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Quantile Regression for Time-Series-Cross-Section Data*

Marcus Alexander[†], Matthew Harding[‡] and Carlos Lamarche[§]

Abstract

This paper introduces quantile regression methods for the analysis of time-series-cross-section data. Quantile regression offers a robust, and therefore efficient alternative to least squares estimation. We show that quantile regression can be used in the presence of endogenous covariates, and can also account for unobserved individual effects. Moreover, the estimation of these models is no more demanding today than that of a least squares model. We use quantile regression methods to re-examine the hypothesis that higher income leads to democracy, obtaining a series of new insights not available under traditional approaches.

1 Introduction The empirical estimation of comparative economic and political models often relies on the use of time-series-cross-section (TSCS) data. The data usually consists of a number of time series on macroeconomic or political indicators typically collected at the national level and only updated at quarterly or yearly frequency. It is still common however for practitioners to use standard micro-econometric techniques for the analysis of

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† *Mailing Address:* Stanford School of Medicine, 300 Pasteur Drive, Stanford, CA 94305; *Email:* marcalex@stanford.edu.

‡ *Mailing Address:* Department of Economics, Stanford University, 579 Serra Mall, Stanford, CA 94305; Phone: (650) 723-4116; Fax: (650) 725-5702. *E–mail:* mch@stanford.edu.

§ *Mailing Address:* Department of Economics, University of Oklahoma, 729 Elm Avenue, Norman, OK 73019; Phone: (405) 325-5857. *E–mail:* lamarche@ou.edu.

this data. Traditional econometric techniques however were developed for Gaussian models and do not typically account for the heterogeneity encountered in TSCS data, which usually consists of an often loose association of different time series into one dataset (Nuamah, 1986; Beck and Katz, 2007).

This paper shows that quantile regression can provide a broader statistical alternative to least squares in the real word of research. Quantile regression offers the possibility of investigating how covariate effects influence the location, scale and possibly the shape of the conditional response distribution. It has a random coefficient interpretation, allowing for slope heterogeneity drawing from non-Gaussian distributions. Furthermore, quantile regression models for TSCS data are easy to estimate using the R package `quantreg` and additional functions we make available for applied researchers.

In this paper we focus on three aspects of heterogeneity and investigate the latest econometric methods available to address these issues. The first problem we investigate is the robustness to distributional assumptions, and we contrast the use of quantile regression methods with more standard mean regression techniques. We argue that in addition to more robust estimation, the use of quantile regression methods allows us to obtain deeper insights into the effect of the regressors on the outcome of interest by allowing for heterogeneous marginal effects across the conditional outcome distribution. Quantile regression methods can therefore identify more subtle effects which would be missed by the application of mean regression. The second problem we investigate is estimation of a model with endogenous variables when the practitioner has different choices of instruments. We demonstrate that quantile regression can accommodate to the possibility of reverse causation, although the results are typically very fragile with respect to the instrument set and that even in relatively simple situations it is difficult to find convincing sets of instruments. The third problem we investigate concerns the effect of individual level heterogeneity and the appropriate econometric specification of individual effects.

Rather than focusing on a set of Monte-Carlo results we choose to address a real substantive question in social science, the effect of economic development on political development, which has recently received a lot of attention in the applied literature. Not only is this question of first order importance in determining policy for advanced nations, but it has also been studied in detail using what we consider a typical dataset for this class of economic models, a cross-country panel of economic and political indicators collected at yearly frequency and as such provides a natural starting point for our investigation.

The reason why the empirical question addressed in such studies is of first order importance from a policy perspective is because far from being defined by the growing dominance of democracy, the second part of the 20th century was characterized by the entrenchment of two very distinct, yet equally common political regime types — liberal democracy guaranteeing political rights on one hand and autocracies characterized by poor institutions and lack of political and civil rights on the other. The earliest systematic formulation of the connection between political and economic development is due to Lipset (1959) and Lipset (1963), but the question of how income affects democracy has recently captured the attention of economists (Barro, 1999; Acemoglu, Johnson, Robinson and Yared, 2008).

The starting point for our study recognizes that the distributions of two commonly used numerical measures of democracy are bimodal with most countries concentrated at the extremes. Although it is well known that the distribution of political regimes is bimodal (Jaggers and Gurr (1995), Epstein et al. (2006)), little attempt has been made to question the robustness of least squares mean regression models to capture the effect of interest. This motivates our methodology as a departure from traditional mean regression techniques and instead re-orients the topic of the discussion on the estimation of different effects of the variables of interest at different quantiles of the democracy distribution. Adding our three sets of instruments, we identify the effect of economic development that is stronger in the middle range of the distribution and almost non-existent in the tails. Being acutely aware of the difficulties typically encountered by applied researchers in finding valid instruments, we show that similar results hold when we use a set of geographic instruments, an instrument based on world trade, and a set of instruments designed to capture world economic factors. However, the inverted U-shaped relationship between income and democracy over the quantiles of the distribution of democracy is found to be not robust to the inclusion of controls for geographic regions.

Our most significant finding arises only when we estimate country-specific effects which are allowed to vary by the quantile of the democracy distribution. We allow for the estimation of different effects that are not only country-specific but that furthermore are allowed to vary across the distribution of democracy. We find that once we account for country-specific effects, the inverted U-shaped relationship described above also disappears. While the effect of income on democracy is very close to zero at the lowest quantiles of the democracy distribution, it is negative and significant at the highest quantiles.

Having found that country specific effects matter disproportionately more than economic development in shifting the conditional democracy distribution, we ask whether this is uniformly so over the conditional distribution of democracy. The analysis suggests that the importance of these factors diminishes as countries become more democratic. Even for democratic countries, however, we find evidence of economic development playing a heterogeneous role, a fact consistent with a large literature emphasizing institutional differences in modern democracies (Lijphart, 1999; Hall and Soskice, 2001). Our work complements and further elaborates on the recent quantitative work of Acemoglu et. al. (2008), which analyzes similar data within the context of a mean regression framework.

The structure of the paper is as follows. Section 2 presents the different econometric models considered in this paper. Section 3 briefly introduces the data. Section 4 presents the empirical results and Section 5 discusses their main implications. Section 6 concludes.

2 Econometric Models and Methods We present a model for political and economic development, simply written as,

$$\begin{aligned} D &= \gamma I + \boldsymbol{x}'\boldsymbol{\beta} + \eta && (2.1)\\ I &= h(\boldsymbol{x}, \boldsymbol{w}, \alpha, v) && (2.2)\\ \eta &= \alpha + \lambda + u, && (2.3) \end{aligned}$$

where D denotes democracy, I is income, $\boldsymbol{x}$ is a vector of exogenous variables that affect both income and democracy, $\boldsymbol{w}$ is a vector of instruments which drive income but are uncorrelated with u and v. The terms α, λ, u, and v represent latent variables. While α are geographic or country specific factors affecting the evolution of D and I, λ denotes time effects. The error term u is stochastically dependent on v. We are interested in estimating γ, the causal effect of income on democracy, at different quantiles of the conditional distribution of democracy in time-series-cross-section data or cross-sectional models. Throughout we ignore issues of dynamics due to the inherent econometric difficulty of estimating models with lagged dependent variables in many of the situations of interest. Much of the time dynamics of interest can be captured through the inclusion of time effects λ. The robustness of the models to different dynamic assumptions is thus not explored in this study but remains a worthy object of interest nevertheless for future research.

2.1 Quantile Models In a typical least-squares regression model approach to the analysis of the relationship between income and democracy, we focus on estimating the conditional expectation of the dependent variable,

$$E(D_{it}|I_{it-1}, \boldsymbol{x}_{it}) = \gamma I_{it-1} + \boldsymbol{x}'_{it}\boldsymbol{\beta}, \tag{2.4}$$

where D_{it} is the normalized democracy for country i at time t. The income variable I_{it-1} is measured at time $t-1$ and it corresponds to the logarithm of per capita GDP. The parameter γ captures the (marginal) effect of income on democracy at the mean level. Any additional controls or variables of interest such as education or population are included in the variables x_{it}.

Consider however the analysis of the relationship between income and democracy and the simple bi-variate plot in Figure 1. As we discussed before, the unconditional distribution of democracy is strongly bimodal with most countries clustered at the ends of the scale. Thus it seems that an analysis focused on the (conditional) mean of the distribution might miss important distributional effects of income and that by looking at the tails of the distribution we may uncover richer evidence. The estimated conditional mean model of democracy crosses between the two clusters in our data, suggesting that economic development is associated with democratization in all countries. Quantile regression will offer a broader view of how economic development influences political development.

We begin with the standard quantile regression model. Let us consider the τ-th conditional quantile function of democracy,

$$Q_{D_{it}}(\tau|I_{it-1}, \boldsymbol{x}_{it}) = \gamma(\tau) I_{it-1} + \boldsymbol{x}'_{it}\boldsymbol{\beta}(\tau). \tag{2.5}$$

The parameter $\gamma(\tau)$ captures the effect of income at the τ-th quantile of the conditional distribution of democracy.[1] This model can be estimated by solving,

$$\min_{\gamma,\beta \in \mathcal{G}\times\mathcal{B}} \sum_{i=1}^{N} \sum_{t=1}^{T} \rho_\tau(D_{it} - \gamma I_{it-1} - \boldsymbol{x}'_{it}\boldsymbol{\beta}), \tag{2.6}$$

[1] The democracy measures could be described as mixed-continuous dependent outcomes, because they are based on a rating system. This may prompt some natural concerns because the dependent variable is not continuous. Notice however, that it is possible to carefully reassign conditional probabilities where the distribution has no mass, without affecting the τ's quantile functions. Moreover, we are not aware of any theoretical reasons to challenge the validity of the empirical results due to this particular data structure.

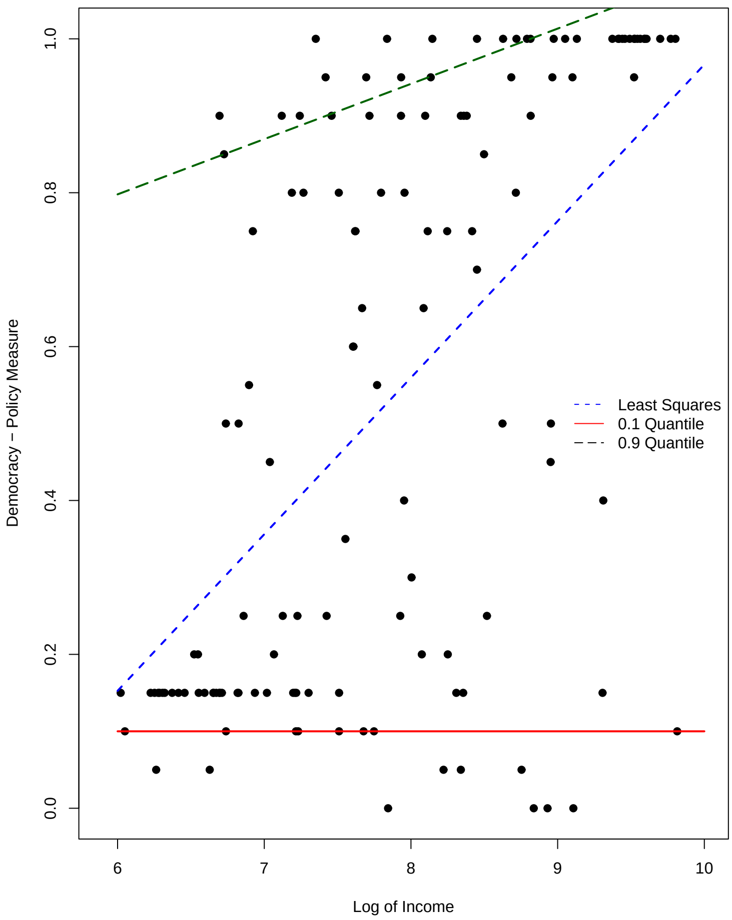

Figure 2.1: Quantile regression estimates of the effect of income on democracy considering the full sample of countries. The dashed blue line presents least squares results for the conditional mean model, and other lines represent the estimated quantile model at the 0.1 and 0.9 quantiles. The Polity measure of democracy corresponds to the year 1990.

where $\rho_\tau(u)$ is the standard quantile regression check function (see, e.g., Koenker and Bassett (1978), Koenker (2005)). The resulting estimator obtained from 2.6 will be referred to as the pooled quantile regression estimator.

If we now return to Figure 1 we can easily see how a quantile regression approach will naturally relate income to democracy in the different quantiles of the democracy distribution. Notice how the estimated quantile functions at the 0.1 and 0.9 quantiles are quite different since they place different weights on data in the lower and upper quantiles of the distribution of democracy. While the effect of economic development is negligible in countries with low levels of political development, it has a modest effect in countries with high levels of political development.

This form of parameter heterogeneity has a random coefficients interpretation. We can write $D = \gamma(u)I + \boldsymbol{x}'\boldsymbol{\beta}(u)$, where $u|I, \boldsymbol{x} \sim \mathcal{U}(0,1)$, and $\mathcal{U}(\cdot)$ denotes a uniform distribution. The advantage of this formulation over standard random coefficient models (RCM) for time-series-cross-section data (Beck and Katz 2007) is that allows the marginal distributions of the coefficients $(\gamma, \beta_1, \beta_2, \ldots, \beta_p)$ to be arbitrary, relaxing the simplifying assumption of a multivariate Normal distribution for the heterogeneity. As in the case of RCM, the slopes are allowed to be related to each other.

So far however we have ignored potential issues of endogenous covariates and unobserved heterogeneity. We now briefly present recent extensions to the classical Koenker and Bassett's estimator for pooled data to time-series-cross-section data and also propose a new approach.

Location Shifts The quantile model which allows for fixed effects is given by the following,

$$Q_{D_{it}}(\tau|I_{it-1}, \boldsymbol{x}_{it}, \alpha_i) = \gamma(\tau)I_{it-1} + \boldsymbol{x}_{it}'\boldsymbol{\beta}(\tau) + \alpha_i, \tag{2.7}$$

where α_i is a country effect. This extends the standard pooled model presented in 2.5 by allowing for an individual specific effect α_i, which does not vary across quantiles. These effects should be simply interpreted as country-specific intercepts that shift the conditional quantiles functions by α at each quantile. We call this model the location-shift quantile regression model. This model can be estimated for J quantiles simultaneously by solving,

$$\min_{\gamma,\beta,\alpha \in \mathcal{G}\times\mathcal{B}\times\mathcal{A}} \sum_{j=1}^{J}\sum_{i=1}^{N}\sum_{t=1}^{T} \omega_j \rho_{\tau_j}(D_{it} - \gamma(\tau_j)I_{it-1} - \boldsymbol{x}_{it}'\boldsymbol{\beta}(\tau_j) - \alpha_i), \tag{2.8}$$

using the method described in Koenker (2004). The weight ω_j controls the influence of the

j-th quantile on the estimation of the quantile effects. In the present study, we will employ equal weights $1/J$.

Distributional Shifts. In large T time-series-cross-section data it is possible to estimate a different value of the individual effect for each quantile of the conditional distribution of the response. The data set considered in this study provides a novel opportunity which allows us to evaluate the role of the country effect, and by implication the long run drivers of democracy which it proxies for, as they vary over the distribution of democracy. The τ-th conditional quantile function of democracy for country i at time t is then,

$$Q_{D_{it}}(\tau | I_{it-1}, \boldsymbol{x}_{it}, \alpha_i) = \gamma(\tau) I_{it-1} + \boldsymbol{x}_{it}' \boldsymbol{\beta}(\tau) + \alpha_i(\tau). \tag{2.9}$$

We call this model the distributional-shift country effects quantile regression model. The model can be estimated by setting $J = 1$ in 2.8. The procedure requires the estimation of distributional country specific shifts and thus is only possible for large T.

Endogenous Covariates. Income and democracy may be manifestations of some other latent variable not expressed in the conditional quantile function.[2] This suggests that, $I = h(\boldsymbol{x}, \boldsymbol{w}, v)$, where $\boldsymbol{w}$ is a vector of instrumental variables independent of the structural disturbance but related to income and v is an additional error term correlated with the disturbance of the democracy equation. To estimate the model, we follow the method proposed in Chernozhukov and Hansen (2008) considering three sets of instruments described in the Appendix.

The time-series-cross-section data quantile regression model can be extended to relax the implicit assumption in models 2.7, and 2.9 that income is exogenous. We consider the method proposed by Harding and Lamarche (2009) to estimate 2.9 if the endogenous variable income $I = h(\boldsymbol{x}, \boldsymbol{w}, \alpha, v)$, and v and the error term u in equation 2.3 are not independent. They consider the following objective function for the conditional instrumental quantile relationship:

$$R(\tau, \gamma, \boldsymbol{\beta}, \boldsymbol{\delta}, \boldsymbol{\alpha}) = \sum_{t=1}^{T} \sum_{i=1}^{N} \rho_\tau (D_{it} - \gamma \boldsymbol{I}_{it-1} - \boldsymbol{x}_{it}' \boldsymbol{\beta} - \boldsymbol{d}_{it}' \boldsymbol{\alpha} - \hat{\boldsymbol{w}}_{it}' \boldsymbol{\delta}), \tag{2.10}$$

where $\hat{\boldsymbol{w}}$ is the least squares projection of the endogenous variable income I on the instruments $\boldsymbol{w}$, the exogenous variables $\boldsymbol{x}$, and the vector of individual effects $\boldsymbol{d}$. First, we

[2]It may be argued that it is incorrect to refer to this relationship as "conditional" since we are not conditioning on the endogenous variable. Alternative terminology used in the literature refers to this relationship as the "structural quantile relationship".

minimize the objective function above for $\boldsymbol{\beta}$, $\boldsymbol{\delta}$, and $\boldsymbol{\alpha}$ as functions of τ and γ,

$$\{\hat{\boldsymbol{\beta}}(\tau,\gamma), \hat{\boldsymbol{\delta}}(\tau,\gamma), \hat{\boldsymbol{\alpha}}(\tau,\gamma)\} = \underset{\boldsymbol{\beta},\boldsymbol{\delta},\boldsymbol{\alpha} \in \mathcal{B}\times\mathcal{D}\times\mathcal{A}}{\operatorname{argmin}} \quad R(\tau,\gamma,\boldsymbol{\beta},\boldsymbol{\delta},\boldsymbol{\alpha}). \tag{2.11}$$

Then we estimate the coefficient on the endogenous variable by finding the value of γ, which minimizes a weighted distance function defined on $\boldsymbol{\delta}$:

$$\hat{\gamma}(\tau) = \underset{\gamma\in\mathcal{G}}{\operatorname{argmin}} \quad \hat{\boldsymbol{\delta}}(\tau,\gamma)'\boldsymbol{A}\hat{\boldsymbol{\delta}}(\tau,\gamma), \tag{2.12}$$

for a given positive definite matrix $\boldsymbol{A}$. Inference can be accomplished by the method proposed in Harding and Lamarche (2009).

3 Data The data set used in this paper is similar to the one employed in several studies including Acemoglu et al. (2008). We employ one measure of democracy for which data is publicly available, the Polity scores. The Polity (version IV) score, compiled by an academic panel at George Mason University's Center for International Development and Conflict Management, is defined as the difference between an index of autocracy and an index of democracy for each country. Each government is assigned a number between 0 and 10 on each scale based on a set of weighted indicators designed to capture the extent of competitive political participation, institutionalized constraints on executive power and guarantees of civil liberties and political participation. The primary focus of the index is on central government and it notably ignores the extent to which control over economic resources is shared and the interaction between central government and separatist or revolutionary groups. We use a sample of countries from 1945 to 1999 normalized to range between 0 and 1.

In Table 3.1, we present summary statistics for the measure of democracy employed in this paper disaggregated by geographic regions. As one would intuitively expect, the mean value for the Western world are about 0.9 while those for Sub-saharan Africa are only about 0.3. This measure rely on a substantial amount of subjectivity, and it has been used extensively in quantitative studies as a measure of political freedom (see, e.g., Acemoglu et. al., 2008; Barro, 1999; Fearon and Laitin, 2003). Per capita income is measured in 1985 US dollars and is used in log form, lagged one year. The trade weighted instrument was computed by Acemoglu et. al. (2008) and uses the IMF trade matrix. We labeled this instrumental variable (IV) Set 1. The table also presents descriptive statistics for the geographic instruments. The IV Set 2, including geographic data, is from Fearon and Laitin (2003) and Acemoglu et. al. (2001, 2002). The world factors instruments, labeled IV Set 3, are computed from log per capita GDP using principal components and employing standard normalizations. IV Set 4 contains the principal components of the bio-geographic instruments, which are also used in full as IV Set 5 (biological: plants and animals) and IV Set 6 (geography and climate), following Olsson and Hibbs (2005) and Gundlach and Paldam (2009).

Variables	All countries	West & Japan	E. Europe & Soviet U.	Latin America	Sub-saharan Africa	N.Africa & M.East	Asia
Polity Measure	0.476	0.931	0.325	0.537	0.313	0.289	0.409
of Democracy	(0.376)	(0.217)	(0.314)	(0.335)	(0.284)	(0.321)	(0.332)
Log of GDP per	7.660	8.939	7.684	7.780	6.772	8.029	7.129
capita	(1.054)	(0.591)	(0.884)	(0.595)	(0.630)	(1.083)	(0.803)
Log of Population	9.049	9.595	9.431	8.643	8.500	8.543	9.923
	(1.457)	(1.213)	(1.223)	(1.218)	(1.211)	(1.351)	(1.761)
Trade-Weighted	10.761	11.377	8.466	10.501	9.396	11.146	13.455
World Income (Set 1)	(8.049)	(4.784)	(2.169)	(6.143)	(5.166)	(5.397)	(16.649)
Log of mountainous	2.177	1.991	1.931	2.645	1.558	2.273	2.818
terrain (Set 2)	(1.404)	(1.435)	(1.295)	(1.204)	(1.435)	(1.300)	(1.205)
Absolute geographic	0.291	0.533	0.536	0.175	0.131	0.304	0.244
latitude (Set 2)	(0.189)	(0.107)	(0.062)	(0.097)	(0.084)	(0.039)	(0.140)
Log of air distance	7.958	6.628	7.251	8.356	8.695	8.111	8.223
to nearest port (Set 2)	(0.969)	(1.156)	(0.658)	(0.437)	(0.240)	(0.347)	(0.494)
Global economic	-1.923	-3.236	-1.716	-1.610	-1.135	-2.161	-1.955
factor 1 (Set 3)	(4.745)	(3.251)	(5.317)	(4.588)	(5.482)	(4.473)	(4.658)
Global economic	-5.072	-4.540	-5.230	-4.794	-6.022	-5.294	-4.281
factor 2 (Set 3)	(6.232)	(6.019)	(5.545)	(6.049)	(6.487)	(5.875)	(6.747)
Global economic	10.072	9.789	11.805	10.156	9.425	10.377	9.946
factor 3 (Set 3)	(6.050)	(4.802)	(5.584)	(4.857)	(8.205)	(4.823)	(5.696)
Global economic	-3.010	-3.356	-0.509	-3.329	-3.262	-3.162	-3.271
factor 4 (Set 3)	(7.242)	(6.667)	(7.951)	(6.788)	(7.757)	(6.963)	(7.056)
Global economic	34.308	30.767	35.223	32.036	38.437	34.328	33.985
factor 5 (Set 3)	(13.051)	(13.751)	(13.831)	(13.791)	(10.315)	(12.856)	(13.033)
First principal component	0.000	1.403	1.943	-1.074	-1.369	1.318	0.312
geographical IV (Set 4)	(1.423)	(1.004)	(0.268)	(0.527)	(0.415)	(0.596)	(0.753)
First principal component	0.000	1.203	1.886	-1.120	-1.179	1.886	0.104
biological IV (Set 4)	(1.366)	(1.252)	(0.000)	(0.007)	(0.000)	(0.000)	(0.583)
Animals (Set 5)	3.978	7.190	9.000	0.509	0.000	9.000	6.287
	(4.114)	(3.515)	(0.000)	(0.500)	(0.000)	(0.000)	(2.008)
Plants (Set 5)	13.469	25.904	33.000	3.474	4.000	33.000	7.875
	(13.498)	(12.736)	(0.000)	(1.500)	(0.000)	(0.000)	(6.869)
Climate (Set 6)	2.662	3.667	3.746	2.226	1.742	4.000	2.275
	(1.024)	(0.472)	(0.436)	(0.634)	(0.668)	(0.000)	(0.587)
Latitude (Set 6)	16.979	40.051	46.469	-2.598	-0.822	34.065	19.519
	(26.215)	(25.395)	(3.656)	(19.896)	(14.326)	(3.592)	(14.770)
Axis (over 100, Set 6)	1.545	1.950	2.355	1.088	0.988	1.814	2.069
	(0.685)	(0.613)	(0.000)	(0.355)	(0.066)	(0.664)	(0.666)

Table 3.1: Descriptive Statistics.

	Model including Other Covariates	Region effects	Year effects	Quantiles 0.10	0.25	0.50	0.75	0.90	Mean
Pooled Regressions									
Income	Yes	No	No	0.006	0.035	0.262	0.185	0.071	0.170
				(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.004)
Income	Yes	Yes	No	0.000	0.000	0.000	0.080	0.061	0.093
				(0.004)	(0.002)	(0.003)	(0.007)	(0.003)	(0.005)
Income	Yes	Yes	Yes	0.000	0.000	0.000	0.115	0.083	0.086
				(0.000)	(0.007)	(0.000)	(0.027)	(0.020)	(0.013)
Instrumental Variables Set 1									
Income	Yes	No	No	0.158	0.126	0.261	0.302	0.000	0.210
				(0.013)	(0.011)	(0.013)	(0.038)	(0.056)	(0.020)
Income	Yes	Yes	No	0.117	0.000	0.000	0.000	0.109	0.088
				(0.008)	(0.079)	(0.052)	(0.168)	(0.094)	(0.025)
Income	Yes	Yes	Yes	0.068	0.142	0.000	0.000	-0.239	0.037
				(0.047)	(0.054)	(0.062)	(0.424)	(0.249)	(0.083)
Fixed Effects									
Income	Yes	No	No	-0.001	0.004	-0.005	-0.041	-0.074	0.015
				(0.018)	(0.011)	(0.010)	(0.015)	(0.041)	(0.028)
Income	Yes	Yes	No	-0.003	-0.005	-0.007	-0.015	-0.028	0.015
				(0.012)	(0.008)	(0.006)	(0.010)	(0.026)	(0.029)
Income	Yes	Yes	Yes	-0.010	-0.005	-0.007	-0.021	-0.074	-0.024
				(0.021)	(0.019)	(0.019)	(0.021)	(0.028)	(0.039)

Table 4.2: Regression results for the full sample of countries considering the Polity measure of democracy. The models with covariates include logarithm of population. Regional effect is an indicator variable for the geographic regions presented in Table 3.1. Year effects are included in some models considering Acemoglu et al. (2008) 5-year data. The instrumental variable is trade-weighted world income as in Acemoglu et. al. (2008). Standard errors in parenthesis.

4 Empirical Results In order to facilitate comparisons across model specifications and econometric procedures we present results side-by-side in Table 4.2.[3] The first model consists of the baseline pooled quantile regression for the Polity measure of democracy. It includes a lagged logarithm of GDP per capita and the logarithm of population in the current period. The second model includes the logarithm of GDP, logarithm of population, and five indicators to control for geographic regions. The last model estimated in Table 4.2 provides a direct comparison to Acemoglu et al. (2008) results. We restrict the annual data to be 5-year data and we include, in addition to the controls discussed above, year effects. All variants of the models include an intercept. The estimated coefficients at each of the quantiles are given in the first five columns labeled by the corresponding quantiles τ. The last column labeled "Mean" presents the estimated coefficients of a standard mean regression most closely associated with the quantile regression procedure employed in the corresponding quantile model. Thus, for the pooled quantile regression setup this is just OLS on the entire sample.

4.1 The heterogeneous effect of income on democracy The first question we investigate is whether the effect of income on democracy varies across the vastly different countries which are typically included in such a study from Sub-saharan Africa to Western Europe, each with its own complex set of institutional factors likely to affect the extent to which economic development can influence political development.[4] In particular we wish to investigate whether any evidence exists for the presence of an U-shape relationship between income and democracy, as is often claimed by policy makers who argue that economic development is a potent driver of democratization in "hybrid democracies", that is countries with partially democratic institutions (Epstein et. al., 2006).

In order to investigate this question we shall turn our attention to the evidence de-

[3]As is customary we report standard errors in parenthesis. The standard errors of classical and instrumental variable quantile regression estimators were obtained using standard methods for estimating covariance matrices. The standard errors for the fixed effects and interactive fixed effects estimators were obtained by employing panel-bootstrap methods. We use pair-yx bootstrap, sampling countries with replacement.

[4]In this paper, we focus on one main explanatory variable: income. An earlier version of this paper also explores additional variables such as schooling, economic growth, oil production, ethnicity or religion. We have not found these to affect the results substantively and for reasons of conciseness we are not reporting them here.

rived from the use of quantile regression as introduced above in uncovering the relationship between income and democracy. The pooled quantile regression model for the Polity measure estimates an inverted U-shaped relationship between income and democracy over the quantiles of the democracy distribution. We estimate a coefficient of 0.006 at the $\tau = 0.1$ quantile. The effect increases to 0.262 at the median of the democracy conditional distribution and declines to 0.071 in the right tail of the distribution for $\tau = 0.9$. By contrast the coefficient on lagged GDP per capita is 0.170 if the model is estimated by OLS.

Let us consider the interpretation of these marginal effects. It is immediately apparent that by taking derivatives of the linear model 2.5 with respect to the covariate of interest, we can investigate its impact on the conditional quantile of the response variable. Of course, it is not appropriate to interpret this effect representing the impact of the covariate of interest on the quantiles of the unconditional distribution of the democracy. Thus, strictly speaking it would not be appropriate to derive policy prescriptions for individual countries situated at a given quantile of the world democracy distribution. The effect of economic development has to be considered as conditional on other factors such as population. [5]

The results lean towards providing support for the Epstein et. al. (2006) view that income is a much more potent engine of change in "hybrid democracies". In order to verify that this is indeed a quantile effect and not driven simply by the presence of countries with more unusual characteristics at specific locations within the distribution of democracy we also estimated a number of specifications where we excluded certain countries which may be driving this effect. Thus, we excluded countries in Eastern Europe and the former Soviet Union, certain African countries or Muslim countries. In every case however we obtained a similar inverse U-shape pattern of the estimated coefficients even though the composition of the distribution changed.

The inverse U-shaped relationship was obtained from a pooled quantile regression

[5]Nevertheless in our sample the unconditional and conditional distributions share many similar features. In our working paper version of this manuscript (Alexander, Harding and Lamarche (2008)) we briefly investigate how the marginal effects on the quantiles of the conditional distribution compare to the marginal effects on the unconditional distribution of democracy, considering the approach recently proposed by Firpo, Fortin, and Lemieux (2009). Unfortunately, we can only compare estimates from the simple pooled quantile regression model, because their approach is not generalized to time-series-cross-section data and instrumental variables. The estimated effects of income on the conditional and unconditional distribution of democracy are similar across quantiles, suggesting a relatively invariant inverted U-shaped relationship between income and democracy.

model. We ought to be concerned, however, that the estimated relationship is not econometrically robust due to the inclusion of additional regional factors or due to ignored country specific heterogeneity.

In Table 4.2, we extend the model by adding geographic region effects. This significantly reduces the effect of income on democracy at all quantiles, as one would expect. In the regressions using the Polity measure we see that the estimated inverse U-shaped relationship between income and democracy disappears over the quantiles. The estimated effect is 0.000 at the 0.1 quantile, 0.000 at the 0.5 quantile, and increases to 0.061 at the 0.9 quantile. These findings are relatively similar to the results obtained from using the 5-year data in a model with year effects. The effect of income continues to be negligible at several quantiles, with the exception of the quantiles at the upper tail.

In the next section we discuss different choices of instruments and their relative merits. In Table 4.2, we use the IV Set 1, which corresponds to the trade weighted world income instrument. Using this instrument to account for the potential endogeneity of GDP, we estimate the effect of income on democracy at the previous quantiles. For the Polity measure of democracy, we find that instrumental variable quantile regression results are very similar to the quantile regression results presented above in models without region effects. The estimated inverse U-shaped relationship between income and democracy remains. Thus, the effect of income on democracy falls in the low and high quantiles and is higher at the median. The estimated coefficient on the 0.1 quantile increases from 0.006 to 0.158, while for the median it changes slightly from 0.262 to 0.261. The estimated coefficient at the 0.9 quantile decreases from 0.071 to 0.000.

In order to account for the correlation between income and geography, we include regions effects. As before, the inverted U-shaped relationship disappears, and now the effect at the upper tail is insignificant. (The sole exception is the effect at the lower tail). The model with region and year effects suggests a similar pattern. The effect of income tends to be negligible across the quantiles of the conditional democracy distribution.

To account for unobserved heterogeneity at the country level, we can augment the model by including country specific effects. As we discussed in Section 2.1, in a TSCS data quantile regression model, country effects may imply two different model specifications depending on whether they act as a location shift or distributional shift. The results in Table 4.2 correspond to a location shift model. We notice immediately that the inverse U-shape configuration of the estimated effects disappears altogether. In fact, for the Polity measure in a model with covariates, the estimated coefficients are -0.001 at the $\tau = 0.1$ quantile, -0.005 at the median and -0.074 at the $\tau = 0.9$ quantile. Once we add country effects the estimated relationship between income and democracy disappears at all quantiles, with the exception of the 0.9 quantile. Notice that the mean effect misses important information, because the effect of income on democracy is not negligible at the upper tail.

	Model including							
	Other	Region	Year			Quantiles		
	Covariates	effects	effects	0.10	0.25	0.50	0.75	0.90
			Polity measure - Instrumental Variables Set 2					
Income	Yes	No	No	0.018	0.000	0.284	0.224	0.125
				(0.008)	(0.009)	(0.007)	(0.015)	(0.010)
Income	Yes	Yes	No	0.000	0.000	0.000	0.000	0.000
				(0.017)	(0.022)	(0.035)	(0.052)	(0.043)
Income	Yes	Yes	Yes	0.000	0.000	0.000	0.000	-0.013
				(0.086)	(0.119)	(0.102)	(0.122)	(0.152)
			Polity measure - Instrumental Variables Set 3					
Income	Yes	No	No	0.013	0.000	0.178	0.054	0.000
				(0.013)	(0.016)	(0.041)	(0.033)	(0.014)
Income	Yes	Yes	No	0.072	0.000	0.000	0.000	0.009
				(0.012)	(0.006)	(0.007)	(0.011)	(0.007)
Income	Yes	Yes	Yes	0.000	0.218	0.000	0.189	0.040
				(0.289)	(0.442)	(0.373)	(0.274)	(0.512)

Table 4.3: Sensitivity analysis for the instrumental variables.The second set of instruments includes log of mountainous terrain, geographic latitude, log of air distance to nearest port; the third set includes the five instrumental variables presented in the appendix. The first set of instruments presented in Table 4.2 includes trade-weighted world income as in Acemoglu et. al. (2008). Standard errors in parenthesis.

4.2 Robustness to instrument choice In Table 4.2, we presented the estimation results for the baseline model after we instrument income with the variable considered in Acemoglu et al (2008). In Table 4.3, we extend the analysis to consider two additional sets of instruments. First, we employ geographic variables traditionally associated with economic development. The IV Set 2 includes mountainous terrain, geographic latitude and the distance to the nearest port. Lastly, we use the IV set 3 corresponding to the Global economic factors, and constructed as in Section 7.

Basic statistics of the five factor instruments used are presented in Table 3.1. While it is not necessary nor feasible to interpret the proposed instruments in a concrete economic setting, it is interesting to note that the chosen principal components have similar statistical properties across world regions. The first factor appears to be more important for Western democracies, while the second factor for Sub-saharan African countries. Similarly the fourth factor appears less important for Eastern Europe and the Soviet Union. This is consistent with the notion that we are capturing global economic factors acting as sources for the transmission of international business cycles while still expecting regional variation in their impact.

In models without regional effects, estimation using the second set of instruments, corresponding to the geographic variables, only replicates the inverted U-shaped relationship as described in the previous section. If we now employ our last set of proposed instruments, we find that the inverted U-shape relationship is also preserved. Once again, the inverted U-shaped relationship between income and democracy disappears when we include indicators to account for effects constant over time and common to all countries within a region. The specifications appear to confirm a negligible effect of income on democracy in the middle range of the democracy distribution. Thus, after implementing three different strategies addressing the potential endogeneity of income, we find higher income not to be an important force for democratization in "hybrid regimes" close to the median of the democracy distribution and to have almost no effect in non-democratic regimes.

4.3 Additional TSCS data results Using Figure 4.2, we present results obtained by all the variants of quantile regression methods presented in Section 2 including time-series-cross-section data approaches. Figure 4.2 (panel (a)) compares the estimated quantile effects of income on democracy between the quantile regression (QR) estimator corresponding to the pooled model, and the instrumental variable (IV S1-3) estimators. We see a clear inverted U-shaped relationship between income and the estimated effect, suggesting that the effect of income varies across the conditional distribution of democracy. The effect of income is negligible at the tails, but it seem to cause a movement toward democracy at the center of the conditional distribution. Figure 4.2 (panel (b)) indicates that this conclusion is incorrect. The inclusion of geographic factors, potentially accounting for omitted variable bias, reduces the effect of income at all quantiles. Most of these income effects obtained from IV models are dramatically reduced. In the panel (c), we employ fixed effects quantile regression (FEQR) estimator for a model with a location shift (LS) and a distributional shift (DS), and fixed effects instrumental variable (IVFE) estimator considering the three sets of instruments (S1-S3). While the first class of estimator addresses unobserved country heterogeneity, the second class of methods is designed to address country heterogeneity and the potential endogeneity of income. Although the results are qualitatively different than the results presented in the middle panel, they lead to the same conclusion. Income does not seem to cause a movement toward democracy.

Panel (c) also suggests that allowing the individual effects α_i's to have a distributional shift does not appear to change the estimated coefficients of income, but does potentially provide us with more information on the heterogeneous impact of the long run country specific factors they are designed to capture. In panel (d), we plot the country effects estimated at different quantiles of the conditional Polity measure distribution. Quantile country effects, which are allowed to vary over the distribution of the dependent variable, are estimated at all quantiles measuring the horizontal distances among country's conditional distributions. Because we estimate a model without intercept and N individual effects, the lines represent estimated horizontal displacements at each quantile of the conditional distribution of democracy. Therefore, the results on the lower tail suggest that the conditional distribution of democracy of other (non-western) countries is shifted "downward" by latent variables that are constant over time, possibly associated to historical factors and institutions. Moreover, the evidence in panel (d) is consistent with the claim that income is particularly ineffective at "shifting" political outcomes in the lower quantiles of the democracy distribution.

5 Implications of the Main Results The previous analysis offer two important implications. First, it suggests that income does not exert a distributional shift on the conditional distribution of democracy. This result is in contrast to the recent work in political science but which nevertheless appears to emphasize the heterogeneous nature of political development at different levels of development. Przeworksi and Limongi (1997) and Przeworski et. al. (2000) argue that countries often become democratic for reasons which do not appear to be connected to income, but once they are democratic more prosperous countries are more likely to remain democratic. Epstein et. al. (2006) highlight the impor-

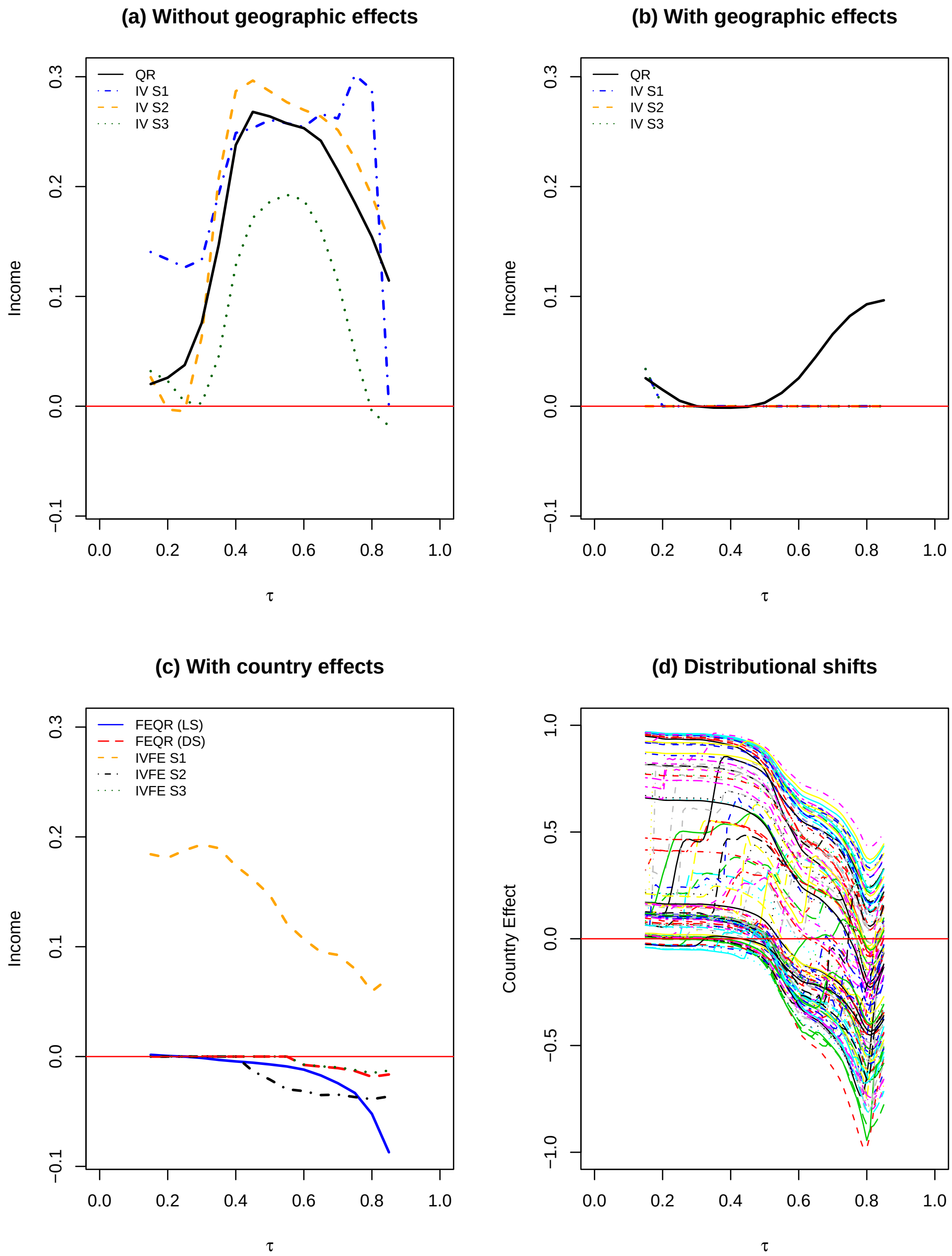

Figure 4.2: Quantile regression estimates of the effect of income on democracy considering the full sample of countries. The panels show point estimates obtained by using quantile regression for the pooled data (QR), instrumental variable with and without fixed effects (IVFE, IV), and quantile regression with fixed effects assuming that the individual effects are either location shifts (LS) or distributional shifts (DS). The instrument sets (S1-S3) are described in Table 3.1.

	Model including		Least Squares Estimation					
	Other	Region	Main Models		Robustness to IV choice			
	Covariates	effects			TSCS		Cross-section	
			(1)	(2)	(3)	(4)	(5)	(6)
Income	Yes	No	0.214	0.263	0.263	0.224	0.181	0.162
			(0.108)	(0.051)	(0.052)	(0.044)	(0.039)	(0.044)
Income	Yes	Yes	0.089	-0.017	-0.165	0.037	0.042	-0.158
			(0.131)	(0.279)	(0.286)	(0.155)	(0.490)	(0.311)
Observations			4735	4640	4640	4640	100	100
Instrument			Set 1	Set 4	Set 5	Set 6	Set 4	Set 5
F statistic	Yes	No	445.3	427.1	403.9	511.8	24.1	19.59
p-value			0.000	0.000	0.000	0.000	0.000	0.000
F statistic	Yes	Yes	425.6	13.75	16.41	59.48	0.220	1.150
p-value			0.000	0.000	0.000	0.000	0.801	0.321

Table 5.4: The effect of income on democracy when regional effects are included in the model. We include logarithm of population, share of population of Muslim religion belief, and indices of ethno-linguistic and religion fractionalizations. IV Set 1 includes includes trade-weighted world income as in Acemoglu et. al. (2008). IV Set 4 includes the first principal component of biological and geographical instruments discussed in Gundlach and Paldam (2009). IV Sets 5 and 6 includes biogeographic variables (Olsson and Hibbs (2005)). While columns (1)-(4) present standard errors clustered by country, columns (5) and (6) present heteroscedastic-robust standard errors.

tance of "partial democracies", countries with fragile democratic status which tend to be volatile and highly heterogeneous. These studies appear to point out varying mechanisms for political development as well as heterogeneous relationship between economic and political development at different stages of democratization. Our results however are consistent with Acemoglu's et al (2008) conditional mean results, suggesting that income does not cause movement toward democracy at different quantiles of the conditional distribution of democracy.

Second, the evidence suggests that it is important to account for omitted variables associated to income. Przeworski et. al. (2000) find that there is a positive association between income and democracy, but it tends to disappear when fixed effects are included in the model. Figure 4.2 suggests that one can address the omitted variable bias simply by adding indicators for geographic regions, which is potentially important for cross-sectional studies.

We illustrate this point by extending the empirical evidence to also consider other conditional mean models recently estimated in the literature. Table 5.4 shows least squares estimation results of the effect of income on democracy, considering the instrument used in Acemoglu et al. (2008) and the instruments used in Gundlach and Paldam (2009) (columns (1) and (2)). Gundlach and Paldam (2009) use the first principal component of biological instruments and geographic instruments, labeled Set 4 in column (2). Additionally, we present results considering other instruments. While Set 5 includes plants and animals as in Olsson and Hibbs (2005), Set 6 includes climate, axis, and latitude as introduced in Olsson and Hibbs (2005). We report in columns (3) and (4) time-series-cross-section data results, and for comparison reasons, we report in columns (5) and (6) results for the year 1991. To avoid biases in terms of precision, we report standard errors clustered by country in time-series-cross-section data models, and robust standard errors in cross sectional specifications.

The results of the first model suggest a positive causal effect from income to democracy, which seem to confirm empirically Lipset's (1959) thesis. Notice however that the result is not robust to the inclusion of controls for geographic regions. The effect of income is reduced and becomes insignificant in all the specifications. The table reveals that the point estimates are reduced from 0.214 to 0.089 in column (1) and from 0.263 to -0.017 in column (2). In the case of cross-sectional data, the point estimates are reduced from 0.181 to 0.042 when we consider the instruments proposed by Gundlach and Paldam (2009). This suggests that their results are not robust to a simple variation in the model. While income is not correlated with democracy in empirical studies using fixed effects, recent studies using standard instrumental variable methods could address the endogeneity of income and the omitted variable bias simply by adding indicators for the regions of the world. This strategy seem to account for omitted variable biases not captured by other control variables, and leads to what it seems to be a unified result that income does not cause democracy.

6 Conclusion This paper introduces quantile regression as a robust, more descriptive statistical method in the analysis of TSCS data. It emphasizes the advantages of a method that allows us to obtain deeper insights into the effect of the regressors on the outcome of interest by allowing for heterogeneous marginal effects across the conditional outcome distribution. The paper shows that the method offers the possibility of addressing endogeneity and different specifications of individual effects. Our analysis has important practical implications for using quantile regression and least squares methods in TSCS data studies and emphasizes the computational ease with which these more advances methods can be implemented by the applied researcher.

From a substantive point of view, this paper reexamines the hypothesis that higher income causes a transition to democracy. We first find that higher income levels have the strongest effects on political development at intermediate levels of democratization and almost no effect in countries at the extremes of the distribution of democracy. This relationship, however, does not survive a number of different identification strategies, disappearing once we account for country specific effects or geographic effects. The evidence also suggests that country effects become less important as a country develops politically towards democracy, which could be interpreted as suggesting that institutions are the key to understand the distance in the political spectrum between authoritarian regimes and liberal democracies. Country-specific effects that include the complex milieu of institutions, historical legacies and culture entirely may explain why countries have authoritarian governments.

7 Appendix It is immediately apparent that one of the main problems we face in estimating the basic model 2.1, is that we need to address the issues of reverse causality. Since the least squares literature offers several standard estimation strategies for the conditional mean model, we focus on the choice of the instrument set and the robustness of the results to different choices.

Trade-Weighted World Income Instrument. As Robinson (2006) remarks, Acemoglu et. al. (2008) are the first ones to propose an instrumental variable approach to the identification of the causal effect of income on democracy. Acemoglu et. al. (2008) use two different instruments for income in their linear specification. The second instrument corresponds to the trade-weighted world income. Let ω_{ij} denote the trade share between country i and j in the GDP of country i between 1980-1989. Then we can write the income of country i at time $t-1$ as,

$$I_{it-1} = \zeta \sum_{j=1, j\neq i}^{N} \omega_{ij} I_{jt-1} + \epsilon_{it-1} \tag{7.1}$$

where income is measured as log of total income and ϵ is a Gaussian error term. Acemoglu et. al. (2008) suggest the use of the weighted sum of world income for each country, $\hat{I}_{it-1}$, as an instrument. Notice that the weights are not estimated but correspond to the actual trade weights. This instrument may be problematic if income in country j, I_{jt-1}, is correlated with democracy in country j which itself is then correlated to democracy in country i. Furthermore, the trade weights, ω_{ij} may be correlated with the relative democracy scores of countries i and j.

Geographic Instruments. While the political science literature on democratization seems to have ignored the potential endogeneity of income in this specification, economics has traditionally stressed differences in geography as a potential determinant of economic development (Acemoglu, Johnson and Robinson, 2001, Sachs and Malaney (2002), Nunn and Puga (2009); see, e.g., Acemoglu, Johnson, and Robinson for a detailed introduction to the geography hypothesis). We will use the log of mountainous terrain, geographic latitude and the log of air distance to the nearest port as instruments.

Global Economic Factors. The world income instrument described above has an appealing interpretation since it is designed to capture the intuition that business cycles are to some extent correlated with events in world markets. A statistical factor model can be employed to recover a set of orthogonal factors that can act as international sources of domestic economic fluctuations (Kose et. al., 2003). These global factors drive, to some extent, the domestic business cycle independently of the political regime of a country. We write,

$$I_{t-1} = \Lambda F_{t-1} + U_{t-1}, \tag{7.2}$$

where I_{t-1} is the observed N dimensional vector of log GDP, F_{t-1} is a p-dimensional vector of global factors and U_{t-1} is a vector of idiosyncratic errors. The coefficient matrix Λ is a matrix of individual specific weights (factor loadings). Since only log GDP is observed we need to use a statistical procedure such as Principal Components Analysis (PCA) applied to the covariance matrix $\Sigma = (1/T)I_{t-1}I'_{t-1}$ to recover the latent factors $\hat{F}_{t-1}$.

By construction, this method separates the commonalities F_{t-1} from the idiosyncratic shocks U_{t-1}. In order to further exclude the possibility that the political regime affects the global factors through its effect on income, we construct different values of the instruments for each country by excluding the country from the analysis. Thus, the instruments for country j correspond to the global factors estimated from the matrix of GDP measures for all the countries in the world except country j.

Bio-Geographic and Climate Diversity Instruments. The economic literature has recently explored the use of a novel set of biogeography variables, which could be associated to the very long run determinants of development (Hibbs and Olsson (2004), Olsson and Hibbs (2005), and Gundlach and Paldam (2009)). The premise is that these variables represent exogenous sources of variation, because they are determined in prehistory. The instrumental variable set considered includes animals (number of big mammals in parts of the world in prehistory) and plants (number of annual perennial grasses in regions of the world in prehistory). An additional instrument set that we will explore includes climate, latitude, and axis (relative east-west orientation of a country). These variables were taken from Olsson and Hibbs (2005). Following Gundlach and Paldam (2009), we use them to create the first principal component of biological and geographical instruments.

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