all	all
F test p	—	0.000	0.000	0.000	0.000
R^2	0.571	0.610	0.618	0.630	0.535
N	1343	1319	1286	1040	1286

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.

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

line with expectations raised by the literature on democratic backsliding, all four indicators are significantly related to the hazard of democratic failure.[8]

We now explore the (conditional) effect of inequality and development on these four measures of backsliding. While panel A 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.

[8] 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 C.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	1.047	1.080	1.732	1.754	0.967	1.041	0.900	0.978
	(0.105)	(0.106)	(0.124)	(0.124)	(0.126)	(0.132)	(0.101)	(0.097)
GDP	0.426	0.532	0.714	0.821	0.420	0.671	0.199	0.275
	(0.053)	(0.057)	(0.064)	(0.066)	(0.064)	(0.063)	(0.040)	(0.044)
Inequality × GDP	−0.116	−0.121	−0.199	−0.203	−0.105	−0.119	−0.099	−0.108
	(0.012)	(0.012)	(0.014)	(0.014)	(0.015)	(0.015)	(0.012)	(0.012)
B: Difference of inequality marginal effect at median vs. high GDP								
Difference	−0.136	−0.142	−0.234	−0.238	−0.123	−0.139	−0.116	−0.126
	(0.015)	(0.014)	(0.017)	(0.017)	(0.017)	(0.018)	(0.014)	(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	0.844	0.859	0.823	0.836	0.760	0.792	0.889	0.893
N	4179	4088	4179	4088	4179	4088	4179	4088

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.

D. 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. 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, $\lambda_\eta \to 0$ 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. Beginning with inequality, the function $f_{\mu 1}(t)$ is specified as a penalized spline

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

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

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

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[9], $X_{\mu 3w}$ 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, $\lambda_1 \to 0$ and $\lambda_2 \to 0$ 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

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

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 democratic breakdown. The extended model has the following form:

$$h_i(t) = \exp\left\{f_\eta(t) + f_{\mu1}(w_i(t)) + f_{\mu2}(x_i(t)) + f_{\mu3}(w_i(t), x_i(t)) + r_i'\rho + z_i'\gamma + \xi_i\right\} \tag{D.8}$$

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 $f_{\mu1}$ and $f_{\mu2}$, which can be implemented by suitably transforming the relevant design matrices discussed below. 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, ω_p, $p \in \left\{\omega_\eta^2, \omega_{\beta_{\mu1}}^2, \omega_{\beta_{\mu2}}^2, \omega_{\mu3w}^2, \omega_{\mu3x}^2\right\}$. 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.

E. Simultaneous model of time-varying losers' consent and survival

In this section we discuss our simultaneous model of democratic survival and losers' (lack of) electoral consent. The aim of the model is to simultaneously estimate two processes—the evolution of the backsliding indicator 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

Denote by T_i the time of democratic breakdown for country i ($i = 1, \dots, n$), 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 submodel for losers' consent, $\mu_i(t)$, 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^2_η, which can be learned from the data.

The backsliding process

We now turn to the model of the dynamics of consent of election losers. Denote by $y_i(t_{ij})$ the longitudinal outcome 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 observations in the longitudinal submodel is given by $N = \sum_{i=1}^{n} n_i$. More compactly, we write $y_i(t)$ for the outcome at time t. A key point to understanding the role of this longitudinal submodel is the decomposition of the observed outcome into two parts. A systematic dynamic component $\mu_i(t)$ captures "true" changes in the extent of losers' consent to electoral results in a country at a given point in time. An error component captures stochastic deviations, for example non-systematic measurement error in the V-Dem expert raters. Thus, we specify:

$$y_i(t) = \mu_i(t) + \epsilon_i(t), \;\; \epsilon \sim N(0, \sigma^2). \tag{E.3}$$

It is $\mu_i(t)$ that enters the survival outcome model. We thus need to specify a model for it that captures changes in losers' consent in a flexible fashion.[10] 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 linear or quadratic panel data model specifications. Second, we need to account for the fact that the dynamics of electoral consent are country-specific.

Thus, we specify a functional random effects model (see, e.g., Guo 2002) 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

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

[10] Popular social science models of this form include the well-known class of growth curve models which usually include unit-specific linear or quadratic time trends (in addition to unit-specific effects).

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 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.

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

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, ω_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 a 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 (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.

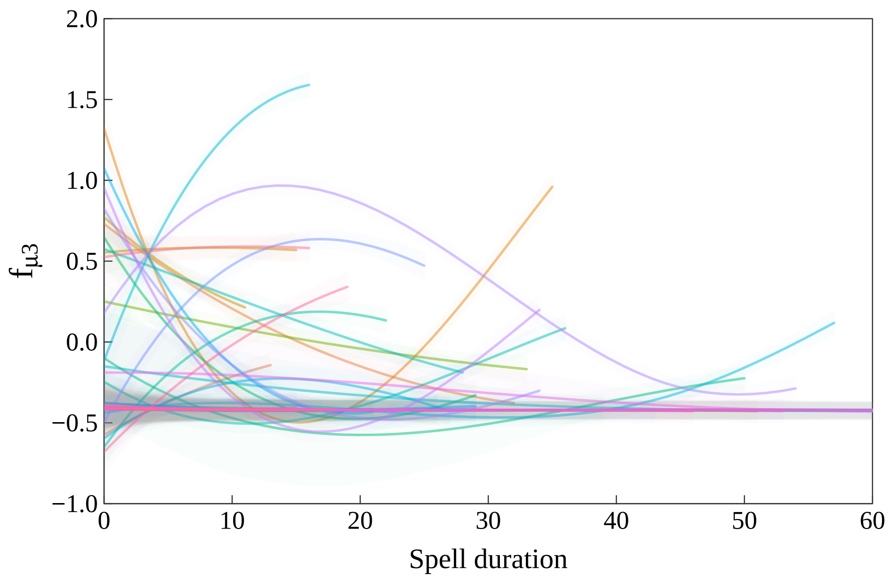

Figure E.1
The dynamics of losers' electoral consent. Estimated functional random intercepts, $f_{\mu 3}(t, i)$, for 50 randomly selected countries

Figure E.1 plots posterior means of $f_{\mu 3}(t, i)$ for the first 60 years of 50 randomly chosen democracies.[11] 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 dynamics of losers' consent enters the hazard of democratic breakdown through via the (non-linear) term $f_\alpha(x_i(t)) \cdot \mu_i(t)$. We

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

display its estimated functional form (on the hazard ratio scale) in Figure VI in the main text and repeat it below for convenience. We find that as x_{it} increases, lack of losers' consent shift the hazard by a decreasing amount.

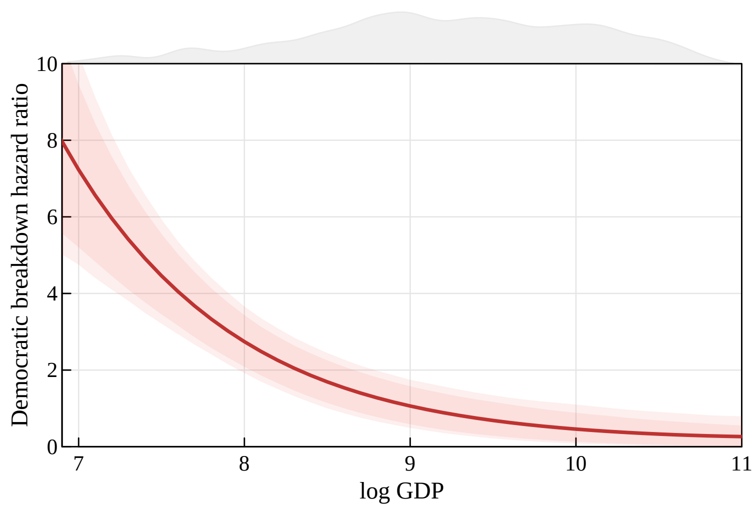

Figure E.2

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 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. For comparison, the dotted lines provide survival curves estimated using the male suffrage definition of the main text. 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.

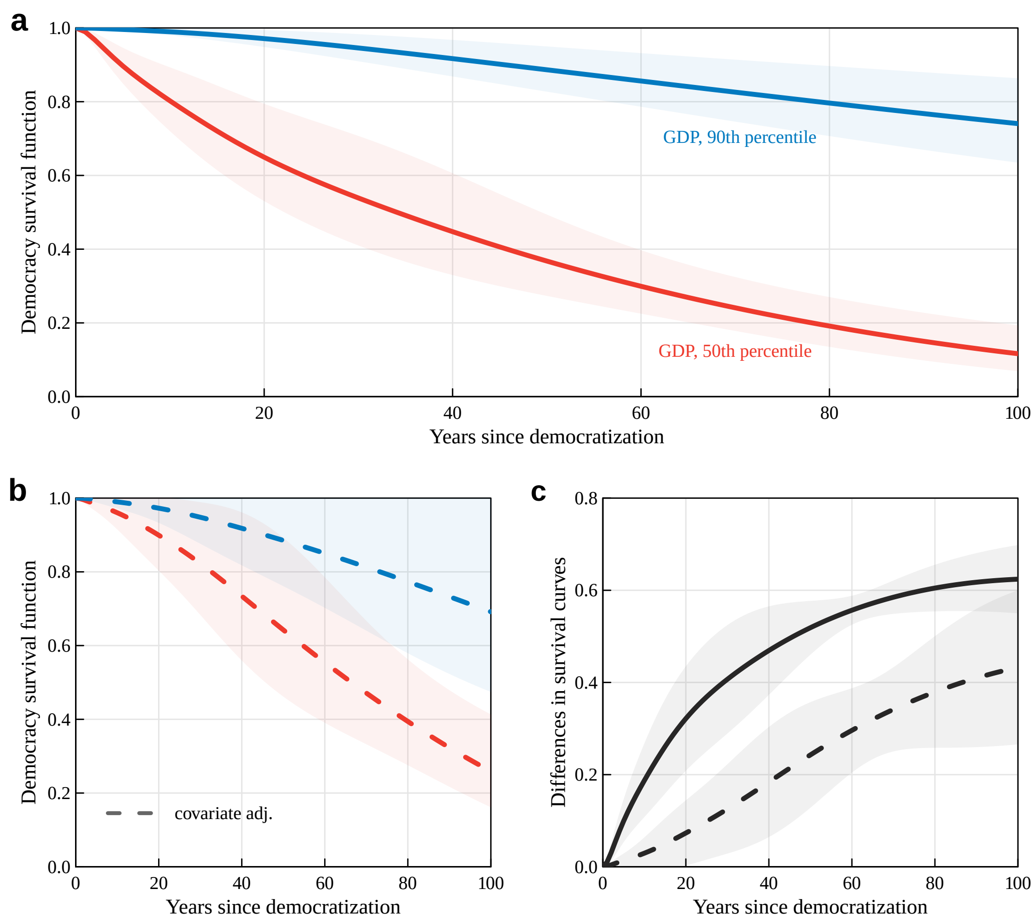

Figure F.1
Democratic survival as function of inequality and development when definition of democracy includes female suffrage.

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