FIRST GMM ESTIMATES FOR CONVERGENCE DATA

WORKING PAPER

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ABSTRACT

Keywords . · · · ·

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1 General remarks

In the following examples I have used GDP per capita growth as the dependent variable. I have used three types of data: first, the 5-year averages from our original study, secondly, yearly data, and thirdly, 5-year averages as used in Bond *et al.* (2001). The five-year averages we use for the main regressions yield to very long time intervals considered when we talk about differences and lagged differences. [An alternative would be to use only one observation in each 5-year interval (as done in, e.g., Acemoglu *et al.*, 2008). The main motivation for Acemoglu *et al.* (2008) to do so is because the use of averages likely introduces additional autocorrelating that invalidates GMM estimates. In our case, this is, however, not happening so I think we are save to use averages.} Thus, yearly data might be a better alternative, at least to the extent that we do not get too much autocorrelation (at it might be more useful for system GMM than for difference GMM). The data from Bond *et al.* (2001) also uses 5-year intervals, yet here GDP_{t-1} is considered to be the first observation in the 5-year interval and ΔGDP_t the difference in logs over the 5-year interval, i.e. the growth rate. For controls variables I used the average over this interval. The interpretation of the variables is, therefore, a bit different in this context.

In the end, we should decide on the based on the diagnostic tests for the regressions, as reported at the end of each section.

The dimension of the data is given below:.

Type	N	Т	Obs
Yearly data	108	30	3240
5-year averages	108	7	756
Bond-like data	108	6	648

The baseline regression, which might be extended with controls and interactions or adjusted to the estimation technique is:

$$GROWTH_{i,t} = \alpha GROWTH_{i,t-1} + \beta_1 GDPpc_{i,t-1} + \beta_2 ECI_{i,t-1} + \beta_3 KOF_{i,t-1} + \gamma X_{i,t} + \mu_i + \delta_t + u_{it}$$
(1)

with μ_i and δ_t being individual and time fixed effects. The models presented below include the standard (but biased) OLS and *within* models as benchmark, the instrumental variables approach by Anderson & Hsiao (1982), the difference GMM and the system GMM. From what the literature says the latter is most likely the most plausible one, yet the assumptions are strong and carry theoretical assumptions about countries being on their long-term equilibrium path (Blundell & Bond, 1998) - something that one might discuss on a more fundamental level. Also, one might discuss the estimation equation in the sense that growth needs another lag treatment than the other variables since it already is a difference in logs of GDPpc.

In any case, below the results for the different data sets. I do make some comments, but to avoid repetition I do so mainly in the first case.

2 Five-year averages

2.1 Benchmark models: OLS and Within

First, I do the estimations using the five-year averages data we have compiled and that Philipp has used for the 'conventional' panel models. In the following we see basically the standard panel regressions we already did, except that they now contain both country and time fixed effects (see table 1).

Also, I am not sure whether we should use the lag of our openness measure or the contemporaneous value. In the literature one usually says: use contemporaneous value if the variable is strictly endogenous (unlikely, in my view), one lag if it is predetermined (uncorrelated with past, correlated with future errors), and two or more lags if it is endogenous. While we used the contemporaneous value so far, I think the alternatives are more likely to be correct.

We next test whether including a lag of the dependent variable can improve upon the results. Results can be found in table 2.

These results are plausible in the sense that it has been shown that in a dynamic context the *within*-estimator suffers from a downward, and the OLS-estimator from an upward bias for the autoregressive parameter. In all the models above $\alpha_{OLS} > \alpha_{within}$. Any convincing model should yield estimates for α that lie within this corridor (Bond *et al.*, 2001, 145). On top of this, Bond *et al.* (2001); Roodman (2009b) argues that credible estimates are most likely between zero and one since larger values would imply an autoregressive process away from equilibrium values.

2.2 The Anderson-Hsiao instrumental variable estimator

The simplest next step is the IV estimator of Anderson-Hsiao. While consistent it is not very efficient and, therefore, often yields results that might be far of the true values, especially if the model specification is not 100 per cent accurate, or if past level values are poor instruments for present differences. Because the fundamental idea is to estimate the model in differences (to eliminate country specific effects), and then to instrument endogeneous variables with past level values. Thus, for the minimal model specification with GDP, ECI and KOF as explanatory variables we would estimate:

$$\Delta GROWTH_{i,t} = \alpha \Delta GROWTH_{i,t-1} + \beta_1 \Delta GDP_{i,t-1} + \beta_2 \Delta ECI_{i,t-1} + \beta_3 \Delta KOF_{i,t-1} + \Delta \delta_t + \Delta v_{it}$$

¹If this is not the case, Bond *et al.* (2001) suggests to re-think the reference to an AR(1) process and consider more lags, or a different model altogether.

Table 1

	ruore r			
		Depender	ıt variable:	
		GDP_p	c_growth	
	(1)	(2)	(3)	(4)
lag(Penn_GDP_PPP_log, 1)	-7.584*** (0.647)	-7.658*** (0.649)	-7.951*** (0.654)	-8.528*** (0.657)
lag(eci, 1)	-1.119** (0.526)	-0.933^* (0.528)	6.591** (2.765)	7.402*** (2.727)
lag(kof_econ, 1)	-0.015 (0.031)	-0.017 (0.030)	-0.005 (0.031)	-0.002 (0.030)
popgrowth		-0.548** (0.226)	-0.594*** (0.225)	-0.487** (0.223)
humancapital				7.765*** (1.809)
inv_share		0.049* (0.029)	0.033 (0.029)	0.034 (0.029)
$lag(Penn_GDP_PPP_log, 1) \times lag(eci, 1)$			-0.900*** (0.325)	-1.056*** (0.321)
Observations	647	647	647	647
R^2	0.212	0.224	0.235	0.261
Adjusted R ²	0.041	0.052	0.064	0.094
Note:		*p<	0.1; **p<0.05	5; ***p<0.01

Since at least $\Delta GROWTH_{i,t-1} = GROWTH_{i,t} - GROWTH_{i,t-1}$ is endogenous since it is correlated with $\Delta v_{it} = v_{it} - v_{i,t-1}$ by construction, we need instruments. The suggestions of Anderson & Hsiao (1982) were to use either $\Delta GROWTH_{i,t-2} = GROWTH_{i,t-2} - GROWTH_{i,t-3}$ or $GROWTH_{i,t-2}$. The advantage of the first choice is that it is less costly in terms of observations, however, past levels are less likely to be correlated with current changes, so the second option is more likely to produce good instruments. Only considering the immediate results for the minimal model tend to confirm this:

Table 2: Dynamic panel (5-year averages)

(1) 0.200*** (0.034) 0.726*** (0.219) 0.427** (0.209) 0.043***	(2) 0.124*** (0.034) -8.280*** (0.660) -0.950* (0.521) 0.002	(3) 0.167*** (0.033) -1.220*** (0.228) 0.070 (0.215)	(4) 0.128*** (0.035) -8.429*** (0.666) -0.772	c_growth (5) 0.156*** (0.033) -1.541*** (0.240) 5.402***	(6) 0.115*** (0.035) -8.557*** (0.668) 4.527	(7) 0.139*** (0.033) -2.222*** (0.278)	(8) 0.088** (0.035) -8.958*** (0.668)
0.200*** (0.034) 0.726*** (0.219) 0.427** (0.209) 0.043***	0.124*** (0.034) -8.280*** (0.660) -0.950* (0.521)	0.167*** (0.033) -1.220*** (0.228) 0.070	0.128*** (0.035) -8.429*** (0.666) -0.772	0.156*** (0.033) -1.541*** (0.240)	0.115*** (0.035) -8.557*** (0.668)	0.139*** (0.033) -2.222*** (0.278)	0.088** (0.035) -8.958*** (0.668)
(0.034) 0.726*** (0.219) 0.427** (0.209) 0.043***	(0.034) -8.280*** (0.660) -0.950* (0.521)	(0.033) -1.220*** (0.228) 0.070	(0.035) -8.429*** (0.666) -0.772	(0.033) -1.541*** (0.240)	(0.035) -8.557*** (0.668)	(0.033) -2.222*** (0.278)	(0.035) -8.958*** (0.668)
(0.219) 0.427** (0.209) 0.043***	(0.660) -0.950* (0.521)	(0.228) 0.070	(0.666) -0.772	(0.240)	(0.668)	(0.278)	(0.668)
(0.209) 0.043***	(0.521)			5.402***	4 527	C 0 10 date:	
	0.002		(0.522)	(1.357)	(2.791)	6.048*** (1.342)	5.607** (2.771)
(0.013)	(0.030)	0.045*** (0.013)	0.0001 (0.030)	0.057*** (0.013)	0.007 (0.030)	0.044*** (0.014)	0.007 (0.030)
		-0.712*** (0.159)	-0.626*** (0.224)	-0.724^{***} (0.157)	-0.650^{***} (0.224)	-0.507*** (0.162)	-0.539** (0.223)
						2.223*** (0.477)	6.959*** (1.834)
		0.097*** (0.021)	0.034 (0.029)	0.092*** (0.021)	0.025 (0.029)	0.088*** (0.021)	0.028 (0.029)
				-0.567^{***} (0.143)	-0.636^* (0.329)	-0.663*** (0.142)	-0.820^{**} (0.328)
5.265*** (1.617)		9.729*** (1.714)		12.559*** (1.838)		13.932*** (1.833)	
646 0.072 0.066	646 0.235 0.068	646 0.123 0.114	646 0.248 0.080	646 0.144 0.134	646 0.253 0.084	646 0.172 0.162	646 0.273 0.107
5.2	265*** 1.617) 646	265*** 1.617) 646 646 0.072 0.235	-0.712*** (0.159) 0.097*** (0.021) 265*** 1.617) 9.729*** (1.714) 646 646 646 0.072 0.235 0.123	-0.712*** -0.626*** (0.159)	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

Note:

*p<0.1; **p<0.05; ***p<0.01

	Dependen	t variable:
	diff(GDP_	pc_growth)
	Level instruments	Diff instruments
	(1)	(2)
lag(diff(GDP_pc_growth), 1)	-0.392	-0.104
	(0.425)	(0.080)
lag(diff(Penn_GDP_PPP_log), 1)	-29.923	-14.544***
	(22.382)	(1.011)
lag(diff(eci), 1)	-19.825	-0.433
	(19.171)	(0.769)
lag(diff(kof_econ), 1)	-0.665	-0.016
	(0.594)	(0.040)
Observations	537	429
\mathbb{R}^2	0.169	0.409
Adjusted R ²	0.156	0.399
Note:	*p<0.1; **p	<0.05; ***p<0.01

The model using levels as instruments is not even significant as a whole (p value of joint F test: 0.27). But irrespective of these considerations, the estimator, while consistent, is likely to perform poorly in practice given its lack of efficiency. Also, it is sensitive to specification issues. This is evident in the results for our case, shown in table 3

This estimator could be expected to yield intermediate results between the OLS and the *within*-estimator. The minimal and full model have α in the expected range, yet standard errors are considerable Also, I am not sure how to instrument for interaction effects. Of course, one could experiment a bit more with the specification, e.g. using contemporaneous differences for ECI and KOF, to lag the further explanatory variables (depends on our assessment of their degree of endogeneity), etc. Note that in the present version I instrumented ECI, KOF, GROWTH and GDP with the past differences, but did not instrument the remaining explanatory variables. This is also one could discuss. Also, one could add the typical diagnostics, e.g. instrument relevance. Instrument validity cannot be tested in the Anderson-Hsiao framework since the system of instruments is exactly identified. It can be tested in the GMM framework below, however.

2.3 Difference GMM

As indicated above, the Anderson-Hsiao estimator is consistent but inefficient. It wastes potential instruments and by having its estimates exactly identified by using the same number of instruments than regressors, it does not allow to test instrument validity. The Differente-GMM estimator can be seen as an extension of the Anderson-Hsiao approach that takes into account longer lags as additional instruments and allows for more flexibility in estimating the variance-covariance matrix. In sum, I think, there is little reason to prefer the Anderson-Hsiao approach over Diff-GMM in theory, but the latter also has a considerable degrees of freedom (i.e. one can make many mistakes), and it is not clear whether its small sample properties of the Diff-GMM really exceed those of the Anderson-Hsiao estimator in all circumstances. This is relevant since the small sample properties are particularly poor when the time series involced are persistent - which is the case for our application.

I do not delve into the details of GMM here. The estimates are in table 4. I want to stress, however, that there are numerous decisions that we may discuss, e.g.:

Table 3: Anderson-Hsiao IV (5-year averages)

		Dependent var	iable:
	d	iff(GDP_pc_g	rowth)
	(1)	(2)	(3)
lag(diff(GDP_pc_growth), 1)	0.182 (0.257)	2.354 (13.121)	1.111 (3.023)
lag(diff(Penn_GDP_PPP_log), 1)	-8.590 (7.808)	12.418 (149.716)	-3.438 (51.429)
lag(diff(eci), 1)	3.685 (10.422)	-15.082 (169.014)	14.413 (85.809)
lag(diff(kof_econ), 1)	0.179 (0.273)	0.814 (5.711)	
lag(diff(eci) *diff(Penn_GDP_PPP_log), 1)		783.106 (4,716.130)	
lag(diff(kof_econ))			0.535 (2.338)
diff(popgrowth)	-0.412 (0.716)	26.471 (160.955)	11.443 (35.531)
diff(inv_share)	-0.017 (0.092)	-0.323 (2.049)	-0.055 (0.629)
diff(humancapital)			-55.590 (186.497)
$lag(diff(Penn_GDP_PPP_log), 1) \times lag(diff(eci), 1)$			383.931 (1,171.723)
Observations	429	429	429
R ² Adjusted R ²	0.143 0.125	0.019 -0.004	$0.008 \\ -0.018$
Note:		<0.1; **p<0.0	

- How many lags should be used as GMM (i.e. internal) instrumtens? I have used lags 3 to 8 for the lagged dependent and for the main explanatory variables; control variables were not instrumented at all (I started with lag 3 because otherwise the Sargan test below had too low p values).
- Which variables should be instrumented at all? I have used GMM instruments the main explanatory variables, yet one may also use 'proper' instruments for some of them or not or more...
- I did not instrument the interaction term
- I followed that at least in my view superior approach to use collapsed instrument matrices and the two-step estimation procedure
- One would need to correct standard errors using the Windmeijer (2005)-correction, resulting in larger standard errors. I did not do this for these cases yet.
- Probably many more points to be discussed....

Fällt halt auch alles nicht in die Range in die es fallen sollte... und man kann noch mehr und systematischer mit den Lags herumarbeiten um hier überall gut abzuschneiden. Das wäre schon wichtig, weil: "Testing whether the Diff-GMM estimates fall into the range between OLS and the within estimator is crucial since Bond *et al.* (2001) show that the Diff-GMM might suffer from finite sample bias if the time series involved are persistent. To test whether the resulting estimate lies between the OLS and within estimate, thus, serves as an indication for the potential presence of such finite sample bias."

Table 4: Difference GMM (5-year averages)

		Depende	nt variable:	
		GDP_p	c_growth	
	(1)	(2)	(3)	(4)
lag(GDP_pc_growth, 1)	-0.281 (0.176)	-0.306* (0.166)	-0.038 (0.132)	-0.096 (0.125)
lag(Penn_GDP_PPP_log, 1)	-20.551*** (5.298)	-22.786*** (5.182)	-18.265*** (3.602)	-18.329*** (3.774)
lag(eci, 1)	1.824 (3.170)	2.248 (3.446)	-20.566* (11.621)	-21.409* (12.084)
lag(kof_econ, 1)	-0.598** (0.269)	-0.663** (0.296)	-0.430*** (0.166)	-0.425** (0.169)
popgrowth		-0.769 (0.776)	-0.587** (0.246)	-0.466^* (0.256)
inv_share		-0.024 (0.070)	0.019 (0.072)	0.020 (0.069)
humancapital				10.323*** (3.936)
lag(eci *Penn_GDP_PPP_log, 1)			2.915** (1.259)	2.971** (1.307)
Observations	108	108	108	108
Note:		*1	o<0.1; **p<0.0	05; ***p<0.01

Hier noch ein paar Punkte zu diagnostic tests:

- Weil wir in Differenzen schätzen, sollte der Arellano-Bond Autokorrelationstest auf Autokorrelation zweiter Ordnung einen möglichst hohen p-Wert haben
- Der p-Wert für den Sargan Test kann nicht groß genug sein
- Man könnte noch ein paar weitere Tests machen, aber das würde ich nur für die Spezifikationen machen, die wir am Ende tatsächlich verwenden

Hier die Übersicht der Tests für die Spezifikationen oben. Alle Werte sind p-Werte. Beim Arellano-Bond test geht es um zweiten Grad Autokorrelation, beim Sargan-Hansen test um Instrumentenvalidität. In beiden Fällen wollen wir bei guter Spezifikation hohe p-Werte sehen.

Modell	Arellano-Bond	Sargan-Hansen
Minimal (1)	0.844	0.265
Sparse (2)	0.702	0.209
Sparse w/ itct. (3)	0.417	0.105
Full (4)	0.417	0.105

Das bedeutet, dass zumindest die volleren Modelle so gar nicht gehen.

2.4 System GMM

The last model is in principle the one that should be preferred for the estimation of growth models (Bond *et al.*, 2001). At the same time, it also comes with strong assumptions, especially on the situation in the first period of observation, where

countries should already be on their equilibrium path (Blundell & Bond, 1998; Roodman, 2009a). The simulations in Roodman (2009a) are very illustrative on this.

The idea of the system GMM is to address the problem of potentially weak instruments, low efficiency and strong small sample bias of the difference GMM by estimating the model not only in differences but also in levels. This brings more moment conditions and potentially stronger instruments. It is the the estimator that most current studies use that deal with questions comparable to ours.

Table 5 shows the results. The diagnostics are below. It is clear that we need to tailor the specification considerably, still. It might well be because of the interaction term. I have not come across a single GMM study with an interaction term.

Table 5: System GMM (5-year averages)

(1)	(2)	oc_growth (3)	(4)
0.308***		(3)	(4)
			(4)
(0.054)	0.272*** (0.060)	0.193*** (0.073)	0.187*** (0.065)
-1.950* (1.100)	-1.437 (0.937)	-0.876 (0.852)	-2.150 (1.640)
0.957 (0.966)	0.344 (1.128)	8.567* (4.623)	5.777 (5.779)
0.012 (0.052)	0.013 (0.051)	0.012 (0.061)	-0.014 (0.060)
	-0.570 (0.474)	-0.562 (0.371)	-0.340 (0.255)
	0.091* (0.055)	0.104** (0.052)	0.106* (0.055)
			3.447 (2.664)
		-1.019** (0.512)	-0.730 (0.626)
108	108	108	108
	(1.100) 0.957 (0.966) 0.012 (0.052)	(1.100) (0.937) 0.957 0.344 (0.966) (1.128) 0.012 0.013 (0.052) (0.051) -0.570 (0.474) 0.091* (0.055)	(1.100) (0.937) (0.852) 0.957 0.344 8.567* (0.966) (1.128) (4.623) 0.012 0.013 0.012 (0.052) (0.051) (0.061) -0.570 -0.562 (0.474) (0.371) 0.091* 0.104** (0.055) (0.052) -1.019** (0.512)

Modell	Arellano-Bond (1)	Arellano-Bond (2)	Sargan-Hansen
Minimal (1)	0.001	0.034	0.094
Sparse (2)	0.002	0.065	0.043
Sparse w/ itct. (3)	0.006	0.040	0.012
Full (4)	0.006	0.040	0.012

3 Yearly data

At this stage I replicate the same estimations as in the section before with the yearly data. The interpretation remains largely the same:

3.1 Benchmark models

		Depende	nt variable:	
		GDP_p	c_growth	
	(1)	(2)	(3)	(4)
lag(Penn_GDP_PPP_log, 1)	-3.647*** (0.556)	-3.739*** (0.556)	-3.979*** (0.560)	-4.635*** (0.580)
lag(eci, 1)	-0.623 (0.399)	-0.633 (0.398)	6.319*** (2.194)	7.441*** (2.205)
lag(kof_econ, 1)	-0.035 (0.023)	-0.038^* (0.023)	-0.021 (0.024)	-0.018 (0.023)
popgrowth		-0.464** (0.181)	-0.497^{***} (0.181)	-0.419** (0.182)
humancapital				6.652*** (1.588)
inv_share		0.073*** (0.022)	0.064*** (0.022)	0.068*** (0.022)
lag(Penn_GDP_PPP_log, 1) × lag(eci, 1)			-0.831*** (0.258)	-0.988*** (0.260)
Observations	3,089	3,089	3,089	3,089
R^2 Adjusted R^2	0.016 -0.030	0.021 -0.025	0.025 -0.022	0.031 -0.016
Note:		*p<	0.1; **p<0.05	5; ***p<0.01

We next test whether including a lag of the dependent variable can improve upon the results. Results can be found in table 6.

3.2 Anderson-Hsiao

We check again the level lag and diff lag version:

Table 6: Dynamic panel (yearly data)

				Depende	Dependent variable:			
				GDP_1	GDP_pc_growth			
	(1)	(2)	(3)	(4)	(5)	(9)	(7)	(8)
lag(GDP_pc_growth, 1)	0.231*** (0.018)	0.189^{***} (0.018)	0.215^{***} (0.018)	0.184^{***} (0.018)	0.209^{***} (0.018)	0.180^{***} (0.018)	0.207^{***} (0.018)	0.177*** (0.018)
lag(Penn_GDP_PPP_log, 1)	-0.310* (0.167)	-4.892^{***} (0.556)	-0.779^{***} (0.178)	-4.980^{***} (0.555)	-1.017^{***} (0.188)	-5.105^{***} (0.558)	-1.560^{***} (0.228)	-5.760^{***} (0.576)
lag(eci, 1)	0.125 (0.160)	-0.238 (0.391)	-0.211 (0.167)	-0.236 (0.391)	3.798*** (1.068)	4.486** (2.141)	4.250*** (1.070)	5.631*** (2.151)
lag(kof_econ, 1)	0.032^{***} (0.010)	-0.020 (0.022)	0.033*** (0.010)	-0.023 (0.022)	0.042***	-0.012 (0.023)	0.034^{***} (0.011)	-0.010 (0.023)
popgrowth			-0.713^{***} (0.123)	-0.612^{***} (0.181)	-0.711^{***} (0.122)	-0.632^{***} (0.181)	-0.558^{***} (0.127)	-0.548*** (0.181)
humancapital							1.639*** (0.389)	6.667*** (1.541)
inv_share			0.082^{***} (0.016)	0.051** (0.021)	0.079***	0.045^{**} (0.021)	0.079***	0.050** (0.021)
$lag(Penn_GDP_PPP_log,\ 1) \times lag(eci,\ 1)$					-0.423^{***} (0.111)	-0.565** (0.252)	-0.489*** (0.112)	-0.726^{***} (0.254)
Constant	3.049** (1.242)		6.647*** (1.349)		8.739*** (1.454)		10.057*** (1.483)	
Observations R ² Adjusted R ²	3,059	3,059 0.051 0.006	3,059 0.075 0.073	3,059 0.057 0.011	3,059 0.079 0.077	3,059	3,059 0.084 0.082	3,059
Note:)>d*	p<0.1; **p<0.05; ***p<0.01	; *** p<0.01

	Dependent variable:		
	diff(GDP_	pc_growth)	
	Level instruments	Diff instruments	
	(1)	(2)	
lag(diff(GDP_pc_growth), 1)	-0.078	0.008	
	(0.334)	(0.030)	
lag(diff(Penn_GDP_PPP_log), 1)	-65.622	-77.216***	
	(117.151)	(2.888)	
lag(diff(eci), 1)	-2.858	0.637	
	(12.373)	(0.513)	
lag(diff(kof_econ), 1)	-0.332	0.135***	
	(1.432)	(0.049)	
Observations	2,928	2,801	
\mathbb{R}^2	0.368	0.387	
Adjusted R ²	0.361	0.380	
Note:	*p<0.1; **p	<0.05; ***p<0.01	

Again, the difference version seems to be superior, although this time both models are significant as a whole. Thus, table 7 contains results for the difference lags.

This does not mean, however, that results are more plausible than above.

3.3 Difference GMM

Estimates can be found in table 8. The diagnostics are below and they do look much better than above.

Modell	Arellano-Bond	Sargan-Hansen
Minimal (1)	0.944	0.303
Sparse (2)	0.778	0.334
Sparse w/ itct. (3)	0.764	0.518
Full (4)	0.764	0.518

3.4 System GMM

Estimates are in table 13, diagnostics below:

Modell	Arellano-Bond (1)	Arellano-Bond (2)	Sargan-Hansen
Minimal (1)	0	0.988	0.002
Sparse (2)	0	0.779	0.001
Sparse w/ itct. (3)	0	0.757	0.016
Full (4)	0	0.757	0.016

4 Bond data

The specification of the regression equation and interpretation of the data is a bit different in this case. The model estimated by Bond *et al.* (2001) is a bit different to ours since they do not control for the actual per capita income level

Table 7: Anderson-Hsiao IV (yearly data)

		Dependent vario	able:
	di	ff(GDP_pc_gre	owth)
	(1)	(2)	(3)
lag(diff(GDP_pc_growth), 1)	-0.717 (4.832)	-0.181 (0.669)	-0.171 (0.622)
lag(diff(Penn_GDP_PPP_log), 1)	-159.068 (897.907)	-56.085 (130.776)	-56.209 (126.064)
lag(diff(eci), 1)	19.505 (111.380)	0.269 (9.805)	0.522 (9.452)
lag(diff(kof_econ), 1)	43.717 (263.101)	12.931 (30.941)	
lag(diff(kof_econ))			12.431 (28.757)
diff(popgrowth)	2.114 (13.200)	0.391 (2.345)	0.420 (2.280)
diff(inv_share)	-1.020 (5.921)	-0.418 (0.866)	-0.402 (0.803)
diff(humancapital)			40.465 (96.154)
$lag(diff(Penn_GDP_PPP_log), 1) \times lag(diff(eci), 1)$		651.588 (1,146.504)	625.563 (1,053.068)
Observations	2,801	2,801	2,801
R^2 Adjusted R^2	0.026 0.014	0.028 0.017	0.029 0.017
Note:		$\frac{0.017}{<0.1; **p<0.0}$	

(which is why I removed β_1 from the equation below). Starting from

$$\ln(GDPpc_{i,t}) - \ln(GDPpc_{i,t-1}) = \alpha \ln(GDPpc_{i,t-1}) - \ln(GDPpc_{i,t-1}) + \beta_2 ECI_{i,t-1} + \beta_3 KOF_{i,t-1} + \gamma X_{i,t} + \mu_i + \delta_t + u_{it}$$

and assuming $y_{it} = \alpha y_{it-1}$ one gets:

$$\Delta \ln(GDPpc_{i,t}) = (\alpha - 1) \ln(GDPpc_{i,t-1}) + \beta_2 ECI_{i,t-1} + \beta_3 KOF_{i,t-1} + \gamma X_{i,t} + \mu_i + \delta_t + u_{it} GROWTH_t = (\alpha - 1) \ln(GDPpc_{i,t-1}) + \beta_2 ECI_{i,t-1} + \beta_3 KOF_{i,t-1} + \gamma X_{i,t} + \mu_i + \delta_t + u_{it}$$
(2)

In their formulation $GDPpc_{i,t-1}$ refers to the value in the first year of the same five-year interval, for which $GROWTH_t$ denotes the overall growth. Correspondingly, $ECI_{i,t-1}$ and $KOF_{i,t-1}$ are the values at the beginning of a five-year interval. The controls in X_t are the means over the interval.

Table 8: Difference GMM (yearly data)

	Dependent variable:				
		GDP_p	c_growth		
	(1)	(2)	(3)	(4)	
lag(GDP_pc_growth, 1)	0.132 (0.145)	0.089 (0.151)	0.204 (0.140)	0.197 (0.140)	
lag(Penn_GDP_PPP_log, 1)	-23.097*** (6.885)	-23.911*** (6.721)	-18.259*** (4.565)	-18.998*** (4.916)	
lag(eci, 1)	3.724 (2.428)	4.102 (2.668)	-1.287 (10.369)	-0.434 (10.228)	
lag(kof_econ, 1)	0.403** (0.199)	0.394* (0.202)	0.308** (0.156)	0.307** (0.156)	
popgrowth		-0.361 (0.323)	-0.453 (0.309)	-0.458 (0.305)	
inv_share		-0.045 (0.100)	-0.051 (0.090)	-0.049 (0.090)	
humancapital				4.779 (4.966)	
lag(eci *Penn_GDP_PPP_log, 1	.)		0.517 (1.263)	0.412 (1.241)	
Observations	108	108	108	108	

Table 9: System GMM (yearly data)

		Depend	lent variable:	
		GDP_	_pc_growth	
	(1)	(2)	(3)	(4)
lag(GDP_pc_growth, 1)	0.203*** (0.043)	0.238*** (0.042)	0.180*** (0.044)	0.182*** (0.043)
lag(Penn_GDP_PPP_log, 1)	1.460 (1.881)	1.449 (1.267)	0.209 (1.200)	1.057 (1.691)
lag(eci, 1)	1.578 (2.589)	-1.001 (2.204)	18.630** (7.627)	17.455** (7.521)
lag(kof_econ, 1)	0.175 (0.139)	0.010 (0.119)	0.173 (0.119)	0.184 (0.130)
popgrowth		0.151 (0.665)	-0.127 (0.572)	-0.507 (0.375)
inv_share		0.005 (0.076)	-0.002 (0.087)	0.020 (0.071)
humancapital				-2.644 (3.506)
lag(eci *Penn_GDP_PPP_log, 1)) 		-2.277*** (0.834)	-2.147*** (0.811)
Observations	108	108	108	108
Note:		*p<	0.1; **p<0.05	; ***p<0.01

4.1 Benchmark models

In some sense there is no immediate equivalent to the non-dynamic panels estimated above since Bond *et al.* (2001) interpret the data to be a dynamic panel simply because of the relationship between growth and GDP per capita level from the previous period. Thus, it makes less sense to include a 'true' autoregressive variable $\Delta \ln(GDPpc_{i,t-1})$ into their model. Although this is certainly something one might discuss. The results for the benchmark thus interpreted can be found in table 10.

4.2 Anderson-Hsiao

We check again the level lag and diff lag version, although I find this logic difficult to be apply to the bond data. The difference of growth on the LHS is now the difference between growth rates in two periods, and the difference in lagged values the difference between starting values of two periods. I am not sure whether we should always use one lag more when taking differences. Notably, Bond *et al.* (2001) do not implement this estimator at all.

	Dependen	t variable:
	diff(GDP _T	oc_growth)
	Level instruments	Diff instruments
	(1)	(2)
diff(GDPpc_first)	-2.579	-1.206***
	(3.026)	(0.356)
diff(eci_first)	-1.056	0.038
	(1.657)	(0.207)
diff(kof_econ_first)	-0.035	-0.019
	(0.043)	(0.031)
Observations	538	431
\mathbb{R}^2	0.237	0.383
Adjusted R ²	0.227	0.374
Note:	*p<0.1; **p	<0.05; ***p<0.01

The difference version seems to be superior. The test for joint significance of all regressors of the difference versions has a p-value of 0.003, while the levels version performs extremely poorly (p value of 0.647). Thus, table 11 contains results for the difference lags.

These results are indeed *very* disappointing, so we might discuss the logic in a bit more depth.

4.3 Difference GMM

Estimates can be found in table 12. The diagnostics are below. As before, the tests are not very convincing, and more discussion about the specification is needed.

Modell	Arellano-Bond	Sargan-Hansen
Minimal (1)	0.996	0.081
Sparse (2)	0.989	0.093
Sparse w/ itct. (3)	0.608	0.008
Full (4)	0.608	0.008

4.4 System GMM

Estimates are in table 13, diagnostics below:

Table 10: Dynamic panel (Bond data)

				Depende	Dependent variable:			
				GDPpc	GDPpc_growth			
	(1)	(2)	(3)	(4)	(5)	(9)	(7)	(8)
GDPpc_first	-0.033*** (0.011)	-0.373*** (0.031)	-0.052*** (0.012)	-0.364*** (0.031)	-0.066*** (0.012)	-0.369*** (0.031)	-0.108*** (0.014)	-0.404*** (0.032)
eci_first	0.029*** (0.010)	-0.023 (0.025)	0.020* (0.011)	-0.028 (0.025)	0.264*** (0.069)	0.110 (0.132)	0.298*** (0.068)	0.148 (0.129)
kof_econ_first	0.002^{***} (0.001)	0.001 (0.001)	0.002*** (0.001)	0.001 (0.001)	0.002^{***} (0.001)	0.001 (0.001)	0.002** (0.001)	0.001 (0.001)
popgrowth_mean			-0.016^* (0.008)	0.030^{**} (0.012)	-0.017^{**} (0.008)	0.029** (0.012)	-0.004 (0.008)	0.036*** (0.012)
invshare_mean			0.004^{***} (0.001)	0.003** (0.001)	0.004^{***} (0.001)	0.003**	0.004^{***} (0.001)	0.003** (0.001)
humancapital_mean							0.134*** (0.025)	0.439*** (0.094)
$GDPpc_first \times eci_first$					-0.026^{***} (0.007)	-0.016 (0.015)	-0.031^{***} (0.007)	-0.024 (0.015)
Constant	0.272*** (0.079)		0.375***		0.496*** (0.093)		0.585*** (0.092)	
Observations	647	647	646	646	646	646	646	646
Adjusted \mathbb{R}^2	0.023	0.040	0.048	0.058	0.065	0.058	0.105	0.093
Note:		2					$\sum_{k} \nabla_{\mathbf{q}} ^{2}$	p<0.1;

Table 11: Anderson-Hsiao IV (Bond data)

	Depe	Dependent variable:		
	diff(C	DPpc_gro	wth)	
	(1)	(2)	(3)	
diff(GDPpc_first)	-1.155*** (0.412)	-0.531 (0.882)	-0.535 (0.780)	
diff(eci_first)	-0.035 (0.267)	0.824 (1.910)	0.804 (1.391)	
diff(kof_econ_first)	-0.018 (0.027)	-0.016 (0.042)	-0.016 (0.045)	
diff(popgrowth_mean)	0.043 (0.055)	-0.142 (0.421)	-0.138 (0.324)	
diff(invshare_mean)	-0.001 (0.004)	-0.004 (0.005)	-0.004 (0.005)	
diff(humancapital_mean)			-0.042 (1.070)	
$diff(GDPpc_first) \times diff(eci_first)$		-2.683 (5.131)	-2.635 (3.877)	
Observations	430	430	430	
R ² Adjusted R ²	0.405 0.394	0.186 0.168	0.190 0.171	
Note:	*p<0.1; **	p<0.05; *	**p<0.01	

Table 12: Difference GMM (Bond data)

		Depender	ıt variable:	
		GDPpc	growth	
	(1)	(2)	(3)	(4)
GDPpc_first	-0.419** (0.201)	-0.455** (0.186)	-0.300** (0.143)	-0.300** (0.139)
eci_first	0.154 (0.200)	0.236 (0.168)	0.528 (0.480)	0.636 (0.490)
kof_econ_first	-0.007 (0.007)	-0.004 (0.006)	-0.0005 (0.005)	-0.001 (0.005)
popgrowth_mean		0.048 (0.032)	0.066* (0.036)	0.066* (0.039)
invshare_mean		0.002 (0.004)	0.004 (0.004)	0.003 (0.004)
humancapital_mean				0.369* (0.188)
GDPpc_first × eci_first			-0.061 (0.054)	-0.074 (0.055)
Observations	108	108	108	108
Note:		*p<0.	1; **p<0.05;	***p<0.01

Table 13: System GMM (yearly data)

		\ \	•	
		Depende	ent variable:	
		GDPp	c_growth	
	(1)	(2)	(3)	(4)
GDPpc_first	-0.046 (0.071)	-0.093 (0.098)	-0.021 (0.048)	-0.116 (0.084)
eci_first	0.068 (0.056)	0.148 (0.094)	0.998** (0.414)	0.535 (0.436)
kof_econ_first	-0.002 (0.003)	-0.001 (0.004)	0.005 (0.004)	-0.001 (0.004)
popgrowth_mean		0.010 (0.044)	0.027 (0.023)	0.003 (0.022)
invshare_mean		0.003 (0.003)	0.0001 (0.003)	0.004 (0.003)
humancapital_mean				0.146 (0.154)
GDPpc_first × eci_first			-0.110^{**} (0.045)	-0.056 (0.046)
Observations	108	108	108	108
Note:		*p<0.1;	**p<0.05; **	**p<0.01

Modell	Arellano-Bond (1)	Arellano-Bond (2)	Sargan-Hansen
Minimal (1)	NaN	0.527	0.009
Sparse (2)	0	0.390	0.029
Sparse w/ itct. (3)	0	0.318	0.012
Full (4)	0	0.318	0.012

Note: I do not think the AR(1) test is meaningful here, yet the results are crap due to the Sargan-Hansen test anyways...

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