Appendix to America's Inequality Trap

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Contents

Appendix A

Further Details of Vector Autoregression

Vector Autoregression (VAR) is a technique for analyzing time series data that is utilized throughout the book. Since it is a technique that is not broadly taught in the social sciences, I provide a description of the method here that can be referenced whenever the technique is applied. A more detailed but still accessible introduction to the method and its application in political science can be found in Freeman, Williams & Lin (1989).

I use a variety of analytical techniques, but much of the analysis assesses changes over time in economic inequality, other economic conditions, and politics. The core questions of the book generally revolve around some variant of the following: how do changes in inequality affect politics and how do changes in politics affect inequality? Those questions are inherently dynamic in nature—they imply a process that unfolds over time.

Many variants of time series analysis are available to answer questions about movement over time in key variables, and most of these techniques are rooted in a classic regression framework in which a dependent variable Y is modeled as a function of key explanatory variables and control variables that are "held-constant" statistically. The idea is to isolate the causal effect of the key explanatory variables by examining co-variation over time and observing temporal ordering. One typical form of time series regression could look something like this:

$$Y_t = \alpha_0 + \beta_0 Y_{t-1} + \beta_1 X_t + \beta_2 Z_t + \epsilon_t \tag{A.1}$$

The subscripts here make reference to points in time, so t means the current period and $t-1$ means the previous period. X_t is an explanatory variable in the current period while Z_t is a control variable in the current period. Y_{t-1} refers to the lagged value of the dependent variable, and explains why a model such as this is often referred to as a lagged dependent variable (LDV) model. This model, then, attempts to estimate the effect of X on Y while statistically controlling for previous values of Y along with values of Z.

The LDV model is a useful foundation for understanding VAR models. The key distinguishing characteristic of an LDV model is the presence of a lag of the dependent variable on the right hand side of the equation. This modeling strategy has a number of benefits. First, one of the core challenges of time series analysis in terms of statistical inference is overcoming the problem of autocorrelation, or the tendency of current values of a series to be correlated with previous values. Autocorrelation can wreak havoc on our ability to draw inferences from observed time series data. Estimating an LDV model often ameliorates concerns about autocorrelation by explicitly including past values of the dependent variable in the model. Previous values of other explanatory variables are also implicitly included in an LDV model to the extent that previous values of the Y are explained by previous values of X and Z.

Second, inclusion of lagged Y as an explanatory variable provides for the possibility of *dynamic causation*, or effects that are spread out over time. Consider equation A.1 above. β_1 provides an estimate of the contemporaneous effect of X on Y. But if there is an effect of X on Y, there is also an effect of X_{t-1} on Y_{t-1}. The effect of X_{t-1} on current values of Y flows indirectly via the effect of Y_{t-1}. You can work your way back in time infinitely with this logic. All of this implies that the overall effect of X on Y combines β_1 with the accumulated historical effect via β_0. That is, the effect of X on Y does not happen all at once but is spread out over multiple time periods. While it can certainly be the case that effects in time series data are static, occurring all at one point in time (and the model can be modified to account for this if need be), it is quite common for causation to be dynamic when dealing with time series data.

Third, LDV models provide substantial protections against problems generated by incorrectly excluding explanatory variables. As is well known, when some variable Z that explains both X and Y is excluded from a regression analysis, spurious results can appear in which the effect of X is inaccurately estimated. Perfectly specified models don't likely exist, so some degree of model misspecification is almost always present in regression analysis. Controlling for lagged Y in a time series analysis provides a shorthand way to control for a host of un-modeled variables. The lag of any excluded variable Z that affects the current value of Y will by definition affect the lag of Y. So by controlling for the lag of Y, lagged values of unmodeled potential confounders are implicitly modeled. To the extent that the current value of a variable is not affected by previous values, of course, the protections against model misspecification are minimized. But given the typical prevalence of autocorrelation in time series data, LDV models are often very useful guards against the exclusion of explanatory variables. In fact, one of the most commonly identified weaknesses of LDV models is that they can *underestimate* the effects of the explanatory variables of interest in the model (Keele & Kelly 2006).

The LDV model and its derivatives are the most commonly estimated time series model in applied applications. This family of models works fairly effectively in many situations, but it is by no means always appropriate. The questions I seek to answer in this book cannot be answered with this type of model. The problem is that I am interested in the interplay of variables over time, in particular how politics and economic inequality affect each other. The model described above has theoretically defined outcomes and explanations. One variable is what we're trying to explain and the other variables are the potential explanation. But the idea of an inequality trap implies feedback. Outcomes in one part of the analysis are explanations in other parts. And to the extent that the feedback implied by an inequality trap is indeed present, estimating a simple LDV model will fail at generating valid inferences.

We need a model that can cope with a theoretical framework that anticipates causation flowing in multiple directions—a model that does not simply assume that the relationship between politics and economic inequality only goes only one way. The VAR model does just that (Box-Steffensmeier, Freeman, Hitt & Pevehouse 2014). And I started with a description of the LDV model above because VARs are related to LDV models in a variety of ways.

In a VAR, the variables in the model are part of a "system" in which each variable is potentially both a cause and an effect. Instead of estimating a single equation in which there is an outcome and the left side and several explanations on the right side, a VAR estimates multiple equations that allow for the possibility of contemporaneous and lagged feedback between the variables in the system. A three variable VAR can be expressed this way:

$$\begin{bmatrix} Y_{1,t} \\ Y_{2,t} \\ Y_{3,t} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \begin{bmatrix} \beta^1_{1,1}, \beta^1_{1,2}, \beta^1_{1,3} \\ \beta^1_{2,1}, \beta^1_{2,2}, \beta^1_{2,3} \\ \beta^1_{3,1}, \beta^1_{3,2}, \beta^1_{3,3} \end{bmatrix} \begin{bmatrix} Y_{1,t-1} \\ Y_{2,t-1} \\ Y_{3,t-1} \end{bmatrix} + \begin{bmatrix} \beta^p_{1,1}, \beta^p_{1,2}, \beta^p_{1,3} \\ \beta^p_{2,1}, \beta^p_{2,2}, \beta^p_{2,3} \\ \beta^p_{3,1}, \beta^p_{3,2}, \beta^p_{3,3} \end{bmatrix} \begin{bmatrix} Y_{1,t-p} \\ Y_{2,t-p} \\ Y_{3,t-p} \end{bmatrix} + \begin{bmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \end{bmatrix} \tag{A.2}$$

What equation A.2 shows is that for each variable in a VAR system, an equation is estimated in which lags of all variables in the system are included on the right hand side. In a three variable system, then, there are three equations that are estimated simultaneously. For each Y, p lagged values of Y and p lags of the other variables in the system are included. This equation shows that the VAR is indeed connected to the LDV model above. The key difference is that effects flow in multiple directions in a VAR model. Another important difference is that only values from previous time points are allowed to explain current values of any variable in the system. In a VAR system contemporaneous values of an explanatory variable and an outcome variable are not analyzed. Rather, a VAR estimates the effect of past values of explanatory variables while controlling for past values of outcome variables. This helps to bolster the ability to make causal inferences.

Still, VARs are rooted in an observational research design that is inherently correlational. And several important determinations must be made prior to the estimation of a VAR. First and foremost, VARs can only be estimated when the variables in the system are either stationary or co-integrated. For each of the VARs reported in this book, I begin by testing each variable in the system for a unit root using a combination of augmented Dickey-Fuller (Dickey & Fuller 1979) and KPSS (Kwiatkowski, Phillips, Schmidt & Shin 1992) tests. When data are non-stationary I test for cointegration prior to estimation and note the results of these tests. Second, the number of lags to include in the model can be a consequential decision. I utilize a test that seeks to maximize the fit of the model based on the Schwartz Bayesian Information Criterion, but at times I estimate models with varying lag lengths and mention whether this selection dramatically changes results.

One of the most complicated aspects of VAR analysis is interpreting results. Particularly as models include increasing numbers of variables and the number of lags increases, the number of coefficients estimated proliferates. This means that individual coefficients will be estimated imprecisely and that using individual coefficients to determine the size of effects is inappropriate. Additionally, since the most general versions of a VARs allow all of the variables in the system to affect each other, there are direct and indirect effects present. That is, while one variable (Y_1) might directly affect another variable in the system (Y_2), that same variable might have indirect effects that happen via effects on other variables in the system (Y_1 affecting Y_3 which then affects Y_2 for example).

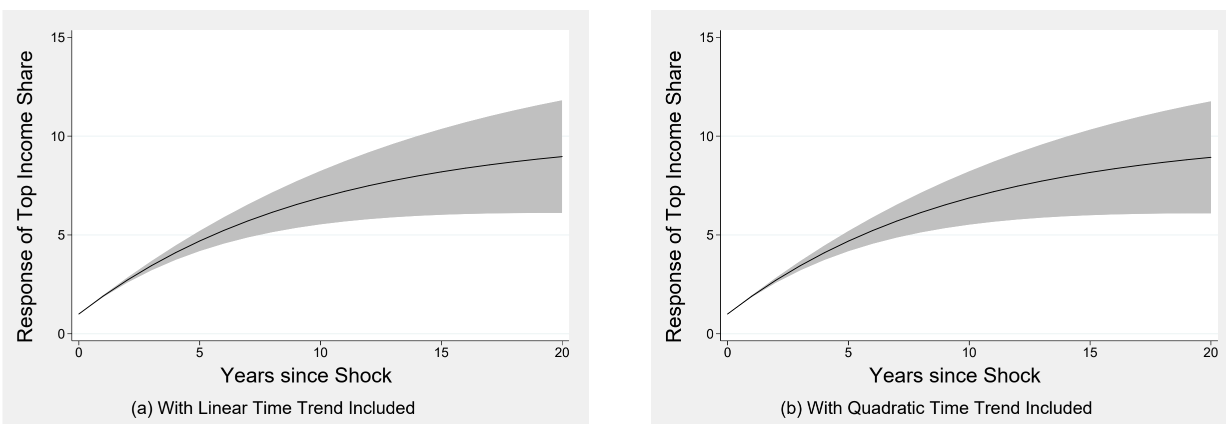
Innovation accounting refers to a group of techniques to make inferences about the size, direction, and timing of effects based on VAR models. The technique I will rely on most heavily is Impulse Response Functions (IRFs). An impulse response function uses information from the VAR model to calculate the effect of some shift in one variable on another variable in the system. I typically report IRFs based on a one standard deviation shift (or impulse or shock). A simple IRF reports the effect of this shock at each point in time for a specified number of periods, starting at the onset of the shock. The IRF, then, provides information about how large and how long a shock in one variable has effects on another variable. I report orthoganalized cumulative IRFs which add up the effects over time to capture the total effect of a shock at a given point in time after the shock. So the cumulative effect of a shock ten periods after the onset of the shock would be the effect at lag 10 plus the effect at all lower lags.

IRFs, importantly, capture not just the direct effects of one variable on an outcome, but also the indirect effects that that variable has via other variables in the system. Constructing an IRF requires an assumption about the ordering of contemporaneous correlations, known as a Choleski decomposition. Whenever I report the results an IRF, you will see a note about the assumed causal ordering of the variables in the system and some theoretical justification for the assumption. I will also note whether changing the assumption about causal ordering affects the results.

Appendix B

Univariate Evidence of Inequality Trap with Inclusion of Trends

When first presenting univariate evidence of an inequality trap in Chapter ??, I mentioned that I had estimated alternative models including time trends. I present the results from those alternative models here in Figure B.1. If the results here are compared with those reported in the main text, there is little substantive difference.



(a) With Linear Time Trend Included

(b) With Quadratic Time Trend Included

Figure B.1: Effect of Current Increase in Top Shares on Future Level of Inequality

Appendix C

Underlying Micro-Level Results from Chapter 3

In the main text I focused on presenting only the essential results of the analysis using visual techniques to make the results more clear. Here I present the detailed results of the underlying micro-level models referenced in Chapter 3. I begin in Table C.1 with models of general redistributive attitudes. These results are based on a multi-level regression model with support for government redistribution to equalize incomes as the dependent variable. Data are from the General Social Survey. Individuals are nested within years, which produces a two-level data structure where the key context-level variable is top income shares.

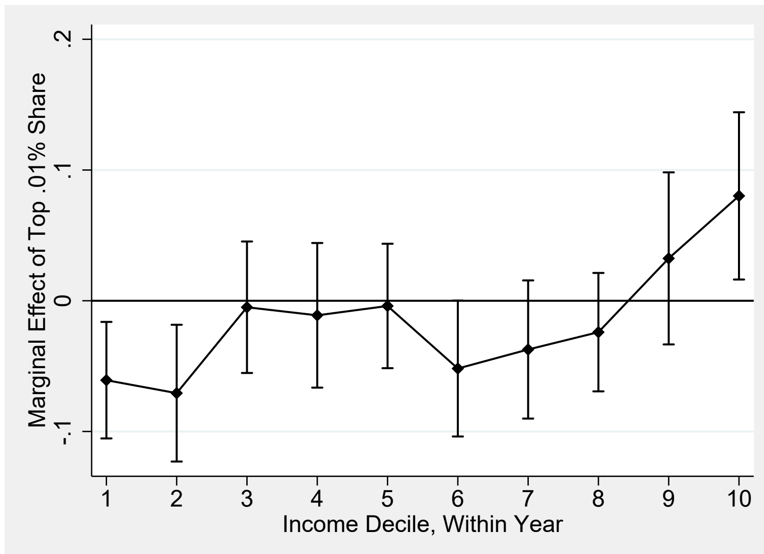
Model 1 is a baseline model including only top income shares along with basic controls for sex, ethnicity, race, age, and education. The control variables produce the expected results, but there is no effect of inequality in this model. In Model 2, however, I add individual-level family income as well as an interaction term between family income and context-level inequality to the model. In that model we see that higher levels of inequality reduce support for redistribution, but that this effect is primarily present among those with low incomes. This was shown in the charts from the main text, and is generated by the fact that the interaction term between family income and inequality is positive. What we can say here is that the coefficient reported for top income shares in this model captures the effect of top income shares for the poorest respondents. But as income increases, the effect of top income

Table C.1: Multi-Level Models of Support for Redistribution

	(1)	(2)	(3)	(4)
Top .01% Share	-0.018	-0.064^{**}	-0.041	0.032
	(0.020)	(0.022)	(0.022)	(0.039)
Female	0.284^{***}	0.249^{***}	0.201^{***}	0.231^{***}
	(0.024)	(0.029)	(0.026)	(0.044)
White, Non-Hispanic	-0.729^{***}	-0.621^{***}	-0.302^{***}	-0.500^{***}
	(0.044)	(0.048)	(0.043)	(0.038)
Age	-0.006^{***}	-0.006^{***}	-0.008^{***}	-0.006^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Education	-0.237^{***}	-0.134^{***}	-0.134^{***}	-0.157^{***}
	(0.021)	(0.025)	(0.020)	(0.024)
Income Decile		-0.137^{***}	-0.120^{***}	-0.116^{***}
		(0.013)	(0.013)	(0.024)
Income Decile × Top Share		0.008^{**}	0.008^{**}	0.003
		(0.003)	(0.003)	(0.005)
Party Identification			-0.251^{***}	
			(0.015)	
Racial Bias				-0.369^{*}
				(0.167)
Top .01% Share × Racial Bias				-0.133^{**}
				(0.043)
Constant	4.348^{***}	4.923^{***}	5.287^{***}	4.933^{***}
	(0.079)	(0.092)	(0.086)	(0.114)
Level 1 N	29796	26877	26401	11380
Level 2 N	22	22	17	22

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$



Source: Author's calculations from GSS data.

Note: Charts plot the predicted marginal effect of an increase in inequality on support for redistribution for those with differing levels of family income. Calculations based on a multi-level logit model including national-level top .01% income share at time of survey, race/ethnicity, sex, age, education, and categorical income along with income interacted with inequality.

Figure C.1: Effect of Top .01% Share on Attitudes Toward Redistribution as Income Increases shares becomes more positive. The interaction is strong enough that the negative effect of inequality is only present among those at the bottom end of the income distribution, as was discussed in the main text. Model 3 simply shows that this effect is maintained when a control for party identification is added. And Model 4 presents the results with a measure of racial bias and its interaction with inequality added. We see that the income effect from Model 2 is completely driven by racial attitudes and that inequality only reduces support for redistribution among those evidencing more racial bias.

Figure C.1 demonstrates that the basic conclusions remain unchanged if we allow the conditioning effect of income on the impact of inequality to be non-linear. This chart is the result of a re-estimation of the core model with income measured categorically rather than continuously. The interaction between income and inequality then, is actually a series of interactions between the income category of a respondent and the level of inequality present. We see that even if we relax the assumption that the conditioning effect of inequality is linear (which is what is assumed in the results presented in the main text), we still see evidence that those at the low end of the income distribution are less supportive of redistribution as inequality rises and those at the top end of the distribution respond to higher inequality differently.

Table C.2 presents three models of support for a minimum wage increase. These models are estimated with data from the 2006 Cooperative Congressional Election Study. The dependent variable is a dichotomous choice between support for a minimum wage increase and opposition. Given the dichotomous dependent variable and the hierarchical structure of the data (individuals nested in states), these models are estimated with a multi-level logit model.

The first model is the one that charts in the main text are based on. There, we see that attitudes toward a specific redistributive policy measured in a cross section follow the same pattern as general attitudes toward redistribution captured over multiple time periods. Those

Table C.2: Multi-Level Models of Support for Minimum Wage

	(1)	(2)	(3)
State Top 1% Share	-0.031^{**}	-0.034^{***}	-0.022^{**}
	(0.010)	(0.010)	(0.008)
Age	-0.001	-0.001	-0.005^{***}
	(0.001)	(0.001)	(0.001)
White, non-Hispanic	-0.242^{***}	-0.241^{***}	-0.647^{***}
	(0.070)	(0.070)	(0.094)
Female	0.773^{***}	0.774^{***}	0.799^{***}
	(0.046)	(0.046)	(0.040)
Education	-0.075^{***}	-0.075^{***}	0.001
	(0.019)	(0.019)	(0.020)
Income	-0.143^{***}	-0.145^{***}	-0.163^{***}
	(0.022)	(0.022)	(0.024)
Party Identification	-0.633^{***}	-0.632^{***}	
	(0.012)	(0.012)	
State Top 1% Share × Income	0.004^{***}	0.004^{***}	0.003^{**}
	(0.001)	(0.001)	(0.001)
State Median Income		0.000	
		(0.000)	
Constant	5.562^{***}	5.395^{***}	2.905^{***}
	(0.210)	(0.250)	(0.198)
Level 1 N	29334	29334	29747
Level 2 N	50	50	50

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

living in states with more inequality tend to be less supportive of a minimum wage increase, but this effect is concentrated among those at the bottom end of the income distribution, which is shown by the positive interaction between family income and state inequality. Model 2 shows that this pattern is robust to the inclusion of state median income at the context level. Model 3 shows that the results are consistent whether or not one controls for party identification.

Table C.3: Multi-Level Models of Support for Capital Gains Tax

	(1)	(2)	(3)
State Top 1% Share	-0.027^{***}	-0.022^{***}	-0.020^{***}
	(0.006)	(0.007)	(0.006)
Age	-0.017^{***}	-0.017^{***}	-0.015^{***}
	(0.001)	(0.001)	(0.001)
White, non-Hispanic	0.021	0.020	-0.436^{***}
	(0.043)	(0.043)	(0.053)
Female	0.660^{***}	0.659^{***}	0.695^{***}
	(0.037)	(0.037)	(0.031)
Education	-0.036^{**}	-0.035^{**}	0.023
	(0.013)	(0.013)	(0.014)
Income	-0.152^{***}	-0.149^{***}	-0.166^{***}
	(0.019)	(0.018)	(0.022)
State Top 1% Share × Income	0.003^{***}	0.002^{***}	0.002^{*}
	(0.001)	(0.001)	(0.001)
Party Identification	-0.567^{***}	-0.568^{***}	
	(0.011)	(0.011)	
State Median Income		-0.000^{**}	
		(0.000)	
Constant	4.611^{***}	4.914^{***}	2.347^{***}
	(0.162)	(0.184)	(0.157)
Level 1 N	30727	30727	31192
Level 2 N	50	50	50

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.3 presents models similar to those in the previous table, but here the dependent variable is opposition to a capital gains tax cut. Since capital gains taxes are progressive, opposing a cut is pro-redistribution. Again, multi-level logit models are used due the nested structure of the data and the dichotomous dependent variable. The results from Model 1 are charted in the main text, where I argue that people living in states with more income concentration are less supportive of redistribution, with that effect being exclusively present for those with low levels of income. Model 2 shows this result is robust to inclusion of state-level median income. And Model 3 shows the result remains even when the control for partisanship is excluded.

Table C.4 simply re-estimates the prior models of support for the capital gains tax and minimum wage but examines the context of inequality at the congressional district level. In these models, the data are modeled as individuals nested within congressional districts. Comparing the estimates from these models to comparable models reported earlier shows that there are similar patterns present. That is, the interaction term between district level inequality and family income is positive. And the estimate for district level inequality in general is negative. But these estimates are much more noisy and do not reach statistical significance.

Table C.4: Multi-Level Models of Support for Redistributive Policy, Inequality Varying at District Level

	Capital Gains	Minimum Wage
District-Level Gini	−2.085	−1.587
	(1.794)	(1.894)
Age	−0.017***	−0.001
	(0.001)	(0.001)
White, non-Hispanic	0.033	−0.214***
	(0.046)	(0.055)
Female	0.663***	0.776***
	(0.034)	(0.039)
Education	−0.036**	−0.075***
	(0.013)	(0.017)
Income	−0.196*	−0.199*
	(0.080)	(0.083)
Party Identification	−0.571***	−0.640***
	(0.010)	(0.012)
District-Level Gini × Income	0.223	0.317
	(0.181)	(0.186)
Constant	4.970***	5.640***
	(0.800)	(0.849)
Level 1 N	30727	29334
Level 2 N	435	435

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix D

Micro Level Voting Behavior Models

I report more details of the micro level models that serve as the basis for much of the analysis in Chapter 4 here. I begin in Table D.1 with models in which a dichotomous indicator indicating support for a Democratic congressional candidate is the dependent variable. These results are based on the analysis of multiple ANES cross-sections, with individuals embedded within years. Due to the hierarchical structure of the data and the dichotomous dependent variable, these results are estimated with multi-level logit. The first model represents the model that was the basis for producing Figure 4.5 in the main text. We see a clear negative effect of top income shares on support for democratic candidates. Model 2 shows that this effect remains when including a linear time trend. And Model 3 shows that the effect is still present with a control for partisanship. Model 4 shows the results that produced Figure 4.6 in the main text. The key point here is that none of the interactions between trust and inequality are statistically significant.

Table D.2 shows similar models but now including racial attitudes and an interaction between racial attitudes and inequality to see how the effect of inequality on voting behavior varies for those with differing degrees of racial bias. The first model is the basis of Figure 4.7 in the main text. There we saw visually what the coefficients in this model show—that rising inequality is associated with more support for Democrats among those with egalitarian racial attitudes while that effect is reversed among those with inegalitarian racial attitudes. Model

Table D.1: Multi-Level Models of Support for Democratic House Candidates

	(1)	(2)	(3)	(4)
Top .01% Share	-0.086^{***}	-0.106^{*}	-0.067^{**}	-0.145
	(0.019)	(0.054)	(0.026)	(0.126)
Female	-0.008	-0.008	-0.038	0.002
	(0.042)	(0.042)	(0.044)	(0.042)
White Non-Hispanic	-1.519^{***}	-1.518^{***}	-0.784^{***}	-1.494^{***}
	(0.060)	(0.060)	(0.073)	(0.058)
Age	-0.006^{***}	-0.006^{***}	-0.002	-0.005^{**}
	(0.001)	(0.001)	(0.001)	(0.002)
Education	-0.077^{***}	-0.077^{***}	0.005	-0.078^{***}
	(0.018)	(0.018)	(0.015)	(0.019)
Income	-0.167^{***}	-0.167^{***}	-0.097^{***}	-0.198^{***}
	(0.023)	(0.023)	(0.020)	(0.020)
Year Trend		0.002		
		(0.006)		
Partisanship			-0.690^{***}	
			(0.031)	
Trust Sometimes				0.337
				(0.319)
Trust Most of Time				0.324
				(0.382)
Trust About Always				0.615
				(0.519)
Trust Some × Top .01% Share				0.047
				(0.111)
Trust Most × Top .01% Share				0.046
				(0.149)
Trust Always × Top .01% Share				-0.026
				(0.169)
Constant	2.888^{***}	-1.205	4.086^{***}	2.633^{***}
	(0.132)	(11.014)	(0.141)	(0.393)
Level 1 N	23404	23404	23269	18214
Level 2 N	27	27	27	23

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.2: Multi-Level Models of Support for Democratic House Candidates, with Racial Attitudes

	(1)	(2)	(3)
Top .01% Share	0.313***	0.338***	0.177*
	(0.032)	(0.038)	(0.088)
Female	−0.111*	−0.080	−0.118**
	(0.047)	(0.060)	(0.037)
Age	0.002	0.000	−0.006**
	(0.002)	(0.003)	(0.002)
Education	−0.061***	−0.073***	−0.105***
	(0.017)	(0.015)	(0.027)
Income	−0.167***	−0.156***	−0.184***
	(0.031)	(0.033)	(0.020)
Conservative Ideology	−0.603***	−0.614***	
	(0.064)	(0.051)	
Racial Inegaliatrianism	0.082**	0.031	
	(0.030)	(0.038)	
Racial Inegaliatrianism × Top Share	−0.084***	−0.073***	
	(0.010)	(0.012)	
White Non-Hispanic		−1.207***	−1.453***
		(0.115)	(0.106)
Civil Rights About Right			−0.257
			(0.229)
Civil Rights Too Fast			−0.179
			(0.248)
About Right × Top Share			−0.139
			(0.094)
Too Fast × Top Share			−0.269*
			(0.112)
Constant	3.213***	4.550***	3.170***
	(0.211)	(0.267)	(0.319)
Level 1 N	9845	8767	9693
Level 2 N	18	18	13

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1 focuses on white non-Hispanics only. Model 2 shows similar results when we focus only on respondents living in northern states. Finally, Model 3 shows that there is a similar pattern when we use a measure of racial attitudes focused on the speed of civil rights progress.

Finally, in Table D.3 I show the underlying models for Figures 4.8 and 4.9 in the main text. These are multi-level models based on CCES data with individuals nested in states. These results simply show what was reported earlier—higher inequality tends to increase support for Trump in rich states and among those with higher levels of education.

Table D.3: Multi-Level Models of Trump Support

	(1)	(2)	(3)
R Partisanship	1.112***	1.112***	1.116***
	(0.024)	(0.024)	(0.023)
Female	−0.170**	−0.170**	−0.182**
	(0.061)	(0.061)	(0.061)
Family Income	−0.016*	−0.016*	−0.014
	(0.008)	(0.008)	(0.008)
Education	−0.293***	−0.293***	
	(0.024)	(0.024)	
Age	0.025***	0.025***	0.026***
	(0.002)	(0.002)	(0.002)
Top 1% Share in State	0.017	−0.065	−0.043
	(0.010)	(0.075)	(0.027)
State Median Income	−0.000***	−0.000*	−0.000***
	(0.000)	(0.000)	(0.000)
Top Share × State Median Income		0.000	
		(0.000)	
High school graduate			−0.772
			(0.670)
Some college			−1.224
			(0.658)
2-year			−1.684**
			(0.650)
4-year			−1.892**
			(0.713)
Post-grad			−2.161**
			(0.690)
High School × Top Share			0.059*
			(0.028)
Some College × Top Share			0.061*
			(0.026)
2-year × Top Share			0.081**
			(0.027)
4-year × Top Share			0.061*
			(0.028)
Post-grad × Top Share			0.063*
			(0.028)
Constant	−3.152***	−1.800	−2.899***
	(0.464)	(1.439)	(0.786)
Level 1 N	29563	29563	29563
Level 2 N	50	50	50

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix E

Partisan Convergence Models

Table E.1 reports two models related to the results reported in the main text in Figures 5.5 and 5.6. Here we see that the negative coefficient for Democratic control of the Senate is negative and significant. However, that effect is erased during the post-1982 period as shown in Model 2 by the interaction term between the period dummy variable and Democratic Senate control.

Table E.2 presents the underlying models for Figure 5.7. We can see in this table that the effect of Democratic control of the Senate generally is a reduction in deregulation. And while the interaction terms are not statistically significant, we saw in the main text that the effect of Senate control is often reduced to insignificance when we take account of the interactive effects.

Table E.1: Effect of Party Power on Financial Deregulation

	(1)	(2)
Δ Democratic President$_t$	-0.111	-0.120
	(0.071)	(0.081)
Δ Democratic Senate$_t$	-0.215^{**}	-0.311^{***}
	(0.077)	(0.081)
Δ Democratic House$_t$	0.008	
	(0.079)	
Post-1982$_t$		0.108^{*}
		(0.044)
Post-1982$_t$ $\times$ Δ Democratic President$_t$		-0.007
		(0.149)
Post-1982$_t$ $\times$ Δ Democratic Senate$_t$		0.307^{*}
		(0.149)
Constant	-0.008	-0.047
	(0.021)	(0.025)
Observations	101	101
R^2	0.138	0.231

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table E.2: The Conditional Effect of Party Power on Financial Deregulation

	(1)	(2)	(3)	(4)	(5)
Δ Democratic Senate$_t$	-0.444^{**}	-0.279^{*}	-2.656	-0.219	-0.483^{**}
	(0.141)	(0.105)	(2.627)	(0.191)	(0.147)
Top Share$_{t-1}$	0.029				
	(0.016)				
Δ D Senate$_t$ $\times$ Top Share$_{t-1}$	0.087				
	(0.058)				
Total Loans Per Capita$_{t-1}$		0.000			
		(0.000)			
Δ D Senate$_t$ $\times$ Loans$_{t-1}$		0.000			
		(0.000)			
Finance Contributions$_{t-1}$			-0.741		
			(0.385)		
Δ D Senate$_t$ $\times$ Contributions$_{t-1}$			2.833		
			(2.911)		
Union Membership$_{t-1}$				-0.001	
				(0.003)	
Δ D Senate$_t$ $\times$ Membership$_{t-1}$				-0.001	
				(0.008)	
Trade Openness$_{t-1}$					0.009^{**}
					(0.003)
Δ D Senate$_t$ $\times$ Openness$_{t-1}$					0.016
					(0.009)
Constant	-0.080	-0.023	0.673^{*}	0.012	-0.131^{*}
	(0.043)	(0.036)	(0.321)	(0.059)	(0.050)
Observations	101	62	34	101	97
R^2	0.172	0.148	0.159	0.118	0.219

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix F

Status Quo Bias Models

In Table F.1 I report the model that produced the results reported in Figure 6.5. The core model is model 1 in the table here. I also report several other specifications showing that the pattern of results reported in the main text are generally maintained under alternative specifications. Model 2 includes partisan control of the House and Senate. Model 3 includes a variety of policy controls. Model 4 adds financialization, union membership, and the size of the economy. Model 5 demonstrates the robustness of the core results in a more parsimonious model.

Table F.1: Models of Top Income Shares

	(1)	(2)	(3)	(4)	(5)
Top 1% Share, Including Capital Gains$_{t-1}$	-0.18^{***}	-0.16^{***}	-0.43^{***}	-0.17^{*}	-0.19^{***}
	(0.05)	(0.06)	(0.09)	(0.09)	(0.05)
Δ Senate Median to Filibuster Pivot Distance$_t$	6.77^{*}	5.45	7.17^{*}	7.03^{*}	8.57^{**}
	(3.66)	(3.93)	(3.92)	(4.07)	(3.58)
Senate Median to Filibuster Pivot Distance$_{t-1}$	8.16^{***}	6.14^{*}	6.18	9.12^{***}	7.71^{***}
	(2.80)	(3.28)	(4.80)	(3.32)	(2.74)
Δ Maximum Preference Distance$_t$	-0.17	-0.52	0.80	-0.10	
	(0.88)	(0.92)	(0.91)	(1.35)	
Maximum Preference Distance$_{t-1}$	0.09	-0.28	-0.81	-0.13	
	(0.70)	(0.81)	(0.91)	(1.06)	

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Table F.1 – continued from previous page

	(1)	(2)	(3)	(4)	(5)
Δ Congressional Policy Product$_t$	0.01	0.01	0.01	0.01	
	(0.02)	(0.02)	(0.02)	(0.02)	
Congressional Policy Product$_{t-1}$	-0.04^{***}	-0.02^{*}	-0.05^{**}	-0.05^{***}	-0.04^{***}
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Δ House Party Polarization$_t$	9.22	7.32	2.20	6.95	
	(6.02)	(6.81)	(6.02)	(7.64)	
House Party Polarization$_{t-1}$	4.02	4.02	1.62	0.02	4.43^{**}
	(2.55)	(2.74)	(3.99)	(5.96)	(1.75)
Filibuster Distance*Top Share$_{t-1}$	1.75^{**}	1.08	2.59^{**}	1.95^{*}	1.48^{*}
	(0.75)	(0.90)	(1.04)	(0.98)	(0.74)
Maximum Distance*Top Share$_{t-1}$	0.34	0.34	0.13	0.24	
	(0.26)	(0.27)	(0.29)	(0.33)	
Congressional Policy Product*Top Share$_{t-1}$	-0.01^{**}	-0.01^{*}	-0.01^{***}	-0.01^{*}	-0.01^{*}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
House Party Polarization*Top Share$_{t-1}$	-3.00^{***}	-2.18^{**}	-3.57^{***}	-3.32^{**}	-2.30^{***}
	(0.90)	(1.07)	(1.31)	(1.29)	(0.76)
Δ Democratic Senate$_t$		-0.75			
		(0.59)			
Democratic Senate$_{t-1}$		-0.68			
		(0.44)			
Δ Democratic House$_t$		0.48			
		(0.69)			
Democratic House$_{t-1}$		0.11			
		(0.50)			
Δ Top Capital Gains Tax Rate$_t$			-0.04		
			(0.05)		
Top Capital Gains Tax Rate$_{t-1}$			-0.04		
			(0.04)		
Δ Top Marginal Tax Rate$_t$			-0.02		
			(0.03)		
Top Marginal Tax Rate$_{t-1}$			-0.06^{**}		
			(0.02)		
Δ Financial Deregulation$_t$			1.50^{**}		
			(0.65)		

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Table F.1 – continued from previous page

	(1)	(2)	(3)	(4)	(5)
Financial Deregulation$_{t-1}$			0.01		
			(0.48)		
Δ Prime Rate$_t$			-0.48^{**}		
			(0.18)		
Prime Rate$_{t-1}$			-0.25^{**}		
			(0.11)		
Δ Financial Profits, % GDP$_t$				0.12	
				(0.88)	
Financial Profits, % GDP$_{t-1}$				0.16	
				(0.56)	
Δ Union Membership Rate$_t$				0.03	
				(0.19)	
Union Membership Rate$_{t-1}$				0.01	
				(0.10)	
Δ Real GDP Per Capita (2005 USD)$_t$				-0.00	
				(0.00)	
Real GDP Per Capita (2005 USD)$_{t-1}$				0.00	
				(0.00)	
Constant	0.27^{*}	0.60	6.45^{***}	-1.03	0.30^{**}
	(0.14)	(0.41)	(2.13)	(3.37)	(0.14)
Observations	67	67	67	67	67
R^2	0.55	0.57	0.69	0.56	0.48

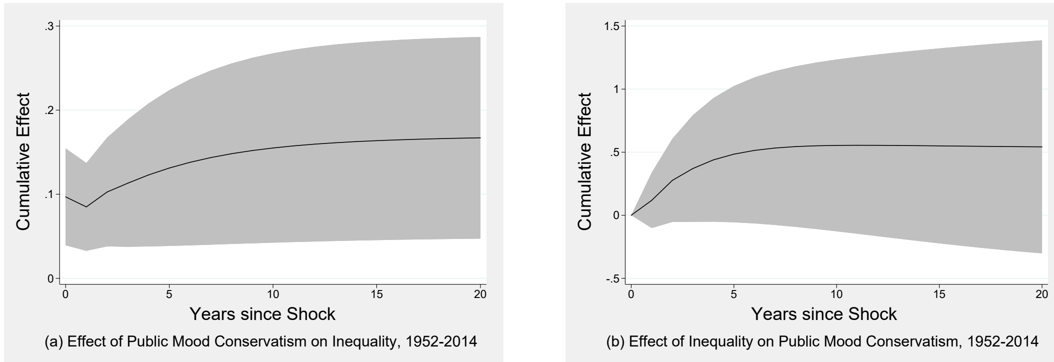
Prais-Winsten estimates with standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; two-tailed tests

Appendix G

Alternative Causal Ordering Assumptions for Creation of Impulse Response Functions

At several points in the main text, I mention that I considered a different assumption regarding the causal ordering of variables in a VAR model when creating impulse response functions. Most notably, I typically report results in the main text that assume that inequality is the final variable in a causal chain. However, since the theory of an inequality trap explicitly posits that inequality may be a driver of politics, it is sensible to test whether different assumptions about causal ordering when depicting long run effects produce different inferences. In particular, I re-estimated most of the VARs reported in the main text shifting inequality from the final variable in the causal chain to the first variable in the causal chain. The results are reported here. The main conclusion is that the assumptions about causal ordering do not substantially alter the conclusions reported in the main text. The one result that changes slightly is seen in Figure G.3d, where the results reported in the text do not identify feedback between inequality and presidential election outcomes but such feedback is seen here when the causal ordering assumption is altered.



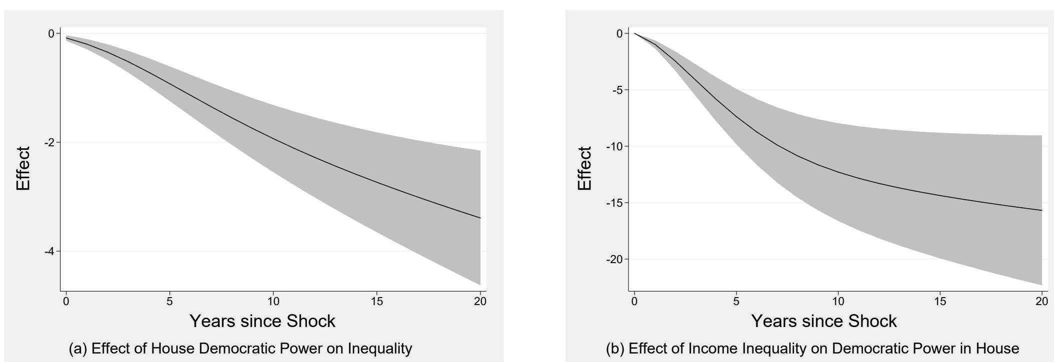
(a) Effect of Public Mood Conservatism on Inequality, 1952-2014

(b) Effect of Income Inequality on Public Mood Conservatism, 1952-2014

Source: Author's calculations from annual data, 1952 to 2014.

Note: Charts plot orthogonalized cumulative impulse response functions based on a vector autoregression including top .01% income share and public mood conservatism. Models also include the top capital gains tax rate, top income tax rate, financial deregulation, and Congressional partisanship. The plot represents the predicted effect of a standard deviation shift in one variable on the other variable over a 20 year period. The figure replicates the analysis reported in Figure 3.2 but with the assumed causal ordering changed to put inequality at the beginning rather than the end of the causal chain.

Figure G.1: Is There a Reciprocal Relationship Between Inequality and Public Opinion?



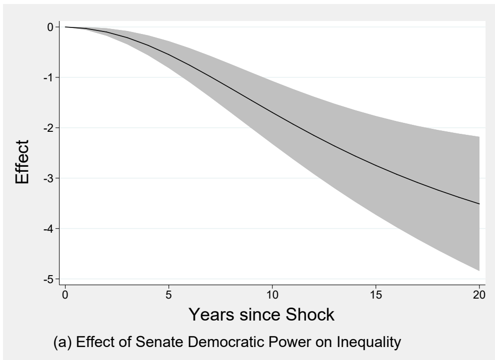
(a) Effect of House Democratic Power on Inequality

(b) Effect of Income Inequality on Democratic Power in House

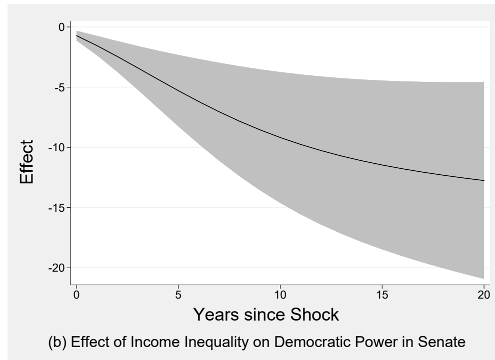
Figure G.2: Is There a Reciprocal Relationship Between Inequality and House Elections?

Source: Author's calculations from annual data, 1913 to 2014.

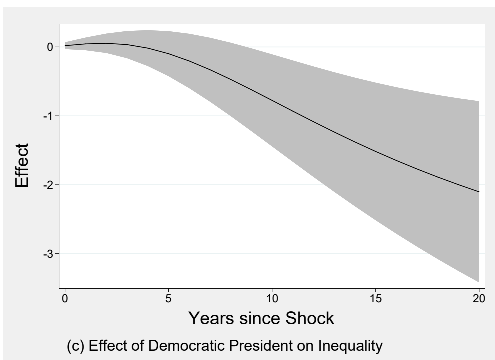
Note: Charts plot orthogonalized cumulative impulse response functions based on a vector autoregression including top .01% income share and the percent of Democratic seats in the House of Representatives. Models also include union strength, financial deregulation, and the top capital gains tax rate. The plot represents the predicted effect of a standard deviation shift in one variable on the other variable over a 20 year period. The figure replicates the analysis reported in Figure 4.2 but with the assumed causal ordering changed to put inequality at the beginning rather than the end of the causal chain.



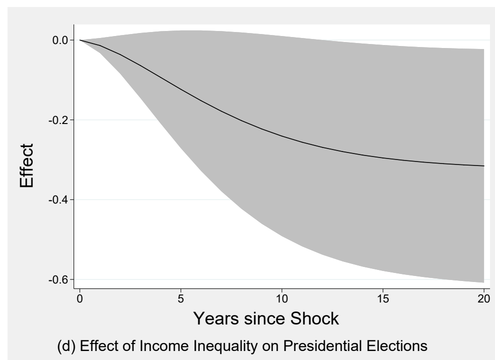
(a) Effect of Senate Democratic Power on Inequality



(b) Effect of Income Inequality on Democratic Power in Senate



(c) Effect of Democratic President on Inequality

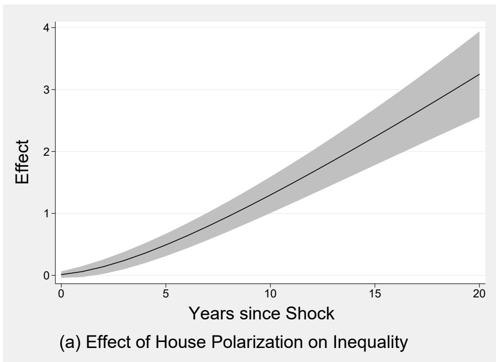


(d) Effect of Income Inequality on Presidential Elections

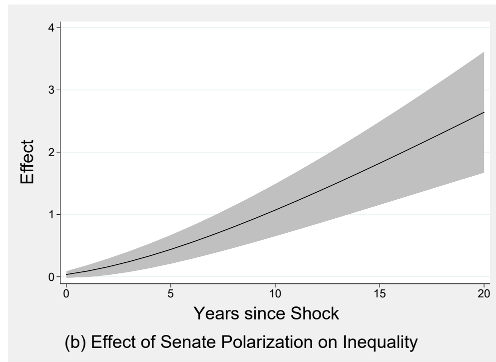
Figure G.3: Inequality and Elections in the Senate and Presidency

Source: Author's calculations from annual data, 1913 to 2014.

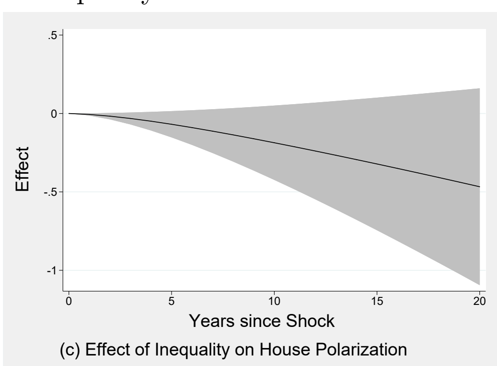
Note: Charts plot orthogonalized cumulative impulse response functions based on VARs. Models include the percent of Democratic seats in the Senate or Democratic control of presidency along with top .01% income share. Models also include union strength, financial deregulation, and the top capital gains tax rate. The plot represents the predicted effect of a standard deviation shift in one variable on the other variable over a 20 year period. The figure replicates the analysis reported in Figure 4.3 but with the assumed causal ordering changed to put inequality at the beginning rather than the end of the causal chain.



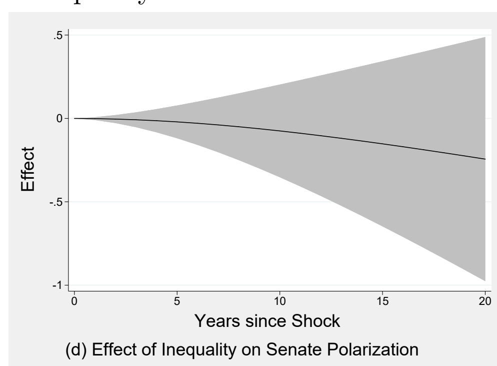
(a) Effect of House Polarization on Inequality



(b) Effect of Senate Polarization on Inequality



(c) Effect of Inequality on House Polarization

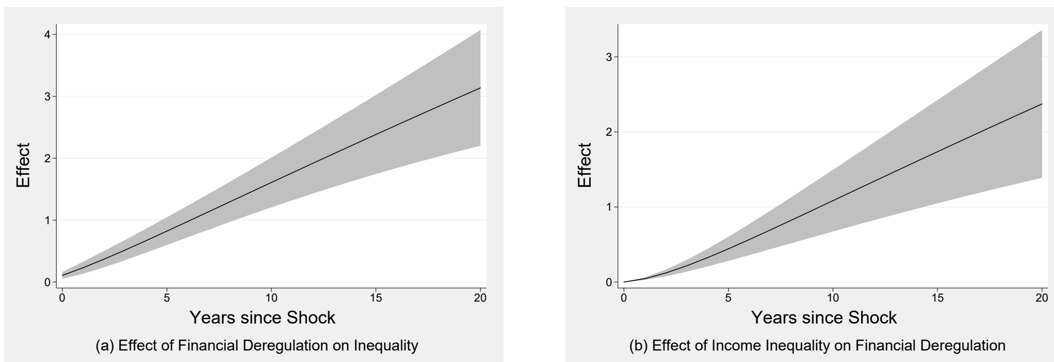


(d) Effect of Inequality on Senate Polarization

Figure G.4: Is There a Reciprocal Relationship Between Inequality and Polarization?

Source: Author's calculations from annual data, 1913 to 2014.

Note: The plot represents the predicted effect of a standard deviation shift in one variable on the other variable over a 20 year period using orthogonalized cumulative impulse response functions based on two vector autoregressions including top .01% income share, either House or Senate party polarization, and a measure of legislative policy stagnation (Grant & Kelly 2008). The figure replicates the analysis reported in Figure 6.2 but with the assumed causal ordering changed to put inequality at the beginning rather than the end of the causal chain.



(a) Effect of Financial Deregulation on Inequality

(b) Effect of Income Inequality on Financial Deregulation

Figure G.5: Is There a Reciprocal Relationship Between Inequality and Financial Deregulation?

Source: Author's calculations from annual data, 1913 to 2014.

Note: Charts plot orthogonalized cumulative impulse response functions based on a vector autoregression including financial deregulation and top .01% income share. The plot represents the predicted effect of a standard deviation shift in one variable on the other variable over a 20 year period. The figure replicates the analysis reported in Figure 5.4 but with the assumed causal ordering changed to put inequality at the beginning rather than the end of the causal chain.

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