A Electronic Appendix for "Institutions, Partisanship, and Inequality in the Long Run"

A.1 Data Description

This section of the appendix defines each of the variables employed in the analysis, identifies the sources used to construct each measure, reports the descriptive statistics, and for selected variables gathered by the authors, reports the value of the measure for each country-year observation.

A.1.1 Variable Definition and Sources

Centralized Wage Bargaining is equal to 1 if there is national centralized wage setting and is equal to 0 otherwise. This variable is derived directly from *Wage Bargaining Centralization* described below. See the description for *Wage Bargaining Centralization* for the sources for this measure.

Decentralized Wage Bargaining is equal to 1 if wages are primarily determined in a decentralized setting, either without collective bargaining at all or bargaining at the plant level and is equal to 0 otherwise. This variable is derived directly from *Wage Bargaining Centralization* described below. See the description for *Wage Bargaining Centralization* for the sources for this measure.

Female Participation is equal to the number of women in the economically active population as a share of the total economically active population. The source is Mitchell (2003).

GDP per capita is equal to GDP in millions of 1990 International Geary-Khamis dollars divided by population in thousands. The source for the GDP and population data is Maddison (2003).

Left Executive takes a value of 1 for those country-years where the head of government (President in a presidential system, Prime Minister/Chancellor in a parliamentary system) was from a "left" party and 0 otherwise. If there was a "left" executive for only part of the year then the variable still takes a value of 1. The exception here is Switzerland which has a seven member Federal Council and no equivalent to a single head of government. For Switzerland the variable takes a value equal to the proportion of the seven seats on the Federal Council held by individuals from left parties. The identity of "Left" political parties is judged based on the information in Caramani (2000) as well as by inference from the partisanship scores in McDonald (2002). Table 1 reports the country-years for which a left executive is coded as present.

Country	Coding for *Left Executive*
Australia	Left Prime Ministers (Labour Party) 1904, 1908-17, 1929-32, 1941-49, 1972-75, 1983-96
Canada	Left Prime Ministers (Liberal Party) 1900-11, 1921-30, 1935-57, 1963-79, 1980-84, 1993-2000
France	Left Prime Ministers (Socialist Party, SFIO, Front Populaire, Republican Socialist Party) 1909-11, 1913-17, 1920-22, 1925-26, 1929, 1932-33, 1936-38, 1946-47, 1956-57, 1981-86, 1988-93, 1997-2000
Germany	Left Chancellors (SDP) 1918-20, 1928-30, 1969-74, 1974-82, 1998-00
Ireland	Left Chairmen of Provisional Government (1922-1937) or Left Prime Ministers (1937-2000) (CG, Fine Gael) 1922-32, 1948-51, 1954-57, 1973-77, 1981-87, 1994-97
Japan	Left Prime Ministers (Social Democratic Party, Japan New Party) 1947-48, 1993-96
Netherlands	Left Prime Ministers (PVDA) 1945-46, 1948-58, 1973-77, 1994-2000
New Zealand	Left Prime Ministers (Labour) 1935-49, 1957-60, 1972-75, 1984-90, 1999-2000
Spain	Left Prime Ministers (Socialist Party) 1931-1936, 1982-1996
Sweden	Left Prime Ministers (Social Democrat) 1920-26, 1932-76, 1982-91, 1994-2000
Switzerland	Left party representation on the seven member Federal Council 1 out of 7 1943-54, 2 out of 7 1959-2000
United Kingdom	Left Prime Ministers (Labour Party) 1924, 1929-1935, 1945-51, 1964-1970, 1974-79, 1997-2000
United States	Left Presidents (Democrat) 1913-21, 1933-52, 1960-68, 1977-80, 1992-2000

Table 1: Coding for *Left Executive*

Non-Democracy is equal to 1 if the country is experiencing a non-democratic year and 0 otherwise. The variable is coded a 1 for the following country years: France 1940-1944, Germany 1900-1918, 1933-1945, Japan 1900-1945, Netherlands 1940-1944, Spain 1939-1975.

Secondary Education Share is equal to the number of students enrolled in secondary education divided by an estimate of the total population between ages 12 and 17. We estimated the total population between ages 12 and 17 by using data on the population for the 10-14 and 15-19 age ranges as provided by Mitchell (2003), based on the assumption of a uniform distribution of ages within each of these two sub-groups. The variable is lagged by 10 years to better indicate the skill attainment of the labor force. The source for education enrollments is Mitchell (2003).

Top1 is equal to the percentage of national income earned by the top 1% of income earners. The original source for this data is Atkinson and Piketty (forthcoming) for all countries except

Japan, Sweden and Spain. The data from Japan come from Moriguchi and Saez (2005). The data for Sweden are from Roine and Waldenstrom (2006). The data for Spain are from Alvaredo and Saez (2006). We use Leigh's (forthcoming) adjusted series for all 13 countries.

Top10 is equal to the percentage of national income earned by the top 10% of income earners. The original source for this data is Atkinson and Piketty (forthcoming) for all countries except Japan, Sweden and Spain. The data from Japan come from Moriguchi and Saez (2005). The data for Sweden are from Roine and Waldenstrom (2006). The data for Spain are from Alvaredo and Saez (2006). We use Leigh's (forthcoming) adjusted series for all 13 countries.

Top10-1 is equal to the percentage of national income earned by the top 10% of income earners less the percentage of national income earned by the top 1% of income earners divided by 100 minus the income earned by the top 1%, all multiplied by 100. The source for this data is Atkinson and Piketty (forthcoming) for all countries except Japan, Sweden and Spain. The data from Japan come from Moriguchi and Saez (2005). The data for Sweden are from Roine and Waldenstrom (2006). The data for Spain are from Alvaredo and Saez (2006). We use Leigh's (forthcoming) adjusted series for all 13 countries.

Trade Openness is equal to the sum of total imports and exports in current US dollars (millions) divided by GDP in current US dollars (millions). The source for this variable is Barbieri (2002).

Union Density is equal to the percent of the total dependent labor force that are members of unions (less the self-employed). The variable is spliced from several series. The primary source for after 1950 is Golden and Wallerstein (2006b) The primary source before 1950 is Kjellberg (1983). When both these sources were missing, we used Visser (1989). Additional sources used were OECD (2004); May, Walsh, Harbridge, & Thickett (2003); and Wallace (2003).

Universal Suffrage is equal to 1 for those country-years for which the country had universal suffrage (male and female) and 0 otherwise. We used the information in Mackie and Rose (1982) and Caramani (2000) to determine whether a country had universal suffrage in a given year. The more detailed information in Caramani was the preferred source and we used Mackie and Rose (1982) for those countries not covered by Caramani.

Wage Bargaining Centralization is equal to 1 if wages are primarily determined in a decentralized setting, either without collective bargaining at all or bargaining at the plant level, equal to 2 if wages are primarily determined at the industry-level, and equal to 3 if there is national centralized wage setting. Each country-year was coded based on data from a number of sources including Campbell (1992); Ebbinghaus and Visser (2000); Blum (1981); Wallerstein, Golden, & Lange (1997); Iversen (1999); OECD (2004); Swenson (1989, 2002); and Golden and Wallerstein (2006b). Table 2 reports the value of this variable for each country-year.

Country	Coding for *Wage Bargaining Centralization*
Australia	1 1900-1953 2 1954-1991 1 1992-2000
Canada	1 1900-2000
France	1 1900-1950 2 1951-2000
Germany	1 1900-1932 3 1933-1945 1 1946-1950 2 1951-2000
Ireland	1 1922-1945 3 1946-1980 1 1981-1986 3 1987-2000
Japan	1 1900-2000
Netherlands	1 1900-1926 2 1927-1945 3 1946-1959 2 1960-2000
New Zealand	2 1900-1989 1 1990-2000
Spain	1 1900-1937 3 1938-1985 2 1986-2000
Sweden	1 1900-1904 2 1905-1951 3 1952-1982 2 1983-2000
Switzerland	1 1900-1944 2 1945-2000
United Kingdom	1 1900-1913 2 1914-1979 1 1980-2000
United States	1 1900-2000

Table 2: Coding for *Wage Bargaining Centralization*

A.1.2 Descriptive Statistics

Variable	Mean	Standard Error of Mean
Centralized Wage Bargaining	0.142	0.023
Decentralized Wage Bargaining	0.437	0.033
Female Participation	0.309	0.010
GDP per capita	9.475	0.387
Left Executive	0.392	0.027
Non-Democracy	0.085	0.018
Secondary Education Share	0.387	0.019
Top1	10.684	0.258
Top10	34.859	0.364
Top10-1	27.178	0.239
Trade Openness	40.282	1.635
Union Density	34.608	1.065
Universal Suffrage	0.768	0.028
Wage Bargaining Centralization	1.704	0.047

Table 3: *Summary Statistics.* Multiple-imputation estimates of the mean of each variable and the standard error of this estimate. The unit of observation is the 5-year periods from 1916 to 2000 used in the main analyses in the paper. There are 219 observations for each variable.

A.2 Unit Root Tests

One important issue for our empirical tests is whether our top income share variables have a unit root. This would preclude a standard regression in levels, unless we could identify a variable or set of variables with which the top income share is cointegrated. One problem with conventional unit root tests is that unless conducted over a long span of data in terms of time, then they will have low power when attempting to distinguish between a series that has a unit root and a series that does not have a unit root but which is highly persistent.[1] One way to increase the power of such a test is to consider a longer span of data, though considering a longer time period increases the risk that there is a structural break in the series, which should bias the test against a finding of stationarity. A complementary possibility is to increase the span of data by conducting the test on a panel of countries.[2] We pursued this approach using the panel unit root test proposed by Maddala and Wu (1999). The Maddala-Wu test combines the significance levels from independent unit root tests for each country series in order to generate

[1] Shiller and Perron (1985) demonstrated that increasing the time span has a dramatic effect on the power of a unit root test while increasing the frequency of observations within a set time span does not.

[2] See Breitung and Pesaran (2005) for a discussion of unit roots in panels.

a statistic for testing against the null that all country series are non-stationary. In our case we used the Philips-Perron test to generate the individual country statistics. Unlike a related test proposed by Im, Pesaran, and Shin (2003), the Maddala-Wu test has the advantage of being possible to implement in an unbalanced panel.[3] Since a test of this type is dependent on the assumption that the individual country test statistics are independently distributed, before performing the test we first demeaned each country series by subtracting the period average for the given top income share. Based on the Maddala-Wu test, we rejected the null that all series are nonstationary for each of the three series.[4] It should be emphasized that we can only conclude from these tests that a significant fraction of the thirteen country series used here is stationary, not that all individual country series are stationary. With this word of caution, we will proceed by estimating regressions in levels. In addition to the test results reported above, one further motivation for this choice is that if we remain uncertain whether the top income shares variables have a unit root, we do know that any bias generated by the presence of a unit root would be a bias in favor of finding that variables like partisanship and the centralization of wage bargaining are significantly correlated with top income shares. Since the principal empirical finding of this paper is that there is less evidence of correlations between these variables and inequality than has been previously believed, any failure on our part to take account of the top income share series being I(1) would only reinforce our conclusions.

A.3 Multiple Imputation

Upon constructing our dataset, there were non-trivial numbers of missing observations for various variables for particular countries and years. The standard approach of deleting cases that have missing values for any of the variables—known as "listwise deletion"—can create two major problems for inference. One is inefficiency caused by throwing away information relevant to the statistical inferences being made. Furthermore, inferences from listwise-deletion estimation can

[3] Note that the stationarity tests discussed here used observed data only and did not employ any imputation methods for missing data such as those discussed and employed below for our main regression analyses. Due to the extent of missing data for Spain, it is omitted from the stationarity diagnostic tests.

[4] For the *Top 1* share $\text{Chi}^2(22) = 38.2$ p=0.01. For the *Top 10* share $\text{Chi}^2(20) = 34.9$, p= 0.02. For the *Top 10-1* share $\text{Chi}^2(20) = 34.3.3$, p< 0.02.

be biased if the observed data differs systematically from the unobserved data.

The most general and extensively researched approach for dealing with a missing data problem like this is "multiple imputation" (King et al 2001, Schafer 1997). Multiple imputation requires a relatively weak assumption in this context that the process generating the missing data is random conditional on the data included in the imputation procedures (this is commonly referred to in the literature as assuming the data are *MAR)*. Multiple imputation yields consistent coefficient estimates and gives correct uncertainty estimates under the *MAR* assumption.[5]

The approach has several variations but always involves three main steps. First, some algorithm is used to impute values for the missing data. In this step, m ($m>1$) "complete" data sets are created consisting of all the observed data and imputations for the missing values. The second step simply involves analyzing each of the m data sets using standard complete-data statistical methods. The final step combines the parameter estimates and variances from the m complete-data analyses to form a single set of parameter estimates and variances. Importantly, this step systematically accounts for variation across the m analyses due to missing data in addition to ordinary sample variation.

The first step in our multiple-imputation procedures was to create imputations in the missing data cells for all the variables included in the analysis plus some additional information that we determined would be helpful in predicting the missing data for a total of 17 variables. The imputations were conducted on the country-year dataset with 1,159 observations before taking five-year averages. The imputation model also included a lagged and lead value by one year of the *Top1* and *Top10* variables as well as country fixed effects. The imputation model was multivariate normal with a slight ridge prior.[6] Altogether we imputed 10 complete data sets. The exact imputation algorithm we used is Honaker and King's bootstrapping-based EM algorithm (2006).[7]

We evaluated the quality of imputations in a number of ways. For example, we checked to see

[5] It is also necessary to assume the parameters describing the missing data process are distinct from parameters of the data model so that the missing data mechanism is ignorable.

[6] Specifically, the ridge prior was set to 29 which is 2.5% of the 1,159 country-year observations in the imputation model.

[7] The imputation procedures were implemented using *Amelia II: A Program for Missing Data* (Honaker, King, and Blackwell 2006).

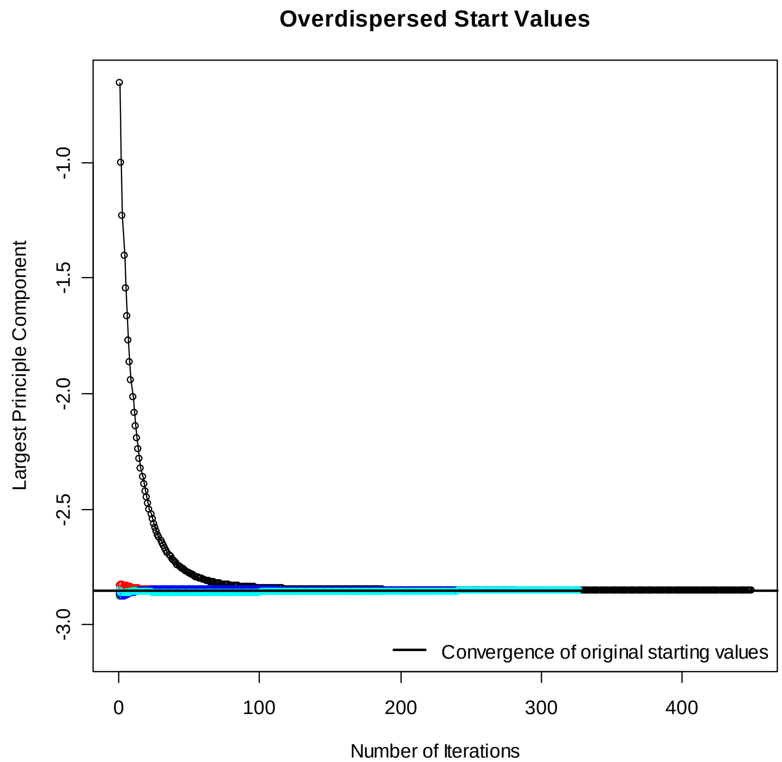

Figure 1: *Convergence to Single Mode.* This figure plots a summary statistic of the parameter space defined by the largest principle component against the number of iterations for 5 EM chains from different starting values.

whether there was evidence that the likelihood for the imputation model was poorly behaved. If it were, the EM algorithm might have problems finding a global maximum and the starting values could affect the imputations. To check this, we ran the EM algorithm from multiple, dispersed starting values and evaluated whether the resulting EM chains converged to the same value. To represent the high dimensional parameter space, we evaluated convergence relative to the largest principle component of the final mode (see Honaker, King, and Blackwell (2006) for further description). Figure 1 plots the largest principle component against the number of iterations in each of 5 EM chains from different starting values. All the EM chains are converging to the same mode which indicates that the imputations are unlikley to be sensitive to the starting values for the EM algorithm.

Although it is impossible to check whether the imputations are close to the unobserved values, it is nonetheless useful to provide some indication of how well the imputation model fits the data. One method for doing this is overimputing. This diagnostic sequentially treats each of the observed values of a variable of interest as if it had actually been missing. For each observed value, a confidence interval can be constructed indicating what the distribution of imputations would have been for that observation had it actually been missing. Then the observed value can be compared with this interval to determine whether these intervals generally include the observed value. If so, this is evidence that the imputation model fits the data. Figures 2 and 3 plot the observed and imputed values for the variables *Top10* and *Top1* respectively. The lines indicate the 90 percent confidence intervals for the imputations with the mean imputation indicated by the dot. The color of the line reports the fraction of missing observations in the pattern of missingness for that observation. For the *Top10* variable, Figure 2 shows that the imputations are relatively tightly distributed around the observed values indicating a good fit.to the data. For the the *Top1* variable, Figure 3 shows that there is greater uncertainty associated with the imputations as indicated by the longer 90 percent confidence intervals. Further, the model does not do very well at predicting cases for which the percentage of income to the top one percent is extremely high. That said, about 90 percent of the confidence intervals contain the observed value and so the model fits reasonably for this variable as well.

The second step in our multiple-imputation analysis was to run the ordinary least squares regressions described above separately on each of the 10 final data sets. The last multiple-imputation step was to combine the 10 sets of estimation results to obtain a single set of estimated parameter means and variances. The single set of estimated means is simply the arithmetic average of the 10 different estimation results. The single set of estimated variances is more complicated than a simple average, because these variances account for both the ordinary within-sample variation and the between-sample variation due to missing data. See King et al. (2001) and Schafer (1997) for a complete description of these variances.

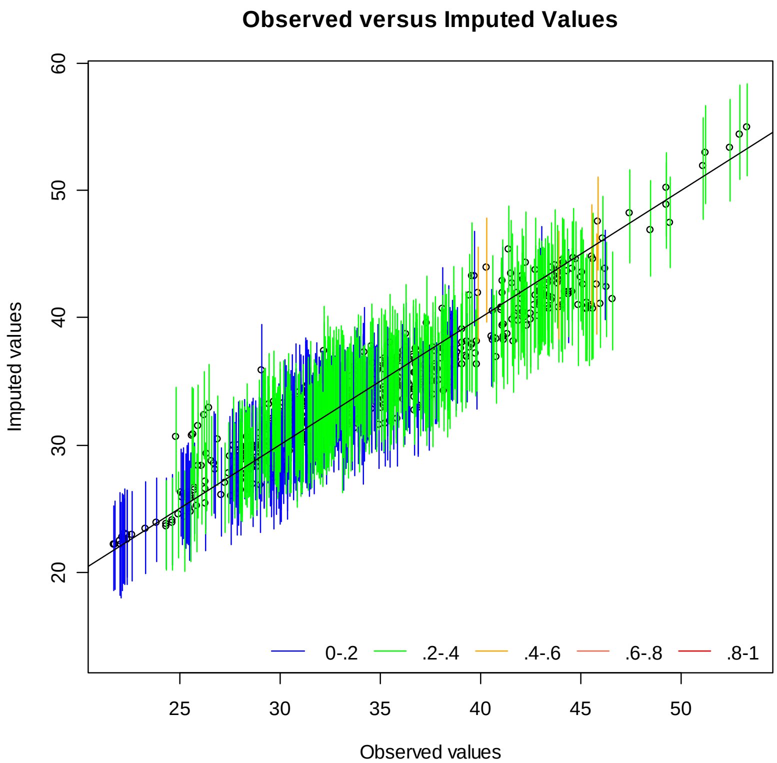

Figure 2: *Observed versus Imputed for* Top10*.* Lines indicate 90 percent confidence intervals for imputations and dots indicate mean imputations. The color of the line represents the proportion of missing observations in the pattern of missingness for that observation.

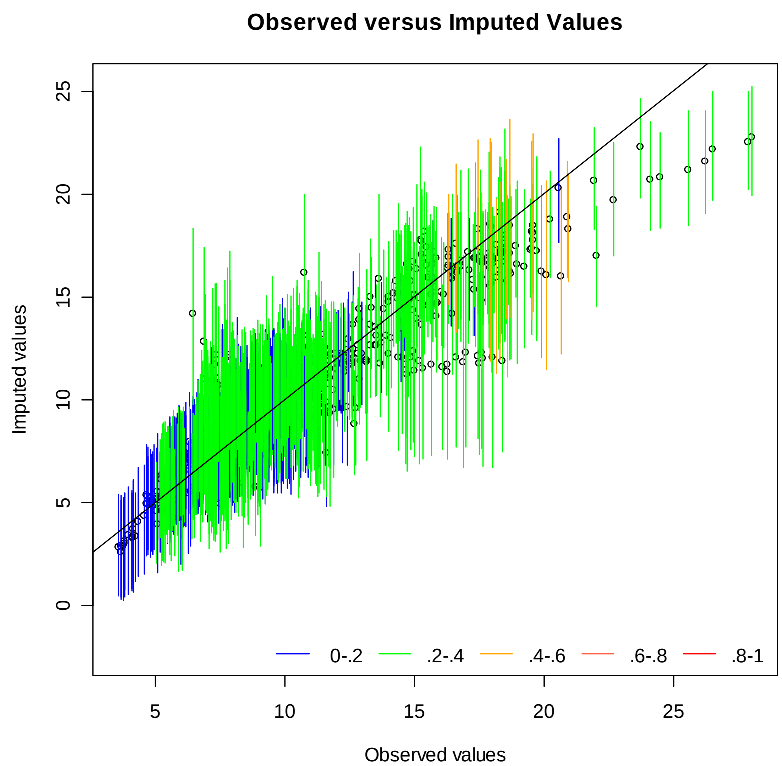

Figure 3: *Observed versus Imputed for Top1.* Lines indicate 90 percent confidence intervals for imputations and dots indicate mean imputations. The color of the line represents the proportion of missing observations in the pattern of missingness for that observation.

A.4 Additional Results

The analysis of the full time series from 1916-2000 has the distinct advantage of allowing a test of the hypothesized role of government partisanship and labor market institutions by identifying off of variation over time. These factors vary significantly over time in our data and it is reasonable to expect these changes to be correlated with changes in income inequality over time. Perhaps the most obvious objection to the analysis is that the results may be biased due to poorly measured variables. In this subsection, we revisit each hypothesis by examining evidence from 1950-2000 using alternative measures, arguably better measured, that are available for this period.

To measure wage bargaining centralization for this period, we use Golden and Wallerstein's coding (2006b). The variable *Bargaining Level–GW* is equal to 1 for plant-level wage setting, 2 for industry-level wage setting, 3 for central wage setting without sanctions, and 4 for central wage setting with sanctions. Following our main analysis, we constructed two dichtomous indicator variables based on the values of this index. *Centralized Wage Bargaining–GW* is equal to 1 if *Bargaining Level–GW* is equal to 3 or 4 and is equal to 0 otherwise. *Decentralized Wage Bargaining-GW* is equal to 1 if *Bargaining Level–GW* is equal to 1 and is equal to 0 otherwise. We also include the *Union Density* variable described above. To measure government partisanship, we use McDonald's (2002) classification of governments on a left-right scale constructed using data produced by Budge et al. (2001) that measures partisan political orientation based on party manifestos. The variable *Government Partisanship* is equal to the government's left-right position as determined by the weighted (by seats in parliament) left-right positions of the parties in government. Note that this variable increases as governments move to the right and so we expect positive coefficient estimates for the variable (the opposite of expectations for the *Left Executive* measure).

In addition to better measured variables for our key hypotheses, it is also possible to use alternative measures of the overall skill levels in a country. The first is *Education Years* equal to the average years of schooling in a country and the second is *Migrant Share* equal to the percent of the population that is foreign born.[8]

Our empirical objective for this analysis is twofold. First, we want to replicate, to the extent possible, the results reported in the previous literature using our measures of income inequality. To do this, we focus on the period from 1976-2000. Second, we want to evaluate whether these findings are also evident in the earlier period from 1951-1975. This will allow us to assess generally the robustness of the results reported for 1916-2000 and to evaluate specifically the extent to which the results from the full time series are biased by poor measurement.

For the 1976-2000 analysis, the results for the government partisanship hypothesis generally mirror the findings in the current literature. Income inequality increases as governments move to the right. Table 4 reports the relevant coefficient estimates for specifications without fixed effects. Across all three measures of income inequality, the estimates for 1976-2000 for *Government Partisanship* are positive and marginally statistically significant.[9] Furthermore, in unreported specifications with fixed effects, the coefficient estimates are also positive and at least marginally statistically significant for *Government Partisanship*.[10] There is evidence consistent with the hypothesis that governments of the left and the right are correlated with levels of income inequality for the 1976-2000 period. Whether this correlation is due to a causal relationship is, as discussed above, not altogether clear, but the correlations that are predicted by partisan theories are evident in the data for this recent period.

Again focusing our attention on the 1976-2000 period, there is also some evidence of a correlation between wage bargaining institutions and income inequality. The coefficient estimates for *Decentralized Wage Bargaining-GW* reported in Table 4 are positive and statistically significant indicating that decentralized wage setting is associated with greater inequality. It is worth mentioning, however, that in unreported specifications using fixed effects, the coefficient estimates for the *Decentralized Wage Bargaining-GW* variable are small in magnitude and not

[8] Our specification here drops the variable *Secondary Education Share* due to the inclusion of these variables. The source for *Education Years* is Barro and Lee, `http://www.nber.org/pub/barro.lee/`. The source for *Migrant Share* is the United Nations, Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat, Trends in Total Migrant Stock: The 2005 Revision, `http://esa.un.org/migration`.

[9] The p-values are 0.078, 0.056, and 0.115 for the dependent variables *Top10-1, Top10,* and *Top1* respectively.

[10] The p-values are 0.055, 0.042, and 0.083 for the *Top10-1*, *Top10*, and *Top1* measures of income inequality respectively.

statistically significant. This test, however, relies on a short time series with limited over time variation in the wage bargaining measure. With or without fixed effects, there is no evidence of a signficant partial correlation between *Centralized Wage Bargaining–GW* and any of the three measures of income inequality, consistent with the results reported in the main analysis.

Further, there is evidence of a negative partial correlation between the union density variable and the *Top10-1* and *Top10* measures of income inequality in the 1976-2000 period. This correlation is also observed in unreported results including fixed effects for each country. These estimates strengthen the evidence that union density is associated with lower levels of income inequality.

Finally, to shed further light on the question, we examine an analogous set of estimates for the 1951-75 period, again using the improved measures available for the last half of the twentieth century. Perhaps the most striking result in these analyses is that the results consistent with a government partisanship effect for the 1976-2000 period disappear. Table 4 reports the coefficient estimates for *Government Partisanship* for the 1951-1975 period. The coefficient is the wrong sign for two out of three of the income inequality measures and statistically insignificant for the third.[11]

The findings for our measures of labor market organization are also informative. Again, there is little evidence of a signficant partial correlation between *Centralized Wage Bargaining–GW* and income inequality.[12] The coefficients for *Decentralized Wage Bargaining-GW* are positive and marginally statistically significant in the specifications without fixed effects for the *Top10-1* and *Top10* measures of income inequality.[13] The magnitude of these estimates, however, are about half the size as those for the 1976-2000 sample and less precisely estimated. In these same specifications, the estimates for the *Union Density* variable are negative as hypothesized

[11] A small caveat to this finding is that in one of the three unreported fixed effects specifications, there is some evidence of a positive and significant partial correlation for the partisanship measure. This estimate is for the *Top1* measure and resonates with the results in the main analysis that if there is a partisan effect at all it is probably on the incomes to the very highest earners. Further, it is again important to keep in mind that the fixed effects results here rely on fairly short time series.

[12] The partial exception here being a negative, significant coefficient in the specification without fixed effects for the *Top1* measure. But again, none of the coefficients for *Centralized Wage Bargaining-GW* are significant in the specifications with fixed effects including the one for the *Top1* measure of inequality.

[13] These results also are not robust to the inclusion of fixed effects.

and at least marginally statistically significant for the *Top10-1* and *Top10* variables.[14] Overall, there is modest evidence for this period consistent with the hypothesis that more organized (particularly unionized) labor markets are associated with lower levels of inequality, but the evidence is weaker than for the 1976-2000 period.

[14] This result does hold up in the fixed effects specifications.

	Top10-1		*Top10*		*Top1*	
	1951-75	1976-00	1951-75	1976-00	1951-75	1976-00
$TopX_{t-1}$	0.660	0.578	0.516	0.661	0.658	0.911
	(0.133)	(0.096)	(0.123)	(0.100)	(0.149)	(0.083)
GDP per capita	-0.098	-0.090	-0.092	-0.062	0.008	-0.009
	(0.089)	(0.082)	(0.089)	(0.102)	(0.055)	(0.056)
Trade Openness	-0.002	0.013	0.016	0.010	0.011	-0.003
	(0.014)	(0.008)	(0.016)	(0.010)	(0.008)	(0.005)
Education Years	-0.075	-0.015	-0.218	0.014	-0.173	0.066
	(0.464)	(0.292)	(0.461)	(0.401)	(0.249)	(0.216)
Migrant Share	0.034	-0.034	0.026	-0.033	-0.004	-0.004
	(0.103)	(0.078)	(0.110)	(0.101)	(0.079)	(0.048)
Female Participation	-3.365	-5.769	-3.699	-6.950	-0.309	-0.876
	(9.260)	(6.628)	(10.834)	(8.243)	(5.844)	(4.422)
Centralized Wage Bargaining–GW	0.114	-0.035	-0.755	-0.185	-1.118	0.280
	(0.811)	(0.618)	(0.698)	(0.909)	(0.428)	(0.454)
Dec*entralized Wage Bargaining–GW*	0.908	2.172	0.969	2.527	-0.162	1.077
	(0.538)	(0.393)	(0.562)	(0.528)	(0.311)	(0.354)
Union Density	-0.051	-0.046	-0.069	-0.048	-0.005	-0.008
	(0.027)	(0.014)	(0.027)	(0.017)	(0.017)	(0.007)
Government Partisanship	-0.015	0.022	-0.010	0.033	0.008	0.012
	(0.014)	(0.013)	(0.013)	(0.017)	(0.008)	(0.008)
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	No	No	No	No	No	No
Number of Countries	13	13	13	13	13	13
Number of 5-Year Periods	5	5	5	5	5	5
Total Observations	65	65	65	65	65	65

Table 4: Labor Market Institutions, Government Partisanship, and Income Inequality: 1950-2000. Table reports the results of OLS regressions for the three measures of income inequality, *Top10-1*, *Top10*, and *Top1* on *Centralized Wage Bargaining–GW*, *Decentralized Wage Bargaining-GW*, *Union Density*, *Government Partisanship* and various control variables for the 5 5-year periods between 1951 and 1975 and 1976 and 2000. The table reports multiple imputation estimates of the OLS coefficients for each variable and their PCSEs in parentheses. A constant term is included in each regression but not reported in the table.