Supplemental Information for: What about the rest of the pie? A dynamic compositional approach to modeling inequality

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Forthcoming at Social Science Quarterly

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1 Data

Table 1: Summary of Data

Variable	**Description**
Inequality	Data comes from the US Census Bureau's Current Population Survey and ranges from 1947 through 2018. Income shares are divided into five quintiles of income share and the top 5%. Thus, final categories are defined as the bottom four quintiles, the 80 - 94th percentile, and the top fifth share of wealth. The Gini index for these data come from the same source. Replication data can be found here.
Polarization	Data comes from DNOMINATE scores. Replication data can be found here.
Top Marginal Tax Rate	Data comes from Volscho and Kelly replication data and ranges from 1913 to 2009. Variable simply represents the effective marginal tax rate for the top income bracket. Replication data can be found here. We extend their data to 2014 using Urban Institute and Brookings Institution's Tax Policy Center (Volscho and Kelly's original source). Data can be found here.
Percent Democrat in Congress	Data comes from same Volscho and Kelly replication data as above. The data are extended to 2014 from the Brookings Institution. Data can be found here.
Returns to Capital	Data is calculated from returns based off of the S&P 500, and ranges from 1928 - 2018. Replication data can be found here.
Returns to Labor	Data is calculated from the Social Security Administration's National Average Wage Index. Data Ranges from 1951 through 2018. Replication data can be found here.

Notes: Because of differences in dates among the variables, our models capture 1952 through 2014.

Table 2: Summary Statistics of Data

Variable	**Min.**	**Mean**	**SD**	**Max.**
Top 5% Income Share	0.144	0.176	0.024	0.215
80-94th Percentile Income Share	0.248	0.263	0.009	0.281
60-79th Percentile Income Share	0.227	0.237	0.005	0.246
40-59th Percentile Income Share	0.151	0.167	0.010	0.181
20-39th Percentile Income Share	0.092	0.110	0.011	0.127
0-19th Percentile Income Share	0.036	0.047	0.006	0.057
Polarization	0.426	0.665	0.221	1.1
Top Marginal Tax Rate	28	57.102	21.979	92
Percent Democrat in Congress	44.368	55.629	6.608	67.850
Returns to Capital	−36.55	12.348	17.552	52.56
Returns to Labor	−1.508	4.558	2.2671	10.066

2 Regression Table

Table 3: Results from the ECM Model

	$\Delta ln(\frac{0-19}{Top5})$	$\Delta ln(\frac{20-39}{Top5})$	$\Delta ln(\frac{40-59}{Top5})$	$\Delta ln(\frac{60-79}{Top5})$	$ln(\Delta\frac{80-94}{Top5})$
Lagged Dependent Variable	-0.241***	-0.294***	-0.286***	-0.270***	-0.261***
	(0.0535)	(0.0493)	(0.0473)	(0.0463)	(0.0469)
ΔPolarization$_t$	-0.119	-0.465	-0.424	-0.396	-0.434
	(0.315)	(0.276)	(0.269)	(0.259)	(0.250)
Polarization$_{t-1}$	-0.167*	-0.184**	-0.134*	-0.0802	-0.0339
	(0.0717)	(0.0646)	(0.0596)	(0.0552)	(0.0515)
Δ% Democrats in Congress$_t$	0.00213	0.00168	0.00205	0.00197	0.00144
	(0.00166)	(0.00143)	(0.00140)	(0.00135)	(0.00130)
% Democrats in Congress$_{t-1}$	0.000375	0.0000871	0.000253	0.000498	0.000519
	(0.00138)	(0.00117)	(0.00115)	(0.00111)	(0.00107)
ΔTop Marginal Tax$_t$	0.00136	0.000926	0.000683	0.000528	0.000349
	(0.00138)	(0.00121)	(0.00118)	(0.00114)	(0.00110)
Top Marginal Tax$_{t-1}$	0.000958*	0.00117**	0.000980*	0.000718	0.000523
	(0.000469)	(0.000421)	(0.000403)	(0.000384)	(0.000370)
ΔWage Growth$_t$	0.0129***	0.00753**	0.00740**	0.00672*	0.00527*
	(0.00333)	(0.00283)	(0.00276)	(0.00265)	(0.00256)
Wage Growth$_{t-1}$	0.00991*	0.00677*	0.00720*	0.00717*	0.00685*
	(0.00387)	(0.00302)	(0.00294)	(0.00283)	(0.00273)
ΔS&P$_t$	-0.000661*	-0.000440	-0.000351	-0.000280	-0.000216
	(0.000319)	(0.000281)	(0.000275)	(0.000264)	(0.000255)
S&P$_{t-1}$	-0.00117*	-0.000636	-0.000582	-0.000556	-0.000424
	(0.000498)	(0.000436)	(0.000426)	(0.000411)	(0.000396)
Constant	-0.318*	-0.111	-0.0194	0.0427	0.0488
	(0.155)	(0.116)	(0.111)	(0.106)	(0.103)
Obs	62	62	62	62	62
R-squared	0.3694	0.3791	0.3864	0.3581	0.3317
Chi-squared	46.44***	59.50***	62.00***	57.20***	51.92***

Note: Coefficients with standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3 Common Approaches To Modeling Inequality: Measuring the Wealth of the Top Group

Our paper proposes an alternative, and more insightful, method to analyze the distribution of income, and thus inequality. Traditional methods of measuring inequality often merely involve analyzing the income share of the top income group relative to the rest, or analyzing an index (e.g. Gini) that summarizes the distribution of income (e.g., Lee 2005; Piketty, Postel-Vinay and Rosenthal 2006; Lindqvist and Östling 2010; Lupu and Pontusson 2011; Freeman and Quinn 2012). In order to demonstrate how our proposed method is an advancement over the more commonly used approaches, we present the results from models in which we simply analyze the income share of the top group and also from those that use the Gini index.

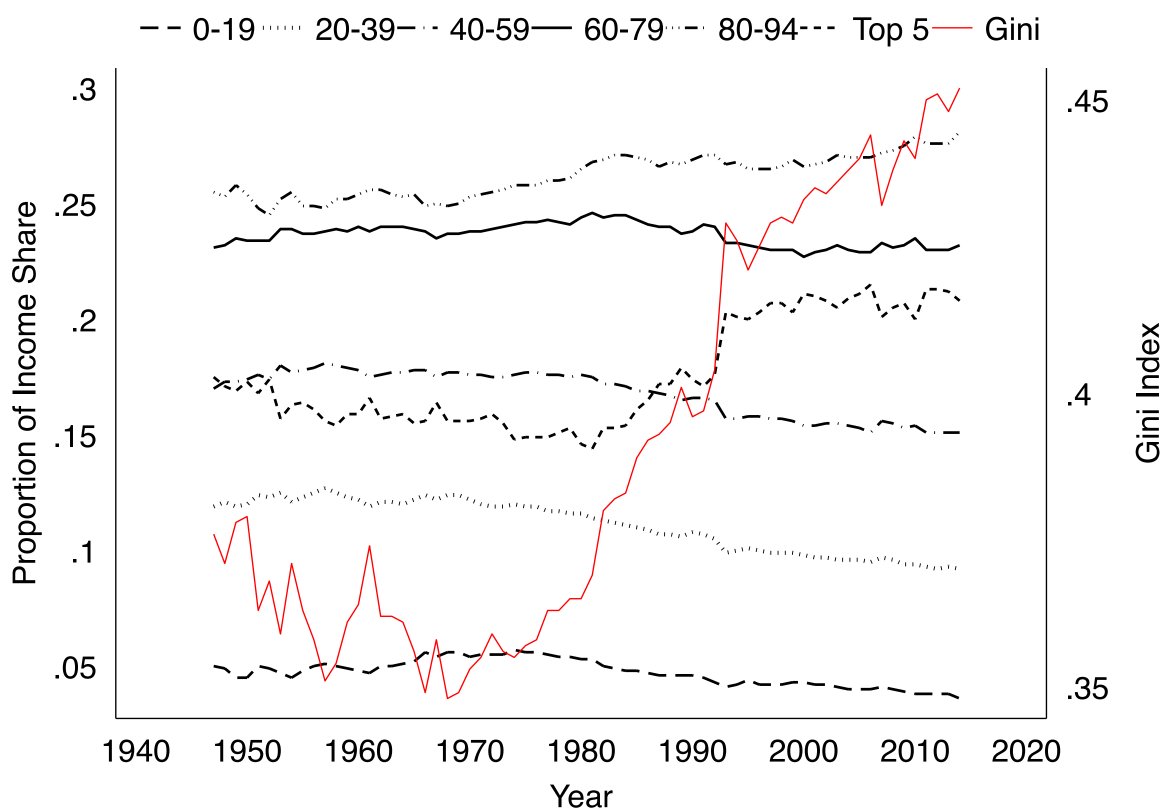


Figure 1: The Proportion of Income and the Gini index in the US, 1947 to 2014

Figure 1 demonstrates the Gini index (solid red line) overlayed on the income distribution in the US between 1947 and 2014. Possible values of the Gini index range from 0 to 1, where 0 implies a perfectly equal distribution of income in the population and a 1 implies that all the income in the population is concentrated with one group. By looking at this figure, one can easily identify that the increase in the Gini index (inequality) is due to increases in the income shares of the 80-94th percentile and top 5% groups and decreases in the income shares of the bottom 60th percentiles. The income share of the 60-79th percentile has remained relatively stable over time.

Prior to analyzing how left power, polarization, top marginal tax rate, returns to capital, and returns to labor affect inequality, we first conducted Dickey-Fuller GLS unit root tests on our independent variables. The income share of the top 5%, the Gini index, % Democrats in Congress, top marginal tax rate, and returns to labor contains unit roots, and returns to capital is stationary. Due to the non-stationarity of our data, we proceed by testing for cointegration. The Engle-Granger test finds support for cointegration for both outcomes—income share of the top 5% and the Gini index. The PSS bounds test provides an inconclusive finding for the income share of the top 5% and finds no support for cointegration for the Gini index. The Johansen test for cointegration, for both outcomes, find support for at least one cointegrating relationship between the variables. Since two out of three of the tests find support for cointegration, we proceed with estimating error correction models.

The results from the ECM models in Table 4 demonstrate that, in addition to the lagged dependent variable, only the change in and the lag of returns to labor (wage growth) have statistically significant and negative effects on the income share of the top 5%. For the Gini index, only the lag of top marginal tax rate (negative effect), polarization (positive effect), and change in wage growth (negative effect) have statistically significant effects. Similar to the main text, however, we produce dynamically simulated plots of the effects of our predictors on the outcome using dynardl (Jordan and Philips 2018). In doing so, we are able to identify how changes in an independent variable affect the dependent variable in the short- and long-run.

Table 4: Results from the ECM Models

	(1) Δ Top 5%$_t$	(2) Δ Gini$_t$
Lagged Dependent Variable	-0.318**	-0.291**
	(0.100)	(0.102)
Δ% Democrats in Congress$_t$	-0.0308	-0.000238
	(0.0226)	(0.000213)
% Democrats in Congress$_{t-1}$	-0.0111	0.0000360
	(0.0199)	(0.000177)
ΔTop Marginal Tax$_t$	-0.00339	-0.000126
	(0.0188)	(0.000178)
Top Marginal Tax$_{t-1}$	-0.0111	-0.000153*
	(0.00628)	(0.0000698)
ΔPolarization$_t$	6.325	0.0445
	(4.206)	(0.0416)
Polarization$_{t-1}$	1.741	0.0335*
	(1.080)	(0.0135)
ΔS&P$_t$	0.00359	0.0000750
	(0.00435)	(0.0000412)
S&P$_{t-1}$	0.00688	0.000110
	(0.00670)	(0.0000649)
ΔWage Growth$_t$	-0.0987*	-0.00125**
	(0.0432)	(0.000426)
Wage Growth$_{t-1}$	-0.106*	-0.000574
	(0.0491)	(0.000486)
Constant	6.070*	0.101*
	(2.665)	(0.0425)
N	62	62

Note: Coefficients with standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

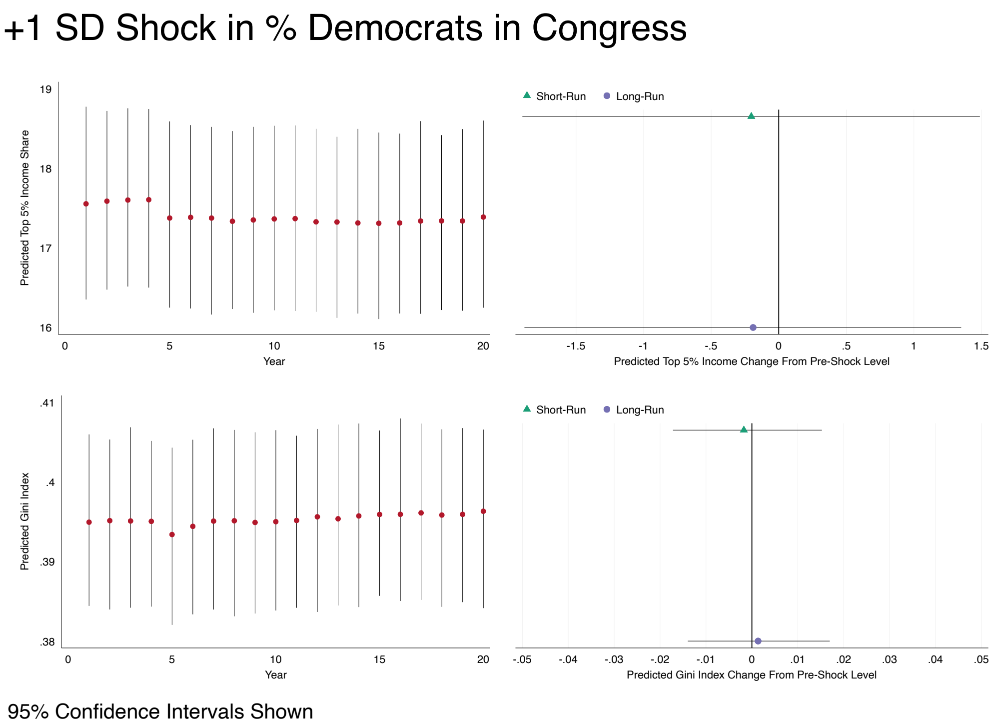


Figure 2: 1 Standard Deviation Increase in % Democrats in Congress

The first column of Figure 2 demonstrates how a one standard deviation increase (at Year = 5) in left power affects the income share of the top 5% percent (top row) and the Gini index (bottom row). The second column demonstrates whether these affects are statistically significant in the short- and long-run. Similar to our results in the Figure 3 in the main paper, we find that an increase in left power has no effect on the income share of the top 5%. We also find that left power does not have an effect on the distribution of income (Gini index). However, in the main text, we find that an increase in left power increases the income share of the 50-94 percentile income groups in the long-run, which affects the distribution of income in the US; a conclusion foregone by merely looking at the changes in the income share of the top 5% and the Gini index.

From Figure 3, we see that a one standard deviation increase (at Year = 5) in polarization affects neither the income share of the top 5% in the short- or long run nor the Gini index in the short-run. However, it does affect the Gini index in the long-run, which means an increase in inequality in the US. By merely analyzing the effect of polarization on the Gini index, we are unable to determine

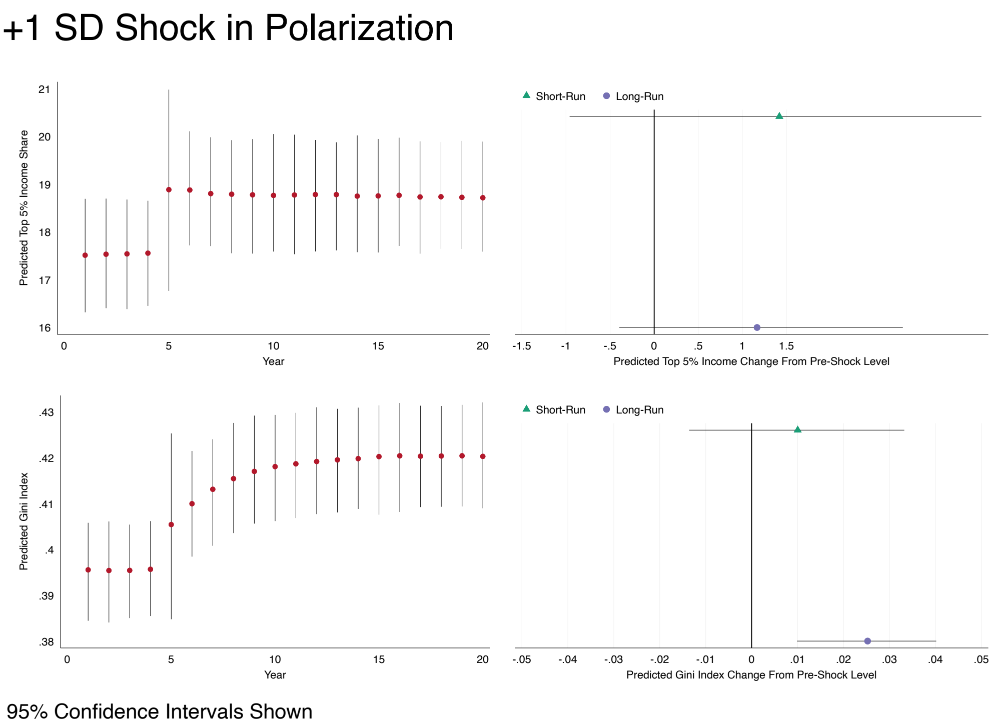


Figure 3: 1 Standard Deviation Increase in Polarization

how the income distribution in the US changes to reflect an increase in inequality. Figure 4 in the main text demonstrates that the increase in inequality due to polarization in the long-run is a combination of an increase in the income shares of the top 20% at the expense of the income shares of the bottom 60%.

Figure 4 shows that a one standard deviation decrease (at Year = 5) in the top marginal tax rate has no effect on the income share of the top 5% or the Gini index in the short- and long-run. However, by modeling the income distribution as a composition, we can see that a decrease in the top marginal tax rate increases the income shares of the top 20% and decreases those of the bottom 80% groups in the long-run (Figure 5 in the main text). The largest increase is to the income share of the top 5% and the biggest decrease is to the income shares of the 20-39 and 40-59 percentiles.

As seen in Figure 5, a one standard deviation increase (at Year = 5) in returns to capital does not affect the income share of the top 5% or the Gini index in the short- and long-run. However, Figure 6 in the main text demonstrates that an increase in returns to capital increases the income

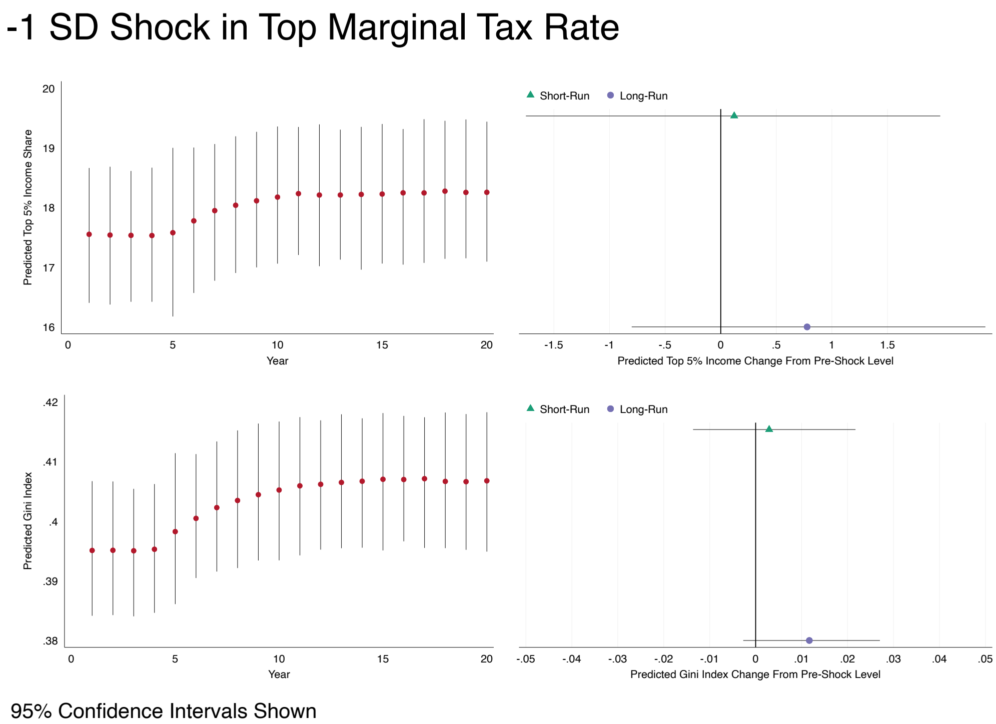


Figure 4: 1 Standard Deviation Decrease in Top Marginal Tax Rate

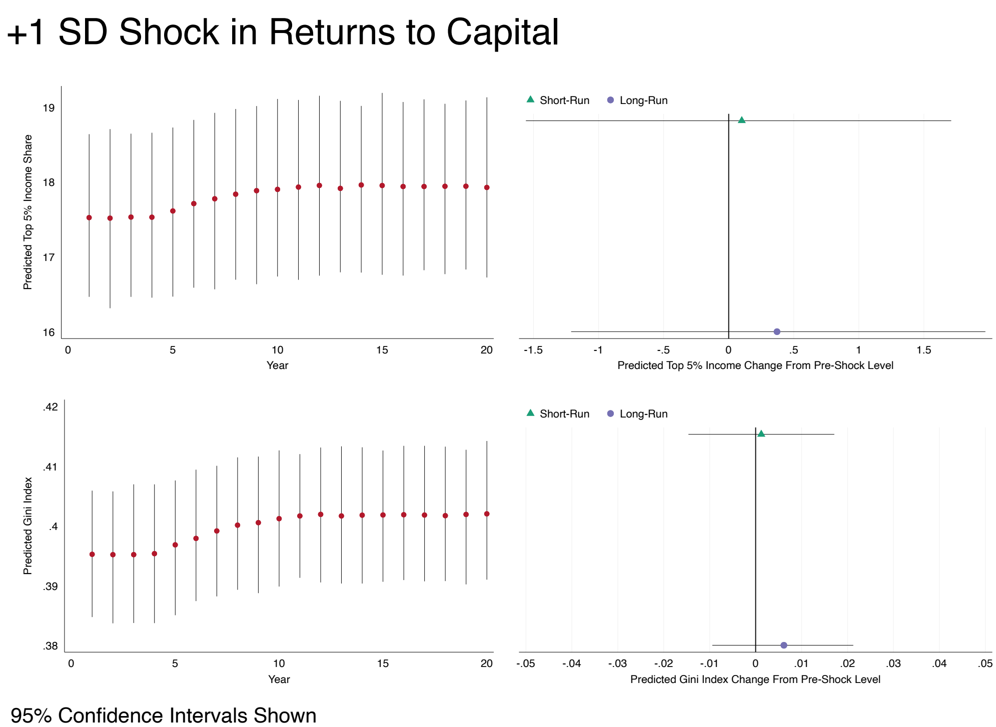


Figure 5: 1 Standard Deviation Increase in Returns to Capital

share of the top 5% at the expense of the income shares of the bottom 60% in the long-run, thus exaggerating the already-stark divide between the income shares of the top 5% and the rest.

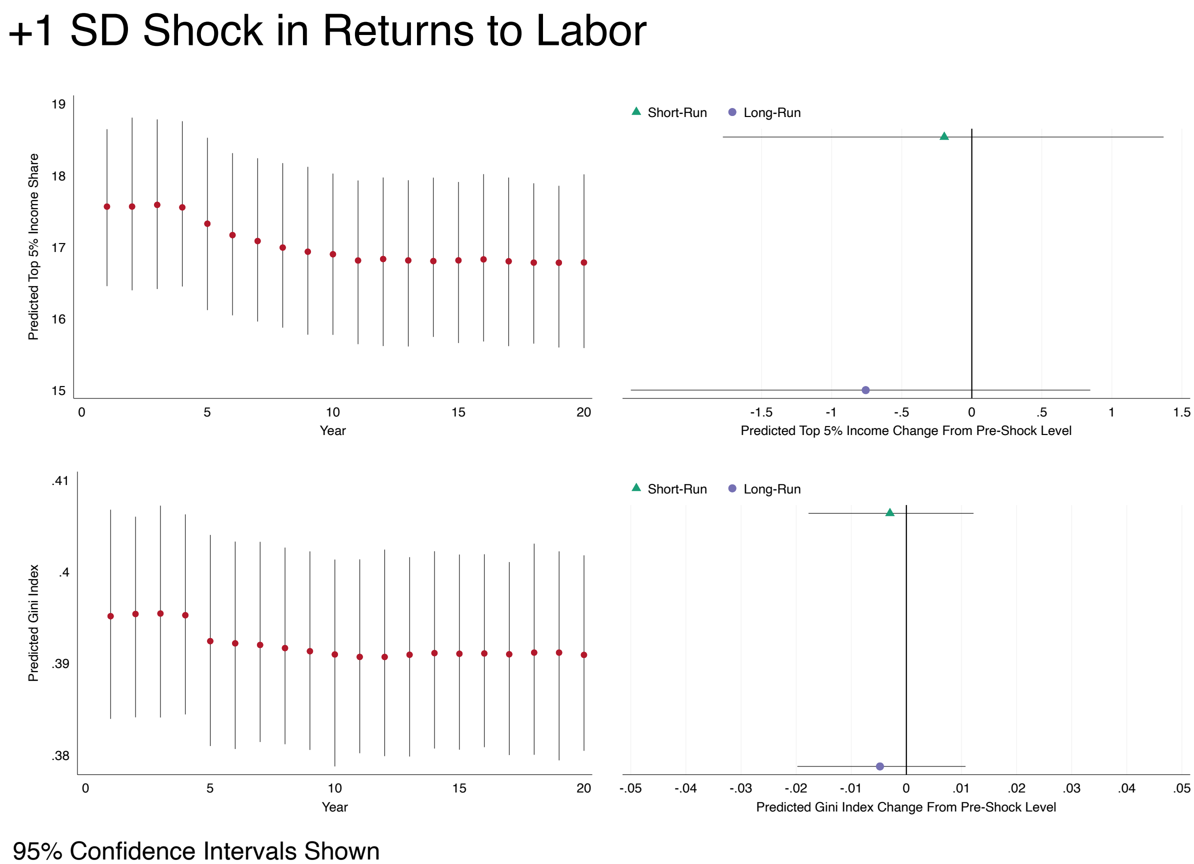


Figure 6: 1 Standard Deviation Increase in Returns to Labor

Figure 6 demonstrates that a one standard deviation increase (at Year = 5) in returns to labor has no short- or long-run effect on the income share of the top 5% or on the Gini index. By modeling the income distribution as a composition, we find that an increase in returns to labor decreases the income share of the top 5% while increasing the income shares of the 0-19, 40-59, 60-79, and 80-94 percentiles in the long-run (Figure 7 in the main text). Further, the increase in the income share of the bottom 20 percentile is also statistically significant in the short-run. These conclusions could not have been reached my merely analyzing the income share of the top 5% relative to the rest or by modeling the Gini index.

The above analyses demonstrate that oft-used measures of income inequality fail to provide a comprehensive answer to whether, and how, predictors influence the distribution of income in the US. We often find that our predictors of interest have no effect on the income share of the top 5% or the Gini index, when in reality, they do affect the income shares of of different groups with different magnitudes. When we do find that our predictors of interest affect the income share of the top 5% or the Gini index, we are unable to tell how the income shares of the other 95% are affected or how changes in the income shares of the various groups influence the summary measure of income distribution. That is, how changes in the income shares of the different groups affect inequality. However, by treating income as a composition, we gain deeper insight into the income distribution and, thus, into inequality, in the US.

4 Regrouping the Income Distribution into Three Groups

While we analyzed the effects of our independent variables on six different income groups in the main text, in this section we regroup the income distribution into three groups to assess the validity of our results in the main text. We now analyze the effects of our independent variables on the income distributions of the top 20%, the middle 40%, and the bottom 40%.

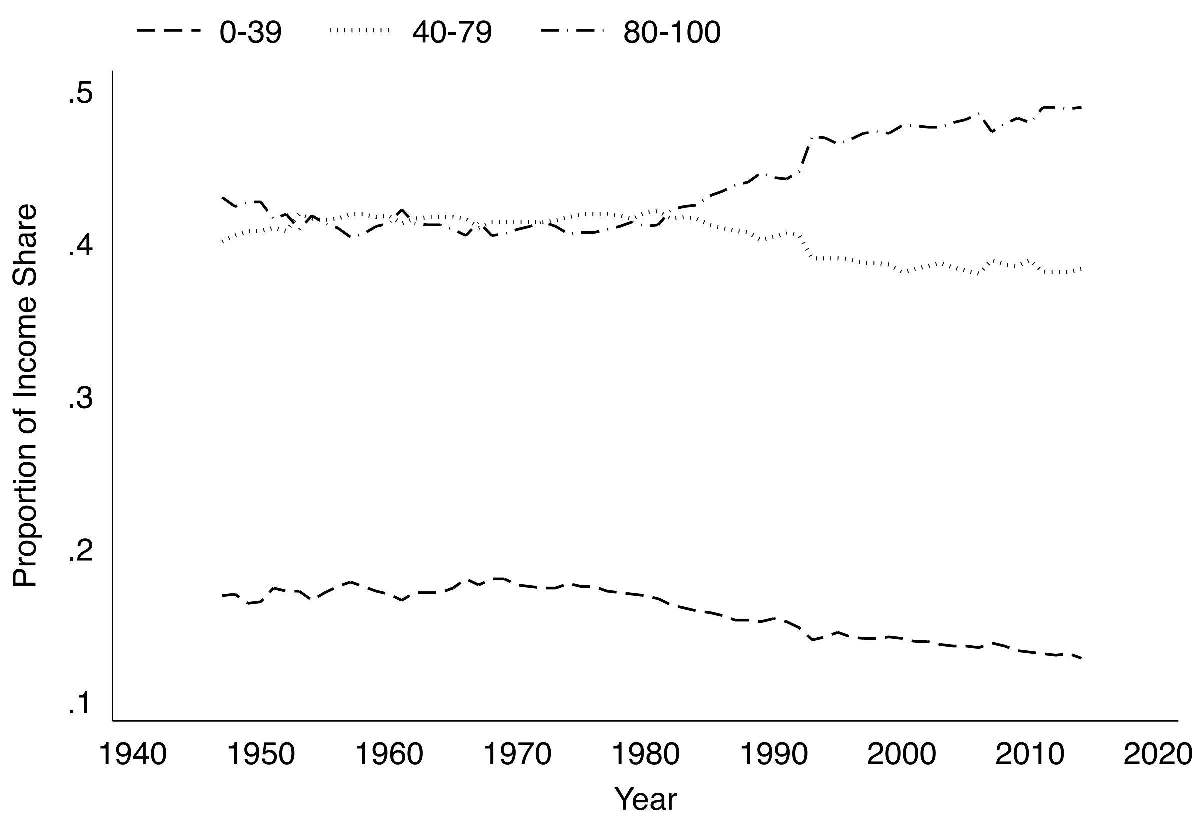
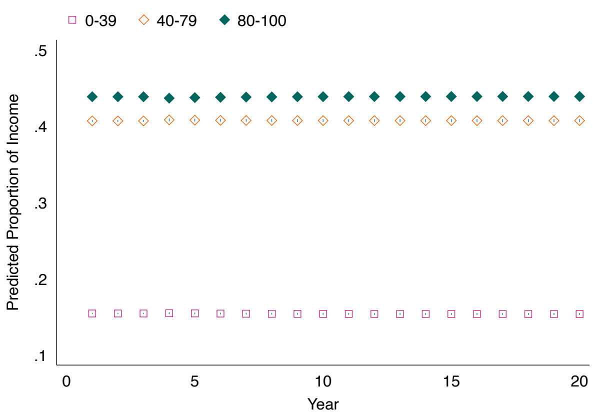


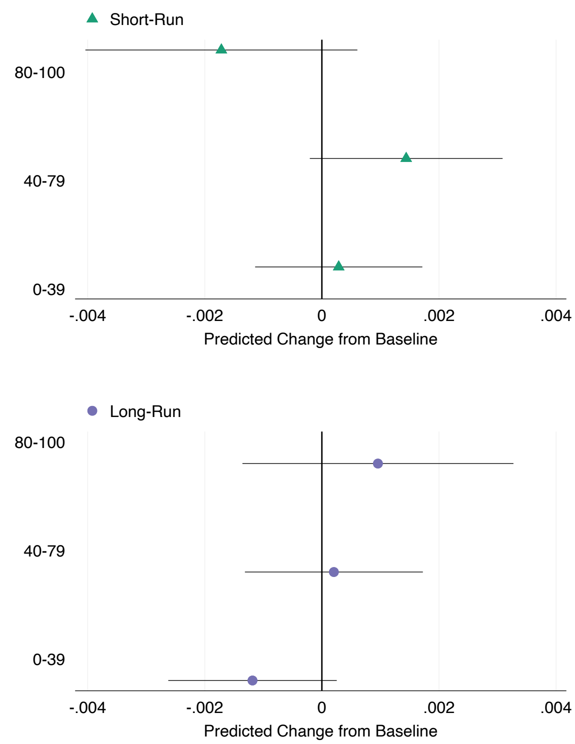
Figure 7: The Proportion of Income in the US, 1947 to 2014

Figure 7 shows the income distribution of the bottom 40%, the middle 40%, and the top 20%. We can see that the income share of the bottom 40% has decreased over time and that of the middle 40% has remained pretty stable, while slightly decreasing in the more recent years. However, the share of the top 20% has risen over time, and accounts for the largest share of the income distribution in the United States.

In order to conduct our compositional analysis on these three groups, we treat the income share of the top 20% as the baseline category for the log-ratios of the bottom and middle groups. These log-ratios are unit roots, as are all of the predictors, except for return to capital. The Engle-Granger test finds evidence of cointegration for both the log-ratios, while the PSS bounds approach concludes no cointegration when the outcome is log-ratio of the bottom 40% and finds evidence of cointegration at the 90% confidence level when the outcome is the log-ratio of the middle 40%. The Johansen test for cointegration finds evidence for at least one cointegrating vector for both outcomes. Based on these results, we proceed in estimating dynamic pie models in which the equations are in error correction form (Philips, Rutherford and Whitten 2016).



(a) Expected Change Over Time

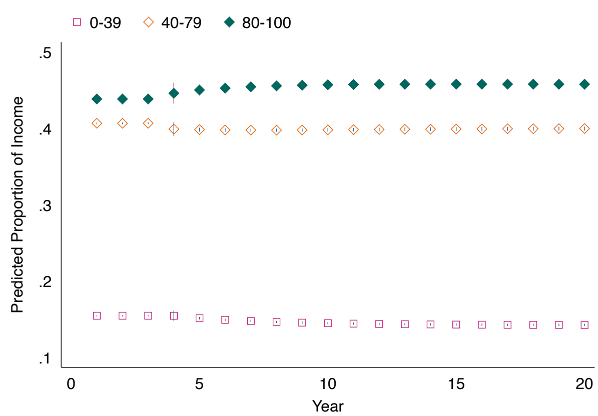


(b) Short and Long Run Effects

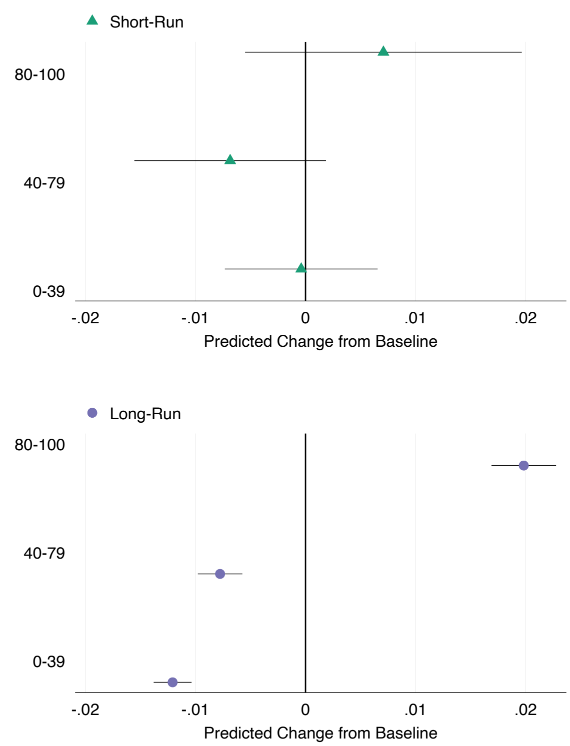
Figure 8: 1 Standard Deviation Increase in % Democrats in Congress

Notes: Left plot shows the expected income shares due to a one-period +1 standard deviation shock to % Democrats in Congress at $t = 4$. Right plot shows the contemporaneous and long-term changes from baseline (sample mean) for each category for the same simulation. All other variables held at sample means. 95% confidence intervals reported.

Figure 8 demonstrates the effect of a one period +1 standard deviation shock at time period 4 to % Democrats in Congress. Figures 8a and 8b demonstrates the % Democrats in Congress has no effect on the income distribution in the US. These findings are inconsistent with our expectations summarized in Table 2 and our results in Figure 3 in the main text. In the main text, we find that increases in the income shares of the 60-79 and 80-94 percentiles are statistically significant in the long-term. However, when we recategorize the income distribution into three categories, we conclude that left power has no effect on inequality in the US.



(a) Expected Change Over Time

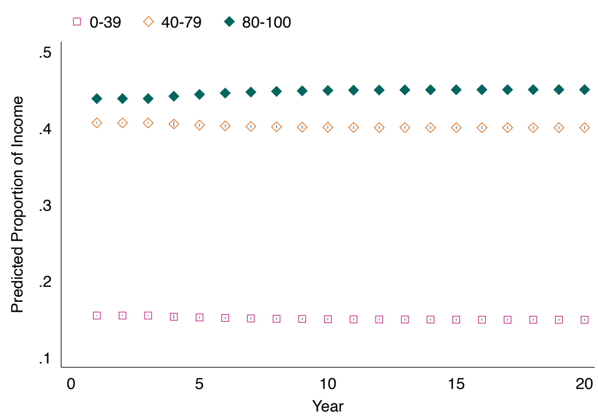


(b) Short and Long Run Effects

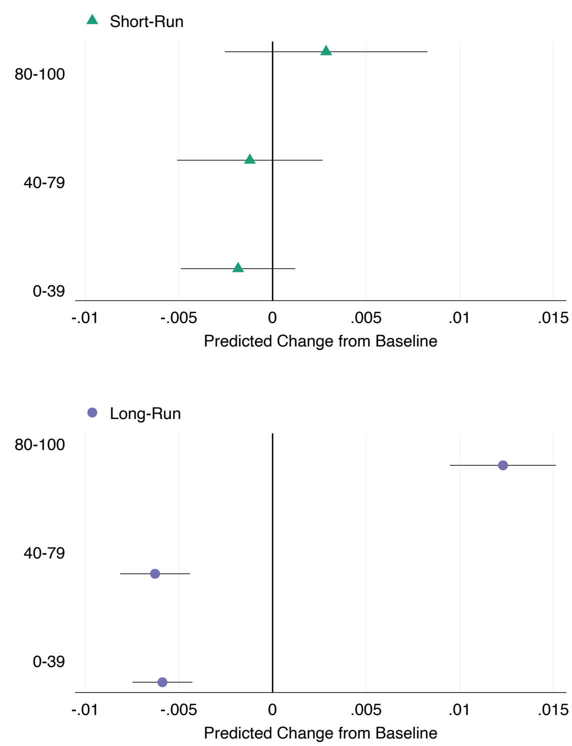
Figure 9: 1 Standard Deviation Increase in Polarization

Notes: Left plot shows the expected income shares due to a one-period +1 standard deviation shock to polarization at $t = 4$. Right plot shows the contemporaneous and long-term changes from baseline (sample mean) for each category for the same simulation. All other variables held at sample means. 95% confidence intervals reported.

The results in Figure 9 shows how a +1 standard deviation shock to polarization affects the income share of the three groups. Figure 9a shows that a shock to polarization increases the proportion of income of the top 20% at the expense of the bottom 40% and middle 40%. As seen in Figure 9b, these changes are not statistically significant in the short-term, but are in the long-term. These results are similar to those in our main text, in which the shares of the 80-94 percentile and top 5% increase in the long-term, and those of the 0-59 percentiles decrease. It is noteworthy that in Figure 4 in the main text, polarization does not have a statistically significant effect on the income share of the 60-79 percentile group. This suggests that the change in the income share of the middle 40% in Figure 9 is mainly being driven by the 40-59 percentile group. Further, comparing the results of Figure 9 and Figure 4 in the main text, we find that the changes in 80-94 percentile and top 5% due to polarization contribute similarly to the overall change in the income share of top 20%. The changes in the bottom 40% are more due to changes in the 20-39 percentile group than due to changes in the income share of the 0-19 percentile group.



(a) Expected Change Over Time

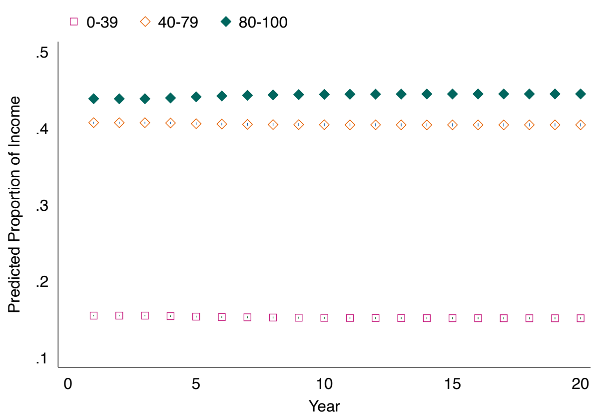


(b) Short and Long Run Effects

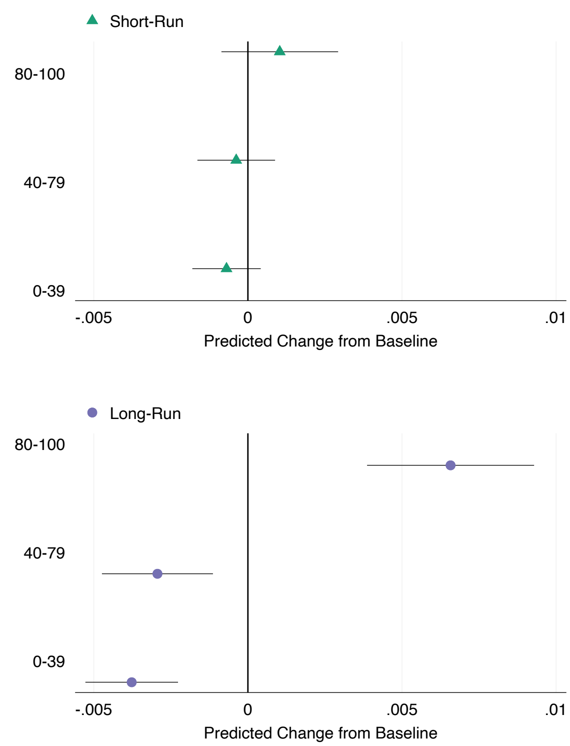
Figure 10: 1 Standard Deviation Decrease in Top Marginal Tax Rate

Notes: Left plot shows the expected income shares due to a one-period -1 standard deviation shock to the top marginal tax rate at $t = 4$. Right plot shows the contemporaneous and long-term changes from baseline (sample mean) for each category for the same simulation. All other variables held at sample means. 95% confidence intervals reported.

Figure 10a demonstrates that a 1 standard deviation decrease to the top marginal tax rate increases the income share of the top 20% while decreasing those of the other two groups. Figure 10 demonstrates that these results are only statistically significant in the long-term. These results are similar to those in Figure 5 in the main text: the top groups benefit at the expense of the other income groups. Comparing both, we find that a decrease in the marginal tax rate has larger effects on the income share of the top 5% than it does on that of the 80-94 percentile. For the middle 40%, the changes in its income share are more due to changes in the income share of the 40-59 percentile than due to the changes in income share of the 60-79 percentile. And, changes in the income share of the bottom 40% is largely due to changes in the income share of the 20-39 percentile as compared to that of the 0-19 percentile.



(a) Expected Change Over Time

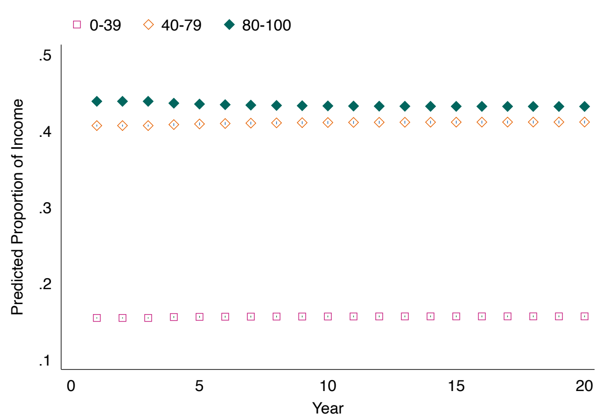


(b) Short and Long Run Effects

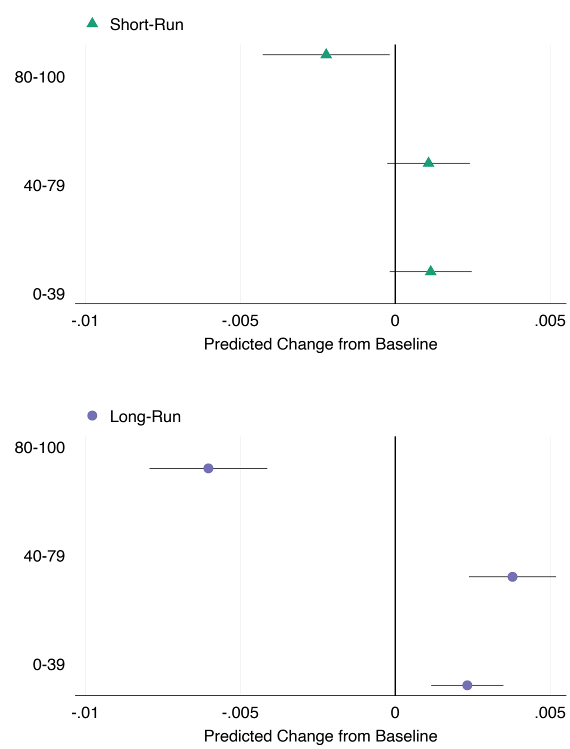
Figure 11: 1 Standard Deviation Increase in Returns to Capital

Notes: Left plot shows the expected income shares due to a one-period +1 standard deviation shock to returns to capital at $t = 4$. Right plot shows the contemporaneous and long-term changes from baseline (sample mean) for each category for the same simulation. All other variables held at sample means. 95% confidence intervals reported.

A +1 standard deviation shock to returns to capital increases the income share of the top 20% at the expense of the bottom 40% and middle 40%. However, as seen in Figure 11, these effects are only statistically significant in the long-run. Further, these results reflect our findings in Figure 6 in the main text that the top group benefits at the expense of the others. When comparing these two figures, we find that the changes in the income share of the top 20% is largely due to the top 5%. An increase in returns to capital has no statistically significant effect on the income share of the 80-94 percentile. The changes in the income shares of the 40-59 and 60-79 percentiles contribute almost equally to the changes in the income share of the middle 40%. Lastly, changes in the income share of the 0-19 percentile contribute more than changes in that of the 20-39 percentile to the predicted income share of the bottom 40%.



(a) Expected Change Over Time



(b) Short and Long Run Effects

Figure 12: 1 Standard Deviation Increase in Returns to Labor

Notes: Left plot shows the expected income shares due to a one-period +1 standard deviation shock to returns to labor at $t = 4$. Right plot shows the contemporaneous and long-term changes from baseline (sample mean) for each category for the same simulation. All other variables held at sample means. 95% confidence intervals reported.

Our last figure in this section, Figure 12, demonstrates that a +1 standard deviation increase in returns to labor increases the income share of the bottom 40% and middle 40% at the expense of the top 20%. These changes are only statistically significant in the long-run. When comparing these results to those in Figure 7 in the main text—which analyzes how the income shares of six groups change—we gain a better understanding of the effects of returns to labor on the income distribution in the US from analyzing six groups instead of regrouping them into three. When comparing both figures, we find that there is a decrease in the income share of the top 20%, but this decrease is the net change due to an increase in the income share of the 80-94 percentile and a decrease in that of the top 5%. The changes in the income share of the 60-79 percentile, as compared to changes in the income share of the 40-59 percentile, contribute more to the changes in the income share of the middle 40%. While the changes in the income share of the bottom 40% are statistically significant in the long-run, Figure 7 in the main text demonstrates that only changes in the income share of the 0-19 percentile are significant in the long-run, while changes in the income share of the 20-39 percentile are not. Lastly, the change in the income share of the 0-19 percentile is statistically significant in the short-term too. This is a conclusion foregone by recategorizing the income distribution into three groups.

The results in this section demonstrate the recategorizing the original income distribution in six groups into three groups can provide less information. While sometimes we reach similar conclusions about the effects of an independent variable on the income shares of the three groups and the six groups, we also reach different conclusions. But, always, analyzing the income shares of the six groups provides a more nuanced understanding of inequality in the United States; a conclusion we also reached from simply analyzing the income share of the top 5% relative to the rest and the Gini index. Lastly, be recategorizing from larger to smaller groups, we restrict the ability of predictors to affect income groups separately although we theorized that certain income groups should be affect similarly. For example, we theorized that an increase in returns to labor should decrease the income shares of the 80-94 percentile and top 5% groups. In Figure 12, when these two groups are combined to form one bigger group, we find empirical support for our expectation in the long-run. However, when the original income groups in the main text are not recategorized into larger groups, we find that an increase in returns to labor only decreases the income share of the top 5% and increases that of the 80-94 percentile group.

5 Regrouping the Income Distribution into Four Groups

In the previous section we divided the income distribution in the United States into three groups—the bottom 40%, the middle 40%, and the top 20%—and in the main text the income distribution constituted six groups—0-19, 20-39, 40-59, 60-79, 80-94, and the top 5%. In this section, we assess the results of our analysis in the main text when the six groups are divided into four. The first bottom two groups are similar to those in the previous section (bottom 40% and middle 40%), but we divided the top 20% into two groups: 80-94 percentile and the top 5%.

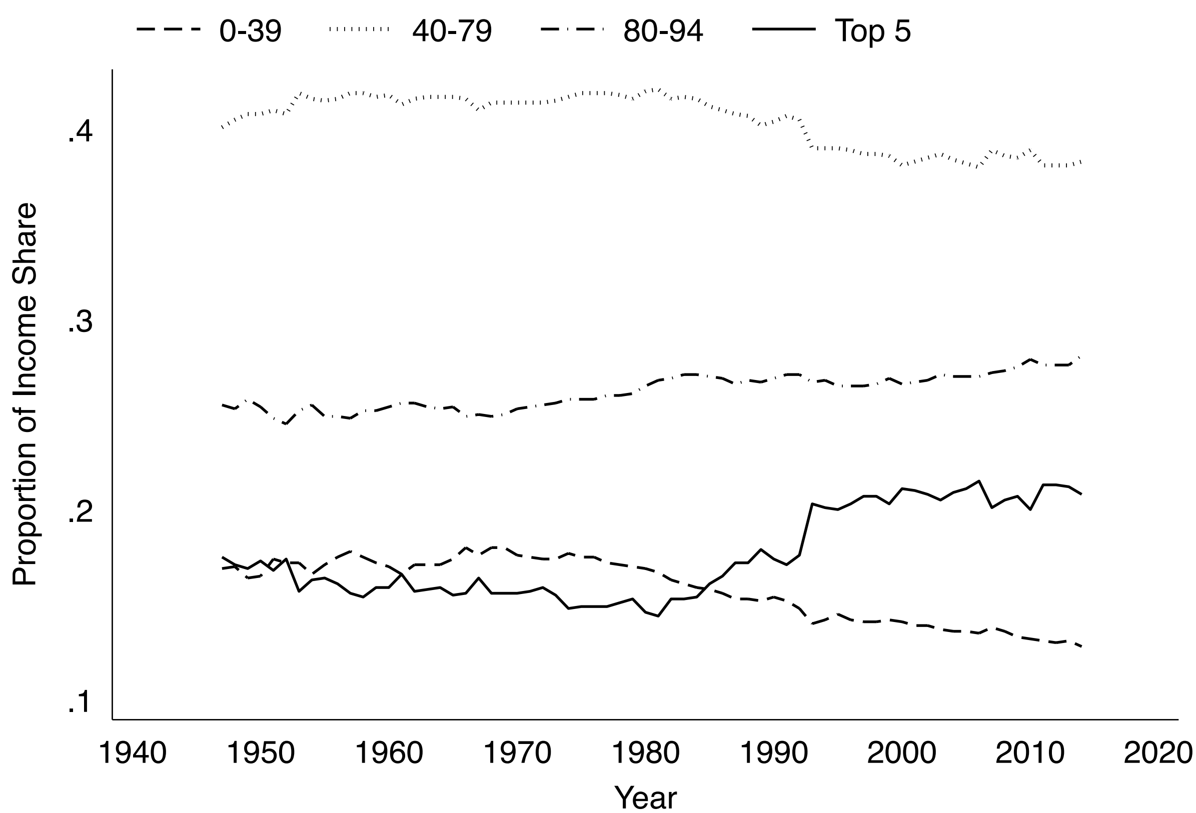


Figure 13: The Proportion of Income in the US, 1947 to 2014

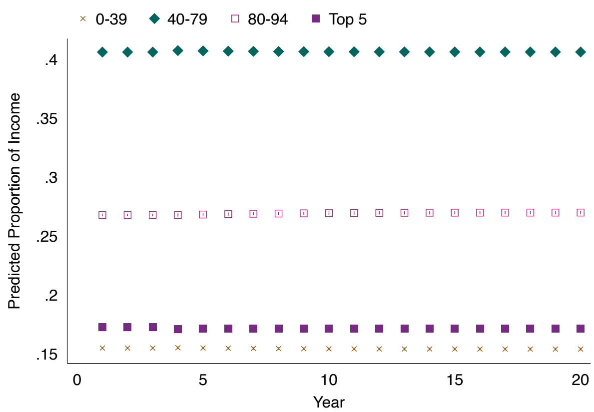
Figure 13 shows the income distribution of the four groups in the United States between 1947 to 2014. In contrast to Figure 7, we now see that the middle 40% holds the largest income share as opposed to the top group (now top 5%, previously top 20%). Notice that the income shares of the

80-94 percentile and top 5% are rising over time mainly at the expense of the bottom 40%. The income share of the middle 40% only decreases slightly over time.

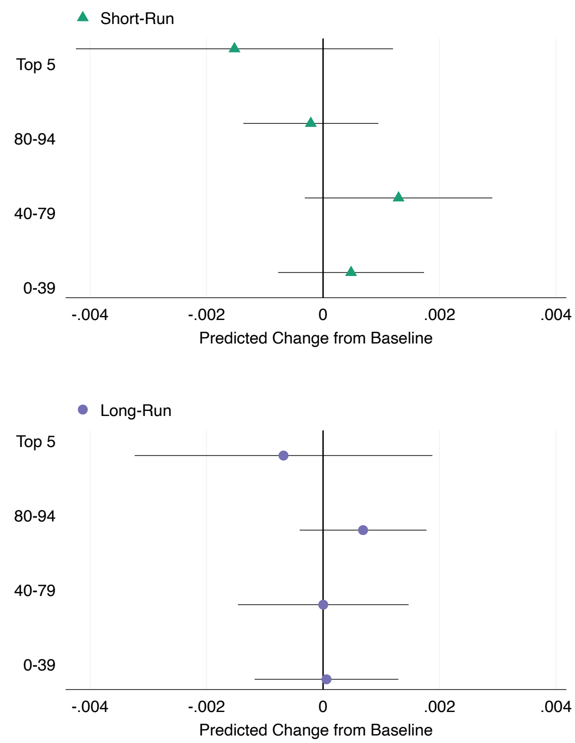
Prior to analyzing the effects of our independent variables on the income shares of these four groups, we assess the stationarity of our independent and dependent variables using the Dickey-Fuller GLS test. % Democrats in Congress, top marginal tax rate, polarization, and returns to labor contain unit roots, and returns to capital is stationarity. For the dependent variables, we set the income share of the top 5% as the baseline and find that the log ratios of the bottom 40%, middle 40%, and 80-94 percentiles are non-stationary. The Engle-Granger test finds that all three log-ratios are cointegrated with the non-stationary predictors. The PSS bounds test is inconclusive about whether the log-ratios of the bottom 40% and middle 40% are cointegrated with the predictors. This test also reaches an inconclusive decision for the log-ratio of the 80-94 percentile, but at the 90% confidence level. The Johansen test for cointegration finds support for at least 1 cointegrating vector for all three log-ratios. Given these results, we estimate error correction models in a seemingly unrelated regression (SUR) framework (Philips, Rutherford and Whitten 2016).

Figure 14 demonstrates the substantive effects of +1 standard deviation change to % Democrats in Congress. Different from our conclusions in the main text, but similar to those in the three group case in the previous section, we find that an increase in left power has no short- or long-run effect on inequality. In the main text, we find that an increase in left power increases the income share of the 60-79 and 80-94 percentiles in the long-term. We find no such effect here. This is likely because by failing to explicitly account for the equations of all six income groups (5 log-ratios), we also fail to account for the correlations in the errors in the models for these groups in the SUR framework.

Figure 15 shows that a +1 standard deviation in polarization increases, in the long-run, the income shares of the 80-94 percentile and top 5% at the expense of bottom 40% and middle 40%. These results match up to those in Figure 4 in the main text and Figure 9 in the previous section. Comparing Figure 15 with Figure 4 in the main text, we can conclude that the decrease in the



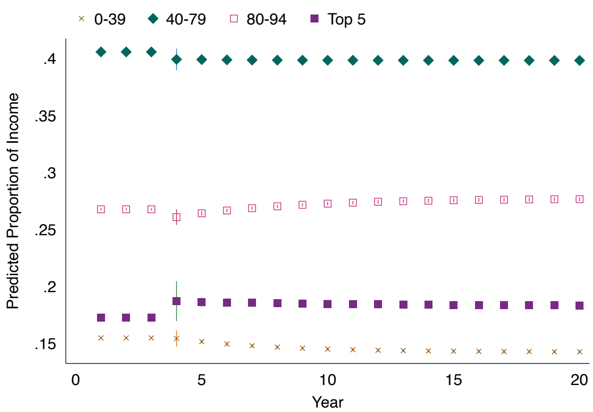
(a) Expected Change Over Time



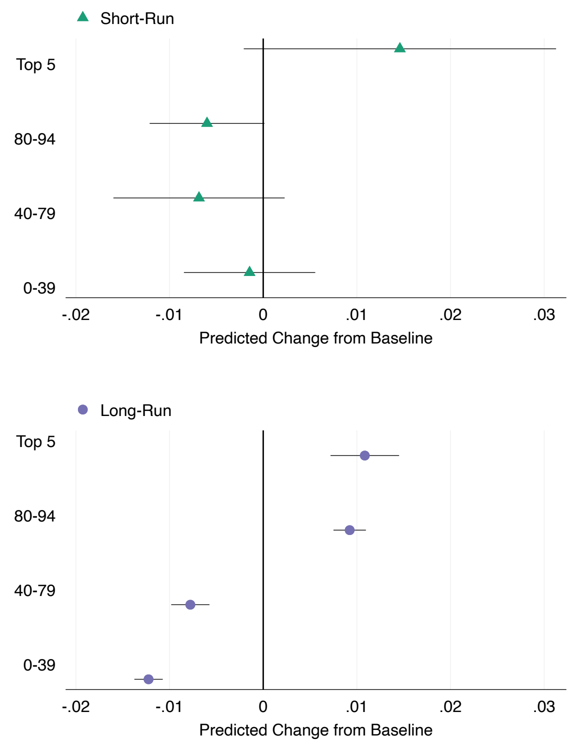
(b) Short and Long Run Effects

Figure 14: 1 Standard Deviation Increase in % Democrats in Congress

Notes: Left plot shows the expected income shares due to a one-period +1 standard deviation shock to % Democrats in Congress at $t = 4$. Right plot shows the contemporaneous and long-term changes from baseline (sample mean) for each category for the same simulation. All other variables held at sample means. 95% confidence intervals reported.



(a) Expected Change Over Time

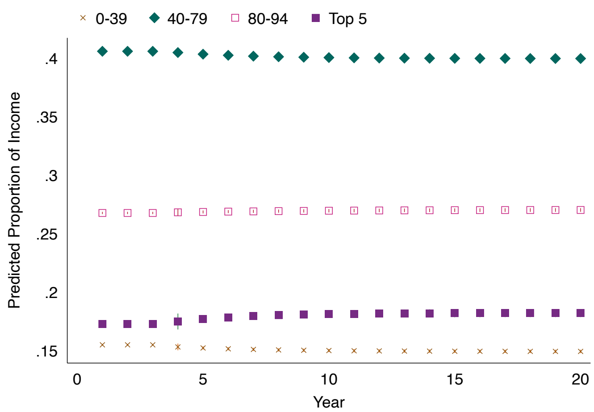


(b) Short and Long Run Effects

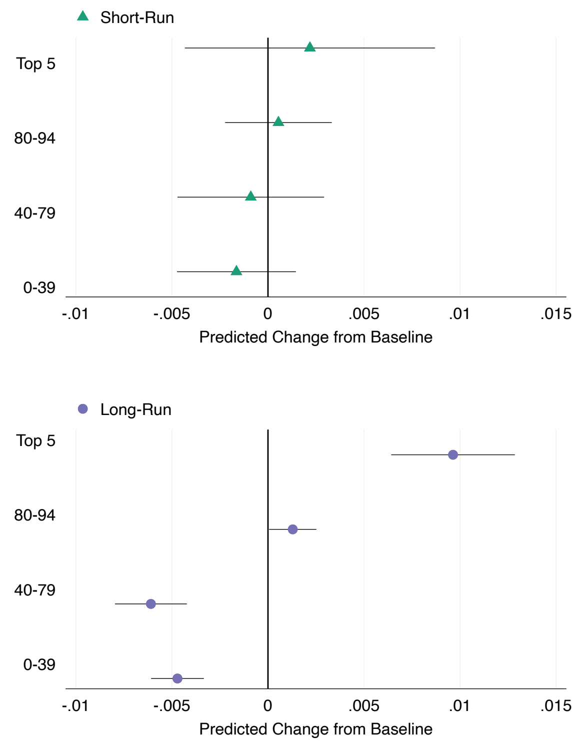
Figure 15: 1 Standard Deviation Increase in Polarization

Notes: Left plot shows the expected income shares due to a one-period +1 standard deviation shock to polarization at $t = 4$. Right plot shows the contemporaneous and long-term changes from baseline (sample mean) for each category for the same simulation. All other variables held at sample means. 95% confidence intervals reported.

income share of the bottom 40% is largely due to the decrease in the income share of the 20-39 percentile, and that the decrease in the income share of the middle 40% is largely due to the decrease in the income share of the 40-59 percentile. Note that in Figure 4 in the main text, polarization does not have a statistically significant effect on the income share of the 60-79 percentile.



(a) Expected Change Over Time



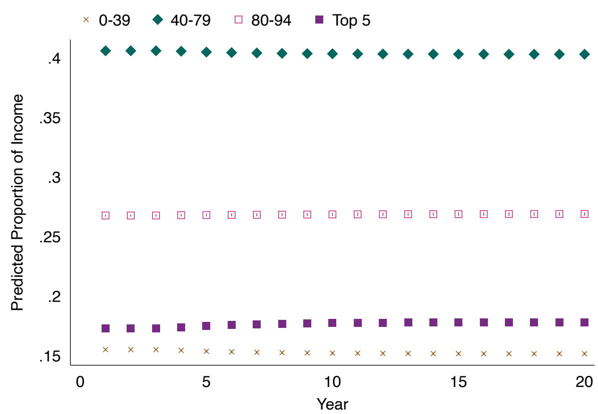
(b) Short and Long Run Effects

Figure 16: 1 Standard Deviation Decrease in Top Marginal Tax Rate

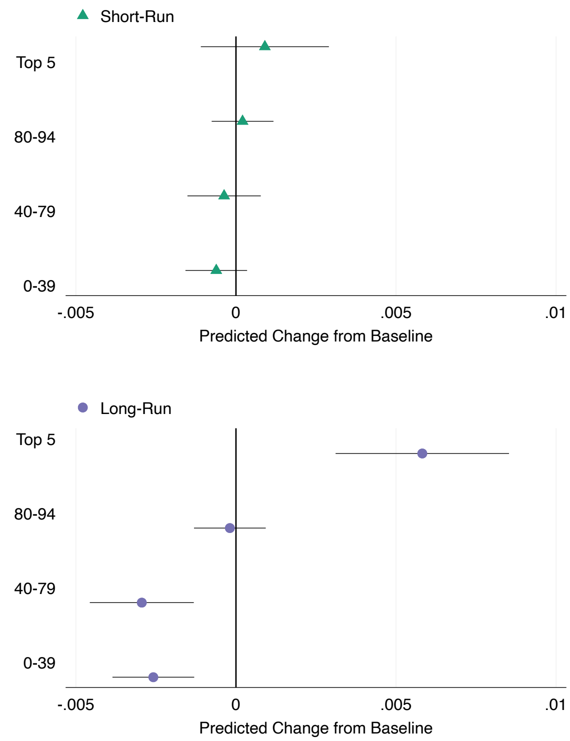
Notes: Left plot shows the expected income shares due to a one-period -1 standard deviation shock to the top marginal tax rate at $t = 4$. Right plot shows the contemporaneous and long-term changes from baseline (sample mean) for each category for the same simulation. All other variables held at sample means. 95% confidence intervals reported.

As seen in Figure 16, a one standard deviation decrease in the top marginal tax rate increase the income shares of the top 5% in the long-run at the expense of those of the bottom 40% and middle 40%. When comparing Figure 16 and Figure 5 in the main text, we see that the changes in the income shares of the bottom 40% and middle 40% groups are largely being driven by changes in the income shares of the 20-39 and 40-59 percentiles, respectively. While the effect of polarization on the income share of the 80-94 percentile is statistically significant in the main text, it is not in

Figure 16. This may be due to failure to explicitly account for the correlation in the errors of the models for all six income groups after recatogerization of six income groups into four.



(a) Expected Change Over Time

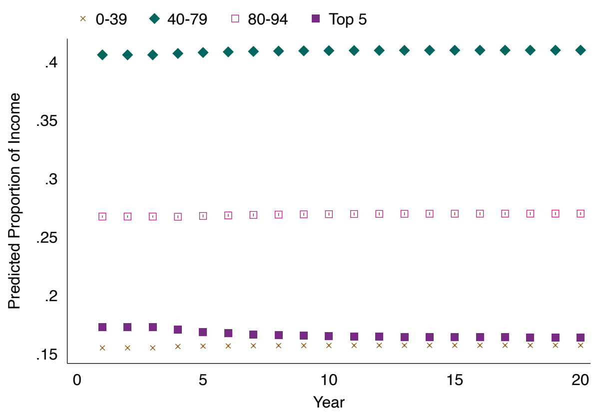


(b) Short and Long Run Effects

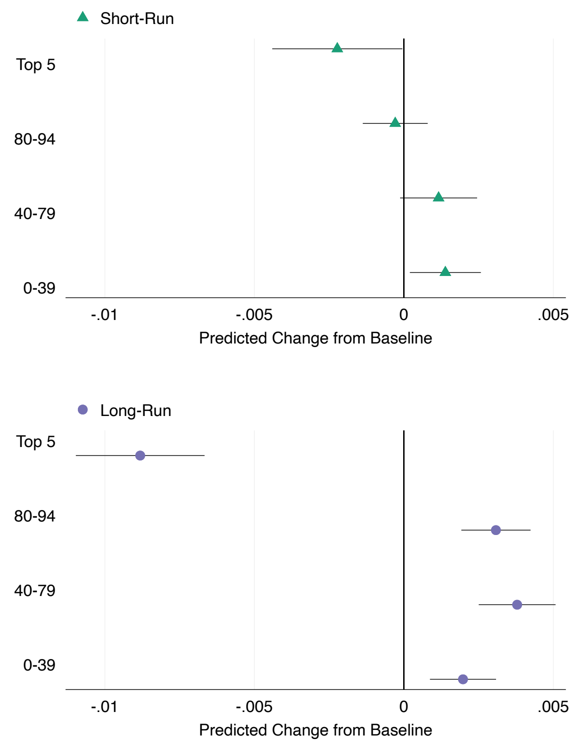
Figure 17: 1 Standard Deviation Increase in Returns to Capital

Notes: Left plot shows the expected income shares due to a one-period +1 standard deviation shock to returns to capital at $t = 4$. Right plot shows the contemporaneous and long-term changes from baseline (sample mean) for each category for the same simulation. All other variables held at sample means. 95% confidence intervals reported.

The results in Figure 17 support our conclusions from Figure 6 in the main text. In both figures, we find that a one standard deviation increase in returns to capital increases the income shares of the top 5% and not the 80-94 percentile in the long run. Further, comparing both figures, we are able to conclude that the decrease in the income share of the middle 40% is almost equally due to decreases in the income shares of the 40-59 and 60-79 percentiles. And, the decrease in the income share of the bottom 40% is mainly driven by a decrease in the income share of the 0-19 percentile.



(a) Expected Change Over Time



(b) Short and Long Run Effects

Figure 18: 1 Standard Deviation Increase in Returns to Labor

Notes: Left plot shows the expected income shares due to a one-period +1 standard deviation shock to returns to labor at $t = 4$. Right plot shows the contemporaneous and long-term changes from baseline (sample mean) for each category for the same simulation. All other variables held at sample means. 95% confidence intervals reported.

Our final set of results in Figure 18 also bear some similarities with our results in Figure 7 in the main text. In Figure 18, similar to Figure 7 in the main text, we find that a one standard deviation increase in returns to labor decreases the income share of the top 5% and increases that of the 80-94 percentile. In Figure 18, this decrease is also offset by increases to income shares of the bottom 40% and middle 40%. The short-run effect of returns to labor on the income share of the bottom 40% is statistically significant, and is largely due to the increase in the income share of the 0-19 percentile in the short-run. In the long-run the increases in the income shares of the bottom 40% and middle 40% are largely due to increases in the income shares of the 0-19 and 60-79 percentiles, respectively. Note that the long-run effect of returns to labor on the income share of the 20-39 percentile is not statistically significant in the long-run in the Figure 7 in the main text.

Overall, by combining multiple income groups into larger categories, we lose out on important information. We concluded similarly in the previous section in which we recategorized six income groups into three. In this section, for example, we found that when the income distribution is grouped into four categories, left power has no effect on income inequality. However, in the main text, in which we analyzed the effect of left power on six categories, we found that an increase in left power increases the income shares of the 60-79 and 80-94 percentile groups in the long-run. Regrouping them, we find that the middle 40% group (40-59 + 60-79 percentile groups) is not affected by an increase in left power. The 80-94 percentile group does not benefit either. The latter conclusion differs from that in the main text even though we have not regrouped the 80-94 percentile. However, this result may suggest that all income groups needed to be explicitly modeled in the SUR framework to correctly account for correlation in the errors between income groups. Regrouping income groups may incorrectly alter the correlation between errors across income groups, and thus affect the statistical significances of the effects of predictors on the income shares of different groups.

References

Freeman, John R. and Dennis P. Quinn. 2012. "The Economic Origins of Democracy Reconsidered." *American Political Science Review* 106(1):58–80.

Jordan, Soren and Andrew Q. Philips. 2018. "Cointegration testing and dynamic simulations of autoregressive distributed lag models." *The Stata Journal* 18(4):902–923.

Lee, Cheol-Sung. 2005. "Income inequality, democracy, and public sector size." *American Sociological Review* 70(1):158–181.

Lindqvist, Erik and Robert Östling. 2010. "Political Polarization and the Size of Government." *American Political Science Review* 104(3):543–565.

Lupu, Noam and Jonas Pontusson. 2011. "The structure of inequality and the politics of redistribution." *American Political Science Review* 105(2):316–336.

Philips, Andrew Q, Amanda Rutherford and Guy D Whitten. 2016. "dynsimpie: A command to examine dynamic compositional dependent variables." *Stata Journal* 16(3):662–677.

Piketty, Thomas, Gilles Postel-Vinay and Jean-Laurent Rosenthal. 2006. "Wealth Concentration in a Developing Economy: Paris and France, 1807–1994." *American Economic Review* 96(1):236–256.