Online Supplement to Article

The Rise of the Super-Rich: Power Resources, Taxes, Financial Markets, and the Dynamics of the Top 1 Percent, 1949-2008.

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Alternative Estimates and Robustness Checks

The estimation of time-series data raises various concerns about robustness and the specific methods used to analyze the data. As suggested by reviewers, we examined not only alternative means of estimation, but took into consideration other variables that may impact the Top 1 percent.

Testing for Trends and 1980 as a Possible Turning Point

One potential issue is that our results might not be robust to the inclusion of a post-1980 dummy variable as well as various specifications of time. It makes good sense to estimate our models while controlling for the pre/post-1980 period and other time-related variables. We present this supplemental analysis below, which includes a dummy variable for post-1980 years and a quadratic term for time (see Table M1). There is no change in the substantive results and neither of these variables are significant predictors of top income shares.

Table M1. Final Model of Top 1 Percent Income Share, Re-estimated to Include Additional Controls, 1949-2008

	Δ Top 1% Share	
Explanatory Variables	(1)	(2)
Top 1% Share$_{t-1}$	-0.80***	-0.70***
	(0.14)	(0.11)
% Congressional Democrat$_{t-1}$	-0.06**	-0.05**
	(0.03)	(0.02)
Divided Government$_{t-1}$	-0.26	-0.30
	(0.21)	(0.19)
Union Membership$_{t-1}$	-0.40***	-0.31***
	(0.11)	(0.08)
Top Marginal Tax Rate$_{t-1}$	-0.01	-0.04***
	(0.02)	(0.01)
Δ Cap Gains Tax Rate$_t$	-0.04	-0.02
	(0.04)	(0.04)
Cap Gains Tax Rate$_{t-1}$	-0.08***	-0.08***
	(0.02)	(0.02)
3-Month Treasury Bill Rate$_{t-1}$	-0.06	0.02
	(0.08)	(0.05)
Δ Trade Openness$_t$	0.08	0.18*
	(0.11)	(0.10)
Log Real GDP$_{t-1}$	5.22	-2.82
	(4.71)	(3.53)
Δ Real S&P 500 Composite Index$_t$	0.007***	0.007***
	(0.001)	(0.001)
Real S&P 500 Composite Index$_{t-1}$	0.004***	0.003***
	(0.001)	(0.001)
Shiller Home Price Index$_{t-1}$	0.04***	0.03***
	(0.01)	(0.01)
Public Mood Liberalism$_t$	-0.01	
	(0.06)	
Δ Public Mood Liberalism$_{t-1}$	0.03	
	(0.03)	
Post-1980	0.40	-0.38
	(0.78)	(0.64)
Time	-0.46	-0.19
	(0.32)	(0.22)
Time^2	0.00	0.00
	(0.00)	(0.00)
Constant	-3.02	48.2**
	(28.4)	(21.8)
Adj. R^2	0.77	0.76
Rho	-0.54	-0.53
BIC	151.5	163.0
N	54	60

Notes: Prais-Winsten GLS coefficients with standard errors in parentheses.
Significance levels: * p < .10; ** p < .05; *** p < .01 (two-tailed tests)

The Potential Effect of Public Opinion

To what extent does public opinion influence the income share of the top 1 percent? While we think this is an extremely interesting issue, we do not feel that it can be adequately addressed in the context of this paper. In the original version of the paper we did not include Stimson's mood measure as an explanatory variable. However, in the supplementary analysis reported in Model 2 in Table M1 above, we include Stimson's mood measure. We feel this measure is a useful indicator of general public sentiment toward economic issues and government spending,[1] but it does not correlate with top shares in the models we estimated.

Are Some of the Independent Variables Being Influenced by the Dependent Variable?

ECMs assume that the explanatory variables are exogenous (in levels and first-differences) to the first difference of the dependent variable. In Table M2, we present the results of relevant exogeneity tests. None of the variables of theoretical interest display any endogeneity issues. Two control variables, stock market valuation and unemployment displayed evidence of endogeneity. We do not focus a great deal of attention on these variables (and unemployment is not significant in any of the models), so we do not bring attention to this issue in this particular article.

[1]Unfortunately more specific items are not available over sufficiently long time-spans to incorporate into our analysis.

Table M2. Testing for Endogeneity of Regressors Included in ECMs

Independent Variable	Δ Top 1% Share Level IV	Δ IV
Democratic President	0.82	0.97
% Congressional Democrat	0.51	0.86
Divided Government	0.52	0.45
Union Membership	0.73	0.82
Top Marginal Tax Rate	0.40	0.29
Capital Gains Tax Rate	0.80	0.67
3-Month Treasury Bill Rate	0.09	0.16
Trade Openness	0.32	0.34
Unemployment Rate	0.03*	0.01*
Log Real GDP	0.11	0.29
Real S&P 500 Composite Index	.00*	0.14
Shiller Home Price Index	0.80	0.24

Note: Cell entries are p-values from bivariate Granger causality tests. Level IV column tests the independent variable in level form. Δ IV tests the first difference of the independent variable. Both are reported because both variables are included in single equation ECMs. Starred entries are significant at the 0.05 level, indicating endogeneity.

Should Other Methods of Time-Series Analysis be Used Instead of the ECM?

As per reviewers, we considered several alternatives to the single-equation ECM reported in the article, but found issues with each. We discuss each of the alternatives below and explain why these alternatives were not suitable.

ARCH. The key strength of a (G)ARCH[2]-type model is that it allows for the analysis of volatility, in addition to the quantity of a dependent variable. Such a model is useful when the variance of a series changes over time. Our dependent variable does vary substantially over time. However, the income share of the super-rich changes only marginally from year-to-year, and the volatility does not substantially shift in the time period that we analyze. Nevertheless, we attempted to estimate a GARCH model using the same explanatory variables as in the original

[2] This acronym stands for Generalized Autoregressive Conditional Heteroskedasticity.

paper. We found that the GARCH estimation would not converge. This is due to the fact that we have 60 time points in our analysis and there is little variation in volatility over time—a lack of which makes estimating the GARCH model analytically difficult. Because we could not estimate a GARCH model, we did not pursue this option further.

VAR. Vector Autoregression (VAR) is a well-known method that allows an analysis of multiple time series in which no assumptions about exogeneity are imposed. All of the variables in the system are permitted to be endogenous. The strength of a VAR is that it places few assumptions on the analysis. The disadvantage is that the estimates produced by VAR are not as accurate because the models are dramatically over-fit. In a VAR, each variable is considered as a dependent variable, and numerous lags of the dependent variable and independent variables are included as explanatory variables in each equation. This produces a proliferation of coefficient estimates, which reduces efficiency in those estimates. Given the number of variables in our system and the limited length of our time series, the inefficiency issue is very important in our analysis. While this was a concern, the primary reason that we did not pursue VAR analysis is that it is not appropriate in the presence of integrated variables. While including several lags of the outcome variable in each separate equation helps to deal with problems of non-stationarity, the spurious regression problem is still present in VAR analysis. Therefore, we did not pursue VAR in the article.

VECM. We are attracted to Vector Error Correction Models (VECM) because, like VAR, the VECM imposes no exogeneity restrictions on the models estimated (though also like VAR, VECMs are radically inefficient). This is particularly attractive in our context because we have strong reason to believe that some of our explanatory factors may be at different points in the causal chain. For example, it is likely that political power resources variables influence some of

the policy and economic variables that are also included as explanations for income inequality. A VECM would more fully capture such relationships and would provide for a more complete accounting of the effects of all of our explanatory variables.

A second advantage of VECMs is that the common way to report the results from these models is through impulse response functions (IRFs) that chart the effects of each explanatory variable at various lags. This is useful because it explicitly shows how the effect of a variable on a particular outcome changes over time. Since a portion of our theoretical story is that the effects of politics and policy on inequality are distributed over time, IRFs are a useful way to show this.

We estimated a VECM using the variables in the original version of the paper. The main substantive results as reported in the revised version of the table remained unchanged. Unfortunately, we encountered a problem when conducting diagnostics prior to reporting the substantive results. Specifically, we could not estimate a VECM specification that would allow us to confidently report the substantive effects of each variable in IRFs (due to violations of the stability condition). We believe this problem is created in part by the fact that our full system is fairly complex and puts a great deal of demands on relatively short time series.

Since we were unable to accurately report the results of a VECM using standard techniques, we revised the analysis to capture as many of the positive aspects of a VECM in our ECM. One advantage of the VECM is the ability to examine the flow of causation more carefully. In the article, we point out that in our models we are only capturing direct effects while acknowledging that some of the variables in our model might be influenced by other explanatory variables. Second, we build our models so that we can speak more directly to the flow of causation. We start with a model of political and economic power resources. We then estimate a model that focuses only on policy variables. These first two models (as reported in the article in

Table 1) provide a useful baseline to which we can compare later models. In the third model we combine the political power resources and policy model. This allows us to speak to whether some of the political variables are working through the policy variables. We find that this is the case for the effect of Congress, and we draw attention to this in the discussion of the results. We then add controls for economic factors and see that this further reduces the effect of political power resources.

While we do not explicitly examine direct and indirect effects of political power resources and policy variables, this could be done even within an ECM framework. We have elected not to do this because our primary concern in this paper is identifying the direct effects of the variables in our model on top income shares. In fact, our approach provides conservative estimates of the effect of political variables on top shares, and we prefer to maintain this conservative approach.

The second major benefit of the VECM is the way substantive results are reported, with the dynamic effects explicitly shown in an IRF. Lag distributions similar to IRFs can also be calculated after ECMs, and we have done that in the article. Figure 2, in the article, shows the effect of a one-unit shift in our key explanatory variables on top income shares at up to four lags. The figure shows visually that the effects of politics and policy are generally distributed over time. Reporting some of our results in this way captures one of the benefits of VECMs in our analysis using more straightforward ECMs.

Fractional ECMs. Fractional Error Correction Models (ECM) are typically discussed in the context of fractional cointegration, in which two or more variables are integrated or near-integrated and maintain a very long-run relationship that returns to equilibrium quite slowly.

Fractional error correction models are often used where the evidence of non-stationarity is not clear.

The use of fractionally differenced variables in the ECM does not substantially alter the results (see Table M3 below). Some coefficients become a bit less significant, the timing of the effect of some variables changes, and the error correction rates are a bit slower as would be expected in a fractional ECM. Beyond that there are few differences between the model reported in the article and the model reported in this supplemental analysis. Focusing on the final model, the inferences reached from both modeling strategies are very similar. The only substantive difference is that divided government barely misses statistical significance in the fractional model. Since divided government is not central to our theoretical argument, this change is relatively minor. While the magnitude of the long-term coefficient for many variables is slightly different in the fractional ECM, the overall size of the long-run effect is generally as large or larger here than in the standard ECM setup. This is due to the fact that long-run effects are calculated as the long term coefficient divided by the error correction rate, and the error correction rate is slightly slower in the fractional model. We report the regular ECM results in the article because such models are more widely accessible to a broader readership.

Table M3. Models of Top 1 Percent Income Share, 1949-2008

	Δ Top 1% Share				
Explanatory Variables	(1)	(2)	(3)	(4)	(5)
Top 1% Share$_{t-1}$	-0.26**	-0.20*	-0.33***	-0.48***	-0.53***
	(0.12)	(0.11)	(0.11)	(0.19)	(0.11)
Δ Democratic President$_{t-1}$	0.47				
	(0.78)				
Democratic President$_{t-1}$	-0.34				
	(0.67)				
Δ% Congressional Democrat$_{t-1}$	0.09				
	(0.07)				
% Congressional Democrat$_{t-1}$	-0.15***		-0.07**	-0.03	-0.04**
	(0.07)		(0.03)	(0.02)	(0.02)
Δ Divided Government$_{t-1}$	0.61				
	(0.89)				
Divided Government$_{t-1}$	-1.39		-0.67*	-0.05	-0.35
	(0.86)		(0.35)	(0.26)	(0.21)
Δ % Union Membership$_t$	0.07				
	(0.21)				
Union Membership$_{t-1}$	-0.20***		-0.16**	-0.26*	-0.27***
	(0.06)		(0.06)	(0.13)	(0.08)
Δ Top Marginal Tax Rate$_t$		0.04			
		(0.05)			
Top Marginal Tax Rate$_{t-1}$		-0.08***	-0.02	-0.03**	-0.04***
		(0.02)	(0.03)	(0.02)	(0.01)
Δ Cap Gains Tax Rate$_t$		0.02	0.08	-0.01	0.00
		(0.09)	(0.09)	(0.04)	(0.03)
Cap Gains Tax Rate$_{t-1}$		-0.12*	-0.14**	-0.11***	-0.10***
		(0.06)	(0.06)	(0.03)	(0.02)
Δ3-Month Treasury Bill Rate$_t$		0.04			
		(0.17)			
3-Month Treasury Bill Rate$_{t-1}$		-0.07	-0.09	0.04	0.04
		(0.13)	(0.08)	(0.06)	(0.05)
Δ Trade Openness$_t$				0.29**	0.26**
				(0.12)	(0.11)
Trade Openness$_{t-1}$				0.04	
				(0.11)	
Δ Unemployment Rate$_t$				0.08	
				(0.22)	
Unemployment Rate$_{t-1}$				-0.07	
				(0.13)	
Δ Log Real GDP$_t$				12.41	
				(10.02)	
Log Real GDP$_{t-1}$				-4.99**	-4.50***
				(2.01)	(1.56)
Δ Real S&P 500 Composite Index$_t$				0.06***	0.06***
				(0.01)	(0.01)
Real S&P 500 Composite Index$_{t-1}$				0.01	0.02*
				(0.01)	(0.01)
Δ Shiller Home Price Index$_t$				0.13	
				(0.14)	
Shiller Home Price Index$_{t-1}$				0.32**	0.33***
				(0.13)	(0.09)
Constant	17.4***	11.3***	17.8***	52.8**	52.7***
	(5.88)	(4.1)	(4.1)	(19.9)	(15.5)
Adj. R^2	0.40	0.37	0.48	0.89	0.87
N	60	60	60	60	60

Notes: Regression coefficients with standard errors in parentheses. Differenced variables are fractionally differenced.
Significance levels: * p < .10; ** p < .05; *** p < .01 (two-tailed tests)