Web Appendix: Compensation or Constraint? How different dimensions of economic globalization affect government spending and electoral turnout

John Marshall* Stephen Fisher†

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1 Economic globalization indicators

Table 1 shows the correlation matrix alluded to in the text of the main paper. As noted, all the globalization transaction variables are fairly highly correlated. However, trade is only moderately correlated with the ownership variables (FDI flows and stocks and portfolio equity flows). Although we do not provide statistical evidence to better identify distinct dimensions—primarily because we are unaware of appropriate factor analytic techniques for panel data—we argue that this provides preliminary support for distinct ownership and trade dimensions of economic globalization.

Table 1: Economic globalization indicator correlation matrix

	FDI flows	FDI stock	Port. equ. stock	Trade
FDI flows (log)	1			
FDI stock (log)	0.83	1		
Portfolio equity stock (log)	0.77	0.86	1	
Trade (log)	0.48	0.50	0.31	1

Note: All pairwise correlations significant at $p < .01$ level.

*Government Department, Harvard University, jlmarsh@fas.harvard.edu.
†Department of Sociology, University of Oxford, stephen.fisher@sociology.ox.ac.uk.

2 Imputation for government spending models

The variables we use for the spending analysis suffer from some concentrated missingness. In particular, the automatic transfers variable is missing for c.20% of cases; several other variables suffer slight missingness. In addition to considerably reducing the sample size, applying listwise deletion induces bias in the estimates of the parametric model unless data is missing completely at random, and even then produces standard errors that are too small.[1] We therefore impute the missing data and thereby increase the sample size from 459 to 700. However, we do not impute for all missing values. Specifically, we do not impute data beyond the bounds of the available series on the dependent variable for any country in order to avoid unwarranted extrapolation. For example, even if all countries other than country x had complete data for the period 1970-2007, if country x only had from 1975-2004 we would not impute for the years 1970-1974 or 2005-2007; we would impute any missing years between 1975 and 2004. Although observations from Greece and Iceland were not used in the final model because no data was available on the automatic consumption variable at all,[2] they remain in the dataset for the imputation procedure as additional sources of information for the imputation model.

We use multiple imputation to create ten datasets that draw from the estimated posterior distribution in order to reflect the uncertainty in our estimates of the missing elements. *Amelia II* allows for dynamics in the imputation model,[3] and is therefore a natural choice for implementing our imputation procedure. For the imputation model we included all of the variables used in the analysis in Table 5 of the main paper, in addition to total government consumption[4] and the Chinn-Ito capital restrictions index[5]—two variables that may be relevant for the rare cases of missingness on the dependent or main independent variables. Fortunately the automatic transfers variable—the variable for which imputation is most needed—is relatively highly correlated with the deficit variable ($r = 0.42$). Quadratic country-specific time trends and lags and leads for all variables suffering any missingness were used to aid the imputation procedure. We treated the PR dummy as nominal and the five-point government party indicator as continuous, as recommended by Honaker and King.[6]

3 Estimation

We wish to estimate the following general model for the aggregate level models for both the government spending and turnout dependent variables y_{it} (equation (2) in the main paper):

$$y_{it} = \alpha y_{it-1} + \tilde{\mathbf{x}}_{it}\boldsymbol{\beta} + \mathbf{z}_{it}\gamma + \mathbf{year}_t\boldsymbol{\delta}_1 + \mathbf{year}_t^2\boldsymbol{\delta}_2 + \mu_i + \varepsilon_{it}; \qquad i = 1, ..., N; t = 1, ..., T_i \quad (1)$$

[1] Honaker and King 2010; King *et al.* 2001.

[2] Many researchers have nevertheless included such observations in their analysis model, but we deem this to be extending the imputation too far and therefore omit Greece and Iceland from the final analyses presented in the final paper and web appendix.

[3] Honaker and King 2010.

[4] OCED 2010.

[5] Chinn and Ito 2008.

[6] Honaker and King 2010.

where y_{it} is the dependent variable, the lagged dependent variable (LDV) y_{it-1} takes coefficient α, $\tilde{\mathbf{x}}_{it}$ is a $1 \times G$ vector of G globalization variables with $G \times 1$ coefficient vector $\boldsymbol{\beta}$, $\mathbf{z}_{it}$ is a $1 \times K$ vector of strictly exogenous control variables with $K \times 1$ coefficient vector $\boldsymbol{\gamma}$, $\mathbf{year}_t\boldsymbol{\delta}_1$ and $\mathbf{year}_t^2\boldsymbol{\delta}_2$ denote $1 \times N$ (standardized) quadratic country-specific time trends multiplied by $N \times 1$ vectors of coefficients for each country, μ_i are N country fixed effects (FEs) and ε_{it} is the error term. The subscripts on the variables denote observations from period t in country i.

When choosing an estimator we compare statistical properties. Nickell[7] has shown that in the presence of unit FEs (or following first-differencing) the LDV becomes endogenous by construction. This causes the OLS estimator to be inconsistent—although this may predominantly affects the estimate of the coefficient on the LDV (here α), it can also significantly affect all other coefficients.[8] Various instrumental variable (IV) estimators have been proposed as solutions to this problem,[9] which are discussed in brief below. As applied researchers we would like to both minimize bias *and* maximize efficiency. Different estimators serve this trade-off differently, with IV approaches typically offering least bias in simulation studies but also offering the greatest uncertainty around estimates.

The bias-efficiency trade-off depends upon the specifics of the data. Simulation studies show that the results differ depending upon the size of the parameters in the data generation process. Moreover, bias changes with the dimensions of the panel: Alvarez and Arellano[10] derive the asymptotic properties of various estimators and show that when T/N is a positive constant the FE and Arellano and Bond estimators produce negative asymptotic biases of order T^{-1} and N^{-1} respectively. Simulation studies show that bias falls considerably for the FE estimator as T increases. Accordingly, researchers have typically employed different estimation strategies for the cases of small T or $N \gg T$ and large T or $T \gg N$. Beck and Katz[11] have referred to this distinction in terms of different types of data, naming the former "panel" data and the latter "time-series cross-sectional" data. This approach generalizes to unbalanced datasets like ours where we instead consider $\overline{T} = N^{-1} \sum_{i=1}^{N} T_i$.

The dimensions of our two datasets differ. For the turnout models, $\overline{T} \approx 11$ and $N = 23$. For the government spending models, $\overline{T} \approx 35$ and $N = 21$. We therefore use different estimators for different panel dimensions, and provide further arguments for our choices below.

3.1 Panels with small T: estimating the turnout models

Despite dynamic panel bias,[12] some researchers nevertheless use OLS to estimate models with small T, like our turnout models. They often argue that they are not explicitly interested in the long run effects that can be inferred from α or that the biases are sufficiently small to be ignored. However, we are both interested in the long-run effects (needed for the estimates in Table 2 in

[7]Nickell 1981.

[8]E.g. Arellano and Bond 1991; Beck and Katz 2004; Jedson and Owen 1999.

[9]E.g. Anderson and Hsaio 1982; Arellano and Bond 1991; Arellano and Bover 1995; Blundell and Bond 1998.

[10]Alvarez and Arellano 2003.

[11]Beck and Katz 1995.

[12]Nickell 1981.

the main paper) and wish to pursue a estimation approach that yields consistent estimates to give greatest possible credibility to our findings. Simulation studies have shown that with small T, including $T = 10$, OLS can yield estimates with considerable bias.[13]

The econometric literature proposes the use of instruments to address the inconsistency of OLS. Anderson and Hsaio[14] first proposed using lags of the LDV and then estimating 2SLS to provide consistent estimates. However, Arellano and Bond's[15] "difference GMM" estimator treats level lags as *GMM* type instruments for the differenced LDV instead because this instrument matrix does not require sacrificing observations when instrumenting and thus allows *all* lags to act as instruments.[16] Exogenous (and predetermined) variables also act as standard instruments. Thus, difference GMM makes possible consistent estimation of our equation without loss of observations (relative to fixed effects models).

For consistent estimation, the standard IV exogeneity assumption must be satisfied. Arellano and Bond[17] identify two main threats to this assumption when instrumenting for endogenous variables: serial correlation in the differenced errors and overidentification. To avoid serial correlation-based endogeneity problems associated with instrumenting Δy_{it-1} with $y_{it-s}, s \geq 2$ and higher-order lags, there must be no s-order serial correlation in the differenced errors.[18] Arellano and Bond[19] provide AR and Sargan tests for these potential violations.

Sargan and AR tests, reported in Table 2 of the main paper, indicate that overidentification and residual serial correlation are not a concern for the turnout models. However, it should be noted that the Sargan[20] test cannot be calculated following robust correction to the variance matrix; in fact, Arellano and Bond[21] find that the statistic is *upwardly* biased without the clustering correction, but such corrections cannot be accommodated because the asymptotic distribution is unknown.[22] This suggests that too many instruments is not a major concern. While weak instruments are often also a concern (because they can induce bias in a particular dataset), our models seem to fit the data well and estimate most coefficients with precision—we take this to suggest that the instruments are not too weak.

Ultimately, we believe that given these diagnostic tests and the risk of considerable bias with

[13]E.g. Alvarez and Arellano 2003; Arellano and Bond 1991; Blundell, Bond and Windmeijer 2000; Kiviet 1995.

[14]Anderson and Hsaio 1982.

[15]Arellano and Bond 1991.

[16]The GMM instrument approach substitutes zeroes for missing elements in the instrument matrix. The Arellano and Bond difference GMM estimator also corrects the variance matrix for heteroskedasticity that may be induced by first-differencing.

[17]Arellano and Bond 1991.

[18]For the difference GMM estimator the following assumption must be satisfied to be able to instrument for Δy_{it} with y_{it-s}: $\mathbb{E}(\Delta\varepsilon_{it}\Delta\varepsilon_{it-s}) = 0, s \geq 2$.

[19]Arellano and Bond 1991.

[20]Sargan 1958.

[21]Arellano and Bond 1991.

[22]Unfortunately an alternative Hansen J test is downward biased as the number of instruments increases, meaning that the null hypothesis is more likely to be accepted.[23] Furthermore, it is computed using the two-step estimator—not the one-step estimator we employ.

the small T we have for the turnout models the GMM-IV approach should be favoured. Alvarez and Arellano[24] and Bond[25] go further and argue that GMM estimators are to be preferred in almost all such situations.

We also make further model specification choices. First, although we could employ the forward-looking orthogonal transformation proposed by Arellano and Bover[26] to remove unit fixed effects instead of the first differencing transformation, this approach is only beneficial if there are gaps in the panel—which is not the case for our data. Unreported analyses show the differences to be negligible. Second, we use the one-step estimator instead of the often more efficient two-step estimator because the robust variance matrix becomes singular, and therefore cannot estimate many of the coefficients in our model. Third, we considered using "system" GMM but chose difference GMM because differencing removes time-invariant FEs whereas system GMM only provides the same estimates (which are not biased by unobserved unit heterogeneity) for the time-varying economic globalization variables—our principal quantities of interest—asymptotically and under the assumption that all instruments for the levels equation are uncorrelated with the FEs (the additional moment condition underpinning system GMM). Roodman[27] notes that we cannot simply include country dummies in the system GMM model to mitigate the first concern. Furthermore, because turnout is not highly autoregressive the gains from system GMM in terms of providing better instruments are unlikely to be large.

3.2 Panels with large T: estimating the government spending models

The relatively large T that comes with the government spending models requires a different estimation approach. First, it should be noted that the IV estimators above were intended for short panels. Given that bias decreases with T, the consistency benefit offered by Arellano and Bond[28] type estimators may be outweighed by loss of efficiency for large T. Simulation studies for a variety of parameter specifications have shown that the root mean-squared error (RMSE) may be lower for FE models than GMM models in this case.[29] In general, corrected versions of the FE model first proposed by Kiviet[30] consistently perform best in terms of RMSE, and often beat the GMM approaches in terms of bias too;[31] this approach has now been generalized to unbalanced panels like ours.[32]

A second important consideration is instrument proliferation with the Arellano and Bond estimator. Arellano and Bond[33] recommend including all possible lags as GMM instruments for the endogenous variables, and the number increases quickly in T. This poses the problem of too

[24] E.g. Alvarez and Arellano 2003.
[25] Bond 2002.
[26] Arellano and Bover 1995.
[27] Roodman 2008b.
[28] Arellano and Bond 1991.
[29] Alvarez and Arellano 2003; Beck and Katz 2004; Bruno 2005; Judson and Owen 1999.
[30] Kiviet 1995.
[31] Bruno 2005; Jadson and Owen 1999; Kiviet 1995, 1999.
[32] Bruno 2005.
[33] Arellano and Bond 1991.

many instruments[34] where the endogenous variable becomes overidentified and tends toward producing the OLS outcome (which suffers from endogeneity bias). This problem is pronounced in our government spending models where difference GMM uses many hundreds of instruments and the Sargan overidentification tests are strongly rejected. Although rejection could imply heterogeneous effects instead, the large number of instruments is clearly a concern. One popular and often reasonable solution is to manually select which instruments to use. However, there is no procedure (or definitive criteria) to identify an "optimal" set of instruments, and the efficiency of the results—and thus our statistical inferences—can be strongly influenced by instrument choice. More importantly though, the choice of instruments affects the bias-efficiency trade-off (and thus the point estimates and their standard errors) and therefore can affect the substantive conclusions that can be drawn from the model.

In light of these considerations we choose to estimate equation (2) in the main paper for the governments spending models with bias-corrected OLS, known as least squares dummy variable correction (LSDVC).[35] Bruno[36] extends this approach to our case of unbalanced panels where observation selection is ignorable, and provides the Stata package `xtlsdvc` for estimation. More specifically, LSDVC first runs OLS and then runs a consistent estimator such as Anderson-Hsaio, difference GMM or system GMM. Treating the consistent estimates as the true parameter values, LSDVC then computes the small sample expected bias associated with OLS using asymptotic expansions; Kiviet[37] enhanced the accuracy of these expansions up to order $N^{-1}T^{-2}$. Finally, using this bias estimate LSDVC corrects the coefficient estimates accordingly. Bruno[38] calculates standard errors by bootstrapping the variance matrix.

At computational cost we use the one-step Arellano and Bond difference GMM estimator rather than the far less efficient Anderson-Hsaio estimator and the most accurate bias calculation available—to the order of $N^{-1}T^{-2}$. Given the LSDVC procedure is computationally intensive under this specification we use only 500 bootstraps for each imputed dataset. Note that this estimation strategy only works for our particular case where the LDV is the sole endogenous variable, and requires all other independent variables to be strictly exogenous.

In summary, we choose LSDVC because it has a lower RMSE than difference GMM and generally performs better in terms of bias—in fact it consistently performs best across an array of parameter specifications and panel dimensions for autoregressive models with unit effects.[39] Furthermore, LSDVC does not require that we make arbitrary choices about the instrument matrix which may affect the substantive conclusions we draw from the results.

[34] E.g. Roodman 2008a.
[35] Bun and Kiviet 2003; Kiviet 1995, 1999.
[36] Bruno 2005.
[37] Kiviet 1999.
[38] Bruno 2005.
[39] Beck and Katz 2004; Bun and Kiviet 2003; Bruno 2005; Kiviet 1995; Judson and Owen 1999.

4 Results from additional analyses

4.1 Country-specific time trends

As noted in the text, spurious correlation is a very serious concern when our independent and dependent variables are so clearly trending. We do not want to completely fit the data using trends, and are constrained by degrees of freedom when it comes to include country-specific polynomials. Nevertheless, it is possible that an omitted time-varying confounder is still correlated with globalization after partialling out quadratic trends for each country. We address this by including a cubic term too. Although seriously pushing degrees of freedom without adding many significant cubic coefficients, results were robust to including cubic country-specific trends with the exceptions that FDI stocks in model (2) and Portfolio equity stock in model (10) only fall just outside significance at the 10% level.

4.2 Government spending models

4.2.1 Social spending

Figure 1: Social spending, 1970-2007

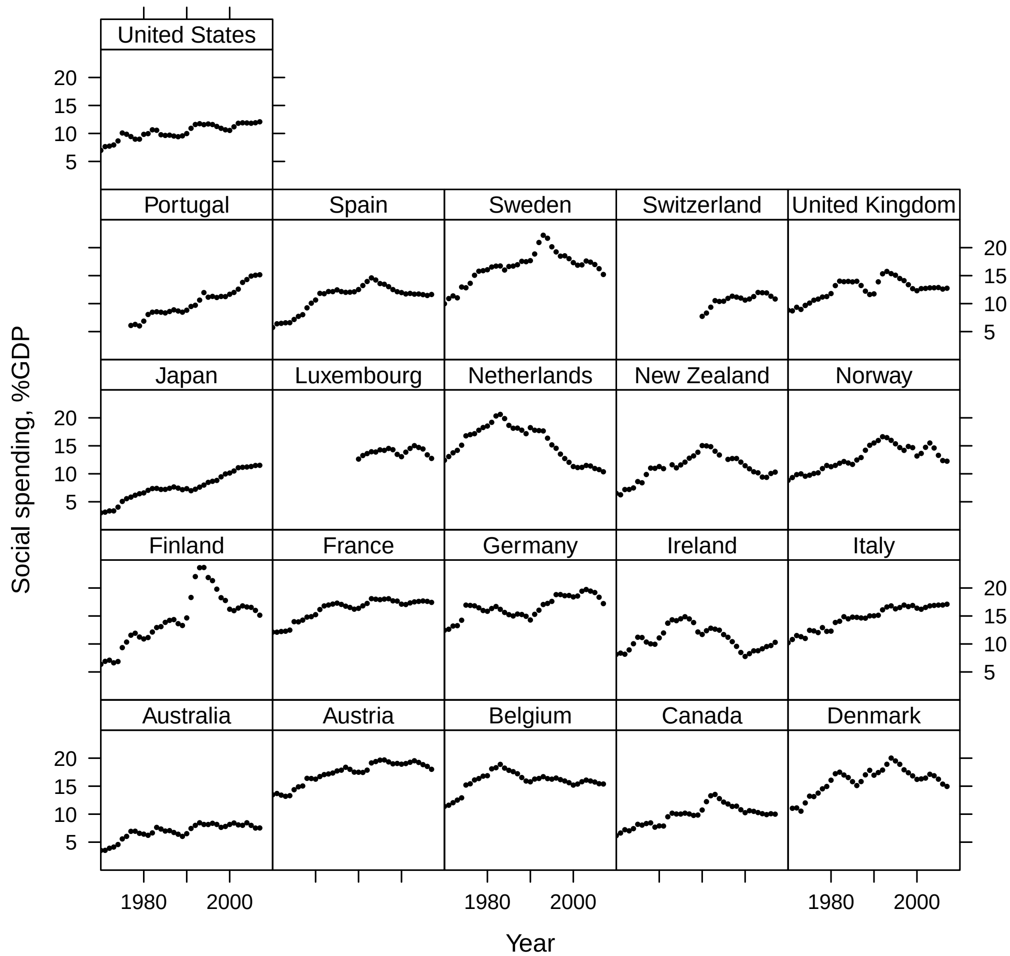

Figure 1 shows trends in *social* expenditures as a percentage of GDP[40] across all 21 countries used in the spending analysis. As with total government spending there has been a general increase in spending on social benefits since 1970. Notice that the trend is linear in many, but not all, countries; accordingly, country-specific time trends are again merited.

Table 2 replicates the statistical analysis from Table 1 in the main paper. The sole exception is that the automatic consumption control is removed given that government consumption is an

[40]OECD 2010.

Table 2: Economic globalization and social benefit spending

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
LDV	0.868	0.844	0.864	0.868	0.867	0.856
	(0.042)***	(0.046)***	(0.047)***	(0.046)***	(0.050)***	(0.048)***
Deindustrialization	0.041	0.055	0.026	0.039	0.034	0.044
	(0.019)**	(0.031)	(0.028)	(0.029)	(0.027)	(0.029)
Partisanship	0.005	-0.006	0.001	-0.004	0.002	-0.012
	(0.020)	(0.021)	(0.021)	(0.020)	(0.020)	(0.021)
Dependent population	-0.108	-0.113	-0.106	-0.136	-0.131	-0.123
	(0.038)***	(0.039)***	(0.037)***	(0.039)***	(0.040)***	(0.040)***
Deficit (lag)	-0.013	-0.013	-0.005	-0.001	0.000	-0.017
	(0.013)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)
PR	-0.024	-0.112	0.033	-0.159	-0.124	-0.107
	(0.234)	(0.242)	(0.264)	(0.244)	(0.236)	(0.257)
Strength of labor	0.001	0.001	0.001	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)*
Unexpected growth	-0.150	-0.164	-0.156	-0.154	-0.156	-0.160
	(0.013)***	(0.015)***	(0.015)***	(0.015)***	(0.015)***	(0.016)***
Automatic transfers	0.448	0.441	0.395	0.402	0.380	0.414
	(0.061)***	(0.066)***	(0.066)***	(0.067)***	(0.062)***	(0.060)***
FDI stock (log)		-0.318				
		(0.123)***				
FDI flows (log)			-0.289			
			(0.051)***			
Portfolio stock (log)				-0.354		
				(0.078)***		
Ownership scale					-0.741	
					(0.194)***	
Trade (log)						-0.787
						(0.319)**
Country FE	Y	Y	Y	Y	Y	Y
Country-specific time trends	Y	Y	Y	Y	Y	Y
Observations	721	721	721	721	721	721
Countries	21	21	21	21	21	21

Notes: All models estimated with LSDVC using difference GMM bias corrections up to order $N^{-1}T^{-2}$. Standard errors were computed using 500 bootstrapped simulations and were combined across ten imputed datasets using Rubin averaging rules. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

independent spending category.

4.2.2 Additional robustness checks

The additional robustness checks cited in the main paper can all be obtained using our replication code. However, given the importance of the EU concern, Table 3 shows the results are robust to respectively splitting the sample into non-EU members and EU members.[41] Despite halving the sample size, the results remain highly robust, with the sole exception of FDI stocks among EU members. These results are cited in the main paper. Unreported interaction models (available in the replication code) using the full sample show essentially identical results; as do interaction models using cumulative years of EU membership. Similarly, our replication code shows results are robust to examining only countries that have ever entered the Eurozone, and in turn restricting this sample to the post-1979 EMS/ERM period.

4.3 Electoral turnout models

4.3.1 Robustness checks

The robustness checks cited in the main paper can all be obtained using our replication code.

4.3.2 Instrumental variable approach

Table 4 shows the results of the Arellano and Bond and 2SLS instrumental variable models. The first five models instrument for the globalization variables with orthogonal lagged levels; the second five models instrument with economic growth and (log) GDP per capita, both lagged by one election. As we can see, the GMM results are very similar to those presented in the main paper in magnitude, except that FDI stock becomes insignificant. We find similar substantive results when taking instruments from outside the model, except that the coefficient on FDI flows trebles in magnitude (in turn increasing the Ownership scale). This rise could be cause for concern, or may suggest that macroeconomic variables are the main determinant and other factors have induced measurement error in the effect of foreign ownership.

4.3.3 Interactions with the position of the median voter

Ward, Ezrow and Dorussen[42] argue that the globalization constraint depends on where the median voter is: where the median is right-wing, there is not a strong constraint because desired policy is likely to already be consistent with globalization's constraints. A similar argument could apply to turnout too. We test this by including De Neve's[43] measure of the median voter's position at as many elections as possible, and also interacting it with our globalization measures. The results are

[41]Given the sample restrictions, cluster-robust standard errors could not be estimated in models (2)-(4), (8) and (10) use homoskedastic standard errors.

[42]Ward, Ezrow and Dorussen 2011.

[43]De Neve 2009.

Table 3: Economic globalization and aggregate turnout—non-EU and EU member samples

	Non-EU members						EU members					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)	Model (11)	Model (12)
LDV	-0.182*	-0.218*	-0.220*	-0.162	-0.200**	-0.186*	-0.182*	-0.227**	-0.220***	-0.208**	-0.216***	-0.176*
	(0.099)	(0.120)	(0.123)	(0.127)	(0.099)	(0.096)	(0.107)	(0.104)	(0.080)	(0.102)	(0.080)	(0.096)
Registered voters (log)	-19.892**	-21.831**	-28.526**	-21.580*	-30.286**	-19.010**	-9.979	-12.803	24.628	-12.121	23.274	-9.928
	(9.869)	(10.992)	(11.830)	(11.421)	(13.715)	(9.567)	(11.280)	(9.720)	(18.231)	(9.445)	(17.647)	(11.746)
%VAP,30-69	0.278***	0.328*	0.225	0.345*	0.256***	0.324***	-0.080	-0.036	0.260	0.126	0.280	-0.076
	(0.098)	(0.179)	(0.188)	(0.187)	(0.096)	(0.101)	(0.186)	(0.232)	(0.213)	(0.242)	(0.218)	(0.179)
Years since last election	0.391	0.429	0.459	0.483	0.511**	0.411	0.413	0.379	0.558**	0.549**	0.589**	0.426*
	(0.273)	(0.366)	(0.399)	(0.381)	(0.199)	(0.260)	(0.257)	(0.260)	(0.258)	(0.260)	(0.258)	(0.245)
US mid-term	-13.145***	-12.852***	-13.500***	-13.699***	-13.979***	-12.987***						
	(1.021)	(2.191)	(2.260)	(2.355)	(1.343)	(1.034)						
Compulsory voting	-3.070***	-2.592	-3.136	-2.197	-2.933***	-3.953***	-1.925	-2.146	-1.573	-1.904	-1.524	-2.290
	(0.886)	(3.984)	(4.053)	(4.138)	(0.594)	(1.435)	(2.193)	(4.671)	(2.170)	(6.422)	(2.093)	(2.083)
Mixed system	-2.078**	0.744	-1.173	-0.636	-0.453	-2.311*	-3.283***		-3.065***			-3.324***
	(1.051)	(3.660)	(3.436)	(3.569)	(1.131)	(1.202)	(1.003)		(1.177)			(1.004)
PR system								2.902		1.906	2.783**	
								(2.160)		(4.081)	(1.115)	
Disproportionality	-7.220**	-4.199	-7.935	-7.365	-7.968**	-6.754*	-15.094***	-15.600**	-17.072***	-14.671**	-16.768***	-15.528***
	(3.015)	(6.343)	(6.638)	(6.397)	(4.061)	(3.513)	(3.818)	(6.573)	(3.846)	(6.645)	(3.964)	(3.450)
ENPS	-0.329	-0.063	-0.880	-0.458	-0.912	-0.257	-0.727	-0.684	-0.816	-0.400	-0.751	-0.782
	(0.845)	(0.860)	(0.992)	(0.891)	(0.811)	(0.897)	(0.724)	(0.575)	(0.763)	(0.569)	(0.728)	(0.711)
Margin	-0.047	-0.025	0.009	-0.044	0.008	-0.048	-0.077	-0.073	-0.093	-0.098	-0.098	-0.079
	(0.054)	(0.061)	(0.066)	(0.063)	(0.066)	(0.051)	(0.080)	(0.060)	(0.088)	(0.060)	(0.087)	(0.078)
FDI stock (log)		-2.671*						-0.315				
		(1.399)						(1.601)				
FDI flows (log)			-2.409***						-1.943**			
			(0.928)						(0.944)			
Portfolio stocks (log)				-1.868*						-3.421***		
				(1.125)						(1.054)		
Ownership scale					-4.099**						-3.196**	
					(1.650)						(1.391)	
Trade (log)						2.218						-1.783
						(4.288)						(2.285)
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-specific time trends	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	133	117	124	117	109	133	125	113	102	110	93	125
Countries	16	13	15	13	13	16	15	15	15	15	14	15

Notes: Models (2), (4), (5), (8), (10) and (11) estimated with Arellano and Bond (1991) one-step difference GMM procedure. Differenced variables are used as standard instruments and all level lags of the dependent variable exceeding three are used as GMM instruments for the LDV and all globalization variables. Remaining models estimated without y_{it-2} as an instrument. Country-clustered robust standard errors in parentheses. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table 4: Economic globalization and aggregate turnout—instrumenting for economic globalization

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)
LDV	-0.230***	-0.251***	-0.208**	-0.231***	-0.165**	-0.209***	-0.226***	-0.186***	-0.211***	-0.219**
	(0.080)	(0.073)	(0.084)	(0.077)	(0.076)	(0.065)	(0.075)	(0.064)	(0.067)	(0.086)
Registered voters (log)	-18.899**	-19.980*	-21.507***	-21.083**	-17.253***	-18.261***	-29.310***	-21.820***	-25.871***	-18.578***
	(7.600)	(11.013)	(6.384)	(10.368)	(6.644)	(7.086)	(10.168)	(6.172)	(8.646)	(6.247)
%VAP,30-69	0.198*	0.217**	0.269***	0.255***	0.163	0.210	0.147	0.330***	0.237*	0.186
	(0.101)	(0.098)	(0.069)	(0.089)	(0.111)	(0.153)	(0.152)	(0.121)	(0.131)	(0.166)
Years since last election	0.381*	0.458**	0.451**	0.509***	0.455**	0.354*	0.487**	0.504***	0.529***	0.351*
	(0.203)	(0.186)	(0.217)	(0.192)	(0.215)	(0.182)	(0.223)	(0.187)	(0.201)	(0.186)
US mid-term	-12.442***	-12.387***	-13.062***	-12.792***	-13.257***	-12.859***	-14.084***	-13.466***	-13.785***	-12.586***
	(1.091)	(1.090)	(1.155)	(1.224)	(1.120)	(1.506)	(1.827)	(1.476)	(1.609)	(2.113)
Compulsory voting	-2.762**	-2.235***	-1.978	-1.483**	-3.538**	-1.845	-2.321	-0.436	-1.584	-1.667
	(1.238)	(0.833)	(1.232)	(0.689)	(1.693)	(2.783)	(3.304)	(2.847)	(2.936)	(2.556)
Mixed system	0.525	-0.819	1.101	-0.002	-0.960	-0.224	-0.212	1.036	0.478	-1.349
	(1.497)	(0.923)	(1.192)	(0.968)	(0.877)	(7.774)	(3.204)	(2.835)	(2.878)	(3.083)
PR system	3.529**	1.906**	2.487*	2.475***	2.263**	2.743	3.288	1.597	2.635	1.705
	(1.462)	(0.794)	(1.386)	(0.793)	(1.082)	(8.088)	(4.237)	(3.618)	(3.757)	(3.227)
Disproportionality	-13.969***	-14.964***	-14.088***	-14.121***	-13.038***	-14.622***	-12.152***	-14.413***	-13.584***	-13.523***
	(3.264)	(3.396)	(3.412)	(3.343)	(3.449)	(4.535)	(4.632)	(3.679)	(4.031)	(5.028)
ENPS	-0.835	-1.077*	-0.678	-0.931	-0.859	-0.816*	-0.993**	-0.695*	-0.928**	-0.747
	(0.588)	(0.594)	(0.492)	(0.570)	(0.571)	(0.420)	(0.488)	(0.382)	(0.438)	(0.652)
Margin	-0.046	-0.030	-0.050	-0.030	-0.041	-0.059*	0.025	-0.068*	-0.014	-0.051
	(0.044)	(0.053)	(0.043)	(0.052)	(0.045)	(0.036)	(0.050)	(0.035)	(0.040)	(0.035)
FDI stock (log)	-1.083					-0.805				
	(0.903)					(6.206)				
FDI flows (log)		-2.173***					-6.603***			
		(0.674)					(2.022)			
Portfolio stocks (log)			-2.340***					-3.533***		
			(0.620)					(1.043)		
Ownership scale				-3.527***					-6.789***	
				(1.000)					(1.875)	
Trade (log)					1.289					2.767
					(2.593)					(15.614)
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-specific time trends	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	254	226	251	226	258	248	220	245	220	252
Countries	23	23	23	23	23	23	22	23	22	23
AR2 test	-2.39	-1.80	-2.11	-1.60	-2.14					
AR3 test	-1.48	-1.15	-0.98	-0.84	-1.43					
AR4 test	-1.46	-1.13	-1.08	-1.22	-1.38					
F test of excluded instruments						1.57	6.85	29.70	14.34	1.25
Sargan χ^2	146.76	132.73	138.43	128.03	149.30	12.00	0.02	0.15	0.30	10.53

Notes: Models (1)-(5) estimated with Arellano and Bond (1991) one-step difference GMM procedure. Differenced variables are used as standard instruments and all level lags of the dependent variable exceeding three are used as GMM instruments for the LDV and all globalization variables. Models (6)-(10) estimated with 2SLS, instrumenting for globalization variables with lagged economic growth and lagged (log) GDP per capita. Country-clustered robust standard errors in parentheses. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table 5: Economic globalization, the median voter and aggregate turnout

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
LDV	-0.240***	-0.247**	-0.215**	-0.304***	-0.197
	(0.087)	(0.108)	(0.091)	(0.079)	(0.120)
Median voter	-0.047	-0.012	0.000	0.027	-0.350*
	(0.040)	(0.031)	(0.016)	0.022	(0.211)
FDI stock (log)	-0.249				
	(1.647)				
FDI flows (log)		-1.758***			
		(0.600)			
Portfolio stocks (log)			-2.112***		
			(0.542)		
Ownership scale				-3.144***	
				(1.113)	
Trade (log)					2.090
					(2.277)
FDI stock (log) × median voter	0.028				
	(0.019)				
FDI flows (log) × median voter		0.032			
		(0.027)			
Portfolio stocks (log) × median voter			0.023*		
			(0.013)		
Ownership scale × median voter				0.014	
				(0.019)	
Trade (log) × median voter					0.090*
					(0.051)
Controls	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y
Country-specific time trends	Y	Y	Y	Y	Y
Observations	184	166	181	158	196
Countries	22	21	22	20	23

Notes: All models estimated with Arellano and Bond (1991) one-step difference GMM procedure. Differenced variables are used as standard instruments and all level lags of the dependent variable exceeding two are used as GMM instruments, except in Models (2) and (5) where third-order lags are used. Model (1) restricts the number of lagged level instruments to 9 to avoid overidentification. Country-clustered robust standard errors in parentheses. * denotes $p < 0.1$, ** denotes $p < 0.05$,*** denotes $p < 0.01$.

shown in Table 5, showing that the main results in this paper are robust. Although never significant at the 5% level and small in magnitude, the interaction term is always positive—consistent with the theory of Ward, Ezrow and Dorussen.

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