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Dynamic Panel Analysis under Cross-Sectional Dependence

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This article investigates inconsistency and invalid statistical inference that often characterize dynamic panel analysis in international political economy. These econometric concerns are tied to Nickell bias and cross-sectional dependence. First, we discuss how to avoid Nickell bias in dynamic panels. Second, we put forward factor-augmented dynamic panel regression as a means for addressing cross-sectional dependence. As a specific application, we use our methods for an analysis of the impact of terrorism on economic growth. Different terrorism variables are shown to have no influence on economic growth for five regional samples when Nickell bias and cross-dependence are taken into account. Our finding about terrorism and growth is contrary to the extant literature.

1 Introduction

Dynamic panel analysis is a prevalent methodology in international relations, international political economy, and other areas of political science. For example, dynamic panel analysis are used to discern the impact of globalization on transnational terrorism (Li and Schaub 2004), the effect of government ideology on military spending (Whitten and Williams 2001), the influence of a dominant state on the military burdens of subordinate states (Lake 2007), the diffusion of democracy to neighboring states (Brinks and Coppedge 2006), the effects of globalization on the welfare state (Garrett and Mitchell 2001), or the determinants of militarized interstate disputes (Green, Kim, and Yoon 2001). These and many other applications in international political economy are investigated with time-series, cross-sectional panels with a lagged dependent variable. Another recent example includes an analysis of the effects of terrorism on economic growth (Blomberg, Hess, and Orphanides 2004; Tavares 2004; Gaibulloev and Sandler 2008, 2009). Surely, the application of dynamic panel will grow in importance, because relationships involving the dependent variable and its past values are relevant when analyzing investment behavior (e.g., foreign direct investment), financial crises, bilateral trade, and conflict.

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Dynamic panel analysis often suffers from two econometric concerns—inconsistency and invalid statistical inference. These concerns are tied to Nickell (1981) bias, which arises from dynamic models with fixed effects. In addition, these issues may stem from cross-sectional dependence, where cross-country observations are influenced by common considerations. This dependence may arise because countries respond to similar political, economic, or spatial stimuli. For instance, transnational terrorism is shown to display considerable cross-country dependence presumably because of terrorist networks, common terrorist training camps, common grievances, and demonstration effects (Gaibulloev, Sandler, and Sul 2013). This means that dynamic panels with transnational terrorism as an independent variable must correct for this dependence for proper statistical inference. Cross-sectional dependence is apt to affect other variables, such as democracy, threat, military spending, and financial measures. Nevertheless, dynamic panel studies have not properly accounted for cross-sectional dependence.

The primary purpose of this article is to present procedures for correcting for Nickell bias and cross-sectional dependence in dynamic panels. For Nickell bias, we highlight its implications and how to avoid its consequences. For cross-sectional dependence, we put forward factor-augmented regressions as a method for accounting for this dependence. Our secondary purpose is to apply our methods and, in particular, factor-augmented regression to re-evaluate the impact of terrorism on economic growth. Although the literature found a negative and significant impact, we show that, when Nickell bias and cross-sectional dependence are addressed, terrorism has no influence whatsoever on economic growth for five regional subsamples. This includes a Western European subsample that previously was shown by Gaibulloev and Sandler (2008) to have a significant effect when cross-sectional dependence had not been addressed.

The remainder of the article contains three main sections. Section 2 discusses the methodological issues associated with dynamic panels, and indicates ways to address Nickell bias and cross-sectional dependence. In the latter case, the method of factor-augmented regression is indicated. In Section 3, we present the application of our methodology to the analysis of the impact of terrorism on economic growth. Section 4 contains concluding remarks.

2 Nickell Bias and Cross-Sectional Dependence

Dynamic panel regressions have two thorny statistical problems: Nickell bias and cross-sectional dependence. We provide a short review of these two problems and offer some solutions.

2.1 *Inconsistency and Invalid Statistical Inference Due to Nickell Bias and Cross-Sectional Dependence*

Consider the following dynamic panel regression:

$$y_{it} = a_i + \theta_t + \rho y_{it-1} + \mathbf{X}_{it}\boldsymbol{\beta} + u_{it}, \tag{1}$$

where y_{it} is the dependent variable for the ith cross-sectional unit at time t; ρ is the coefficient on the lagged dependent variable; $\mathbf{X}_{it}$ is a vector of exogenous variables for the ith cross-sectional unit at time t; $\boldsymbol{\beta}$ is the vector of coefficients for the exogenous variables; a_i is an individual dummy to eliminate fixed effects; and θ_t is a time dummy to control for cross-sectional dependence in the regression error, u_{it}.

First, we consider the econometric consequences of Nickell bias. It is well established that the fixed-effects estimator in equation (1) is inconsistent as $N \to \infty$ for any fixed T (Nickell 1981). The inconsistency occurs because the within-group (WG) transformed regressors become correlated with the WG transformed regression errors. To highlight Nickell bias, we rewrite equation (1) for the time being without the exogenous variables $\mathbf{X}_{it}$ and θ_t. Further, we assume that y_{it} is not cross-sectionally dependent; that is,

$$y_{it} = a_i + \rho y_{it-1} + \varepsilon_{it},\ \ \varepsilon_{it} \sim iid\left(0,\sigma_\varepsilon^2\right). \tag{2}$$

The least squares estimator in equation (2) is the WG estimator, which is also called the fixed-effects (FE) estimator, or the least squares dummy variables (LSDV) estimator. Nickell (1981) showed that as $N \to \infty$, the WG estimator in equation (2) is inconsistent. The formula for this inconsistency is given by

$$\text{plim}_{N\to\infty}(\hat{\rho} - \rho) = -\frac{1+\rho}{T} \quad (3)$$

(see Appendix A1 for details). At this point, readers may conclude that Nickell bias disappears as $T \to \infty$, or can be resolved by including a larger time-series sample. For example, let $T = 10$ and $\rho = 0.8$. The empirical distribution of the WG estimator $\hat{\rho}$ then moves to the left by $1.8/10 = 0.18$. On average, the WG point estimate becomes 0.62 rather than 0.8. When $T = 30$, the magnitude of the bias decreases from 0.18 to $1.8/30 = 0.06$. For a panel with a large T, the Nickell bias problem is thus less of an issue in terms of inconsistency. However, even with a large T, Nickell bias is still a serious concern because the usual t-statistic remains invalid as long as $T < N$. Alvarez and Arellano (2003) showed that as $N,T \to \infty$ jointly but $N/T \to \infty$, the ordinary t-statistics for $\hat{\rho}$ grows larger in absolute value (see Appendix A1 for details). In other words, when the total number of cross-sectional units (N) is larger than the total number of time-series observations (T), the standard deviation for $\hat{\rho}$ becomes smaller than its true value, so that its t-statistic is typically biased upward in absolute value.[1]

Nickell bias differs from the typical inconsistency that results from ignoring fixed effects—also known as unobserved heterogeneity bias—in general panel regressions. Unobserved heterogeneity bias arises when FE are correlated with the means of the explanatory variables. In this case, the pooled ordinary least squares (POLS) estimator is inconsistent, but the WG estimator may solve this inconsistency. However, for dynamic panel regressions, the WG estimator produces Nickell bias. Alternatively, unobserved heterogeneity bias can be addressed by including the time-series means of explanatory variables, as suggested by Honda (1985) and Arellano (1993). Recently, Bafumi and Gelman (2006) put forward a similar treatment and called it a multilevel modeling. However, such treatment does not reduce Nickell bias in dynamic panel regressions, because the inclusion of the time-series mean of the lagged dependent variable can control for the random-effects bias, but, at the same time, this inclusion leads to an additional bias due to the correlation between the time-series mean and the regression error, which is the source of the Nickell bias. Thus, the final bias formula does not change. We also note that the random-effects estimator is inconsistent in dynamic panel regressions, because fixed effects are always correlated with the lagged dependent variable. This inconsistency does not disappear even when T goes to infinity.

When the exogenous variables are included in the dynamic panel, the WG estimator for these variables is also inconsistent. The probability limit of $\hat{\boldsymbol{\beta}}$ in equation (1) is

$$\text{plim}_{N\to\infty}\left(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}\right) = -\text{plim}_{N\to\infty}\left(\tilde{\mathbf{X}}'\tilde{\mathbf{X}}\right)^{-1}\left(\tilde{\mathbf{X}}'\,\tilde{\mathbf{y}}_{-1}\right)\text{plim}_{N\to\infty}(\hat{\rho} - \rho), \quad (4)$$

where $\tilde{\mathbf{X}} = \left(\tilde{\mathbf{X}}_1, \ldots, \tilde{\mathbf{X}}_N\right)'$, $\tilde{\mathbf{X}}_i = \left(\tilde{\mathbf{X}}_{i1}, \ldots, \tilde{\mathbf{X}}_{iT}\right)'$, $\tilde{\mathbf{y}}_{-1} = \left(\tilde{\mathbf{y}}_{1,-1}, \ldots, \tilde{\mathbf{y}}_{N,-1}\right)'$, and $\tilde{\mathbf{y}}_{i,-1} = \left(\tilde{\mathbf{y}}_{i1}, \ldots, \tilde{\mathbf{y}}_{iT-1}\right)'$. The overhead tilde indicates that the variables are transformed into deviations from their time-series means. Because the sign of $\text{plim}_{N\to\infty}(\hat{\rho} - \rho)$ is negative, the direction of this inconsistency depends on the correlation between y_{it-1} and $\mathbf{X}_{it}$. If, for example, $\mathbf{X}_{it}$ is negatively correlated with y_{it-1}, then $\hat{\boldsymbol{\beta}}$ is downwardly biased. So, even when the true $\boldsymbol{\beta}$ is zero, the expected value of $\hat{\boldsymbol{\beta}}$ becomes negative. Moreover, the t-statistic of $\hat{\boldsymbol{\beta}}$ grows larger in absolute value as N increases with a fixed T,

[1]To evaluate the upward bias of the t-statistics, we perform Monte Carlo simulation based on the following data-generating process: $y_{it} = a_i + \rho y_{it-1} + \varepsilon_{it}$, with the variable of interest being $x_{it} = b_i + \rho x_{it-1} + \varphi y_{it-1} + v_{it}$. We set $\rho = \varphi = 0.3, T = 40$, and generate all innovations from i.i.d. N(0,1). After generating pseudo x_{it} and y_{it}, we run the following dynamic panel regression: $y_{it} = a_i + \rho y_{it-1} + \beta x_{it-1} + \varepsilon_{it}$. The null hypothesis of interest becomes $\hat{\beta} = 0$. Regardless of the size of N, the bias of $\hat{\beta}$ is around –0.01, which can be ignored. However, the rejection rate of the null hypothesis is dependent on the size of N. When N is 20, the rejection rate is around 0.067, close to the nominal rate of 0.05. However, as N increases, the false rejection rate also rises. When $N = 200$, the rejection rate is 0.173, which is far higher than the nominal rate of 0.05. In other words, if $N > T$, the null hypothesis is too often rejected even when the null is true. This is a concern for international political economy applications that sometimes include almost two hundred countries and many fewer than two hundred periods. See the supplementary appendix on the *Political Analysis* Web site for further details of the Monte Carlo study.

so that its t-ratio becomes large enough in absolute value to reject the null hypothesis for N sufficiently larger than T. Hence, as the number of cross-sectional units increases, the frequency of falsely rejecting the null hypothesis of $\boldsymbol{\beta} = 0$ increases.

Next, we consider the impact of cross-sectional dependence on consistency and statistical inference. We allow for cross-sectional dependence in the regression error in equations (1) and (2). In the presence of this dependence, the limiting distribution of $\hat{\rho}$ becomes unknown. As the positive cross-sectional correlation with the regression error grows stronger, the true critical value of the ordinary t-statistic becomes larger in absolute value, so that we do not know the proper critical values.

If, moreover, cross-sectional dependence in the error term is correlated with the regressors, which may be the case for many practical applications in international political economy, then the estimated coefficients will be biased and inconsistent. To illustrate, we write the common factor representation in the regression error as

$$u_{it} = \lambda_i' \mathbf{F}_t + e_{it}, \tag{5}$$

where $\mathbf{F}_t$ is a $k \times 1$ vector of unknown common factors and λ_i is a $k \times 1$ vector of unknown factor loadings. Similarly, the regressors $\mathbf{X}_{it}$ have the common factor structure

$$\mathbf{X}_{it}' = \Lambda_{x,i} \mathbf{F}_{x,t} + \mathbf{X}_{it}^{o'}, \tag{6}$$

where $\mathbf{X}_{it}^{o}$ is the idiosyncratic component of $\mathbf{X}_{it}$. If the common factor from $\mathbf{X}_{it}$ is correlated with the common factor from u_{it}, then the regressors are no longer exogenous so that the WG estimator becomes inconsistent. Including the common time effects may reduce the degree of such inconsistency, but does not eliminate it.

2.2 *Solution for Nickell Bias and Cross-Sectional Dependence*

The standard solution for Nickell bias is to use the GMM/IV estimator for a panel when N is large and T is small. Unfortunately, the GMM/IV method performs poorly when ρ is near unity because instrumental variables become very weak. When, however, T is large, Nickell bias is less of a concern in terms of inconsistency, as shown earlier and recognized by Beck and Katz (2011), but the problem of the statistical inference still remains if N is relatively larger than T. A simple practical solution is the use of subgroups—for example, allow the panel to consist of regions instead of the world. For $N = 100$ and $T = 40$, the Nickell bias can be ignored, but the standard t-statistic becomes invalid since $N > T$. Suppose that we form five subgroups so that $N_j = 100/5 = 20$ for all j, where N_j is the total number of cross-sectional units for the jth subgroup. Then, since $N_j < T$, the standard t-statistic becomes valid so that the standard critical value can be used for testing.

Next, we allow for cross-sectional dependence but keep the strong exogeneity assumption. In this situation, the invalid statistical inference problem due to cross-sectional dependence[2] can be handled by using a sieve bootstrapping method, which pins down the empirical critical values when $T > N$. If, however, $N > T$, the limiting distribution of the resulting estimator is not pivotal due to Nickell bias, so that the bootstrapping method does not work asymptotically. For strictly exogenous regressors, the sieve bootstrapping method may provide a good approximation of the unknown empirical distribution.

Now consider the inconsistency problem due to the correlation between common factors from the regressors and the regression errors. In this case, all bootstrap methods fail due to inconsistency. Pesaran (2006), Bai (2009), and Greenaway-McGrevy, Han, and Sul (2012) provided solution to this problem by adding common factors to the panel regressions:

$$y_{it} = a_i + \rho y_{it-1} + \mathbf{X}_{it}\boldsymbol{\beta} + \lambda_i' \mathbf{F}_t + e_{it}. \tag{7}$$

[2]Beck and Katz (2011) recognized the problem of cross-sectional dependence, but do not provide the factor-augmented regression method to fix the problem.

The regression in equation (7) is called a common correlated regression (Pesaran 2006), or interactive FE regression (Bai 2009), or factor-augmented regression (Greenaway-McGrevy, Han, and Sul 2012), and the associated estimators are called common correlated effects (CCE) estimator, iterative principal component (IPC) estimator, and projected principal component (PPC) estimator, respectively.[3] Hereafter, we call equation (7) the factor-augmented regression and refer to the corresponding estimator as PPC.

There are advantages associated with the factor-augmented regression. First, equation (7) nests equation (1); that is, when the error term is not cross-sectionally dependent, the former reduces to the latter. Second, there is no need to perform a pre-test for endogeneity between $\mathbf{X}_{it}$ and $\mathbf{F}_t$, since the factor-augmented regression becomes valid regardless of the correlation between $\mathbf{X}_{it}$ and $\mathbf{F}_t$. Third, the factor-augmented regression is more efficient than the sieve bootstrapping method, even when $\mathbf{X}_{it}$ is not correlated with $\mathbf{F}_t$. This follows because by including common factors as additional regressors, the factor-augmented regression reduces the variance of the WG estimator in equation (7) and sharpens statistical inference.

Since the components of $\mathbf{F}_t$ are not observable, they must be estimated. The estimated common factors, $\hat{\mathbf{F}}_t$, are used for $\mathbf{F}_t$ in equation (7). The CCE estimator uses the cross-sectional averages of y_{it}, y_{it-1}, and $\mathbf{X}_{it}$ as the proxy variables for $\mathbf{F}_t$, whereas both the IPC and PPC estimators use the principal component estimators for $\mathbf{F}_t$. The IPC estimator calculates the common factor $\mathbf{F}_t$ directly from the WG residuals, $\hat{u}_{it}$, whereas the PPC estimator computes the common factor indirectly from the regressors and regressand.

The CCE is very simple but requires the identification condition that the number of common factors is smaller than the number of regressors. Neither the PPC nor the IPC estimator has this requirement. Since the PPC estimator projects out all common factors from $\mathbf{X}_{it}$, this estimator is sometimes less efficient than the IPC estimator. However, the IPC estimator requires the initial value for $\hat{\boldsymbol{\beta}}$ and uses the inconsistent WG estimator as the initial value. Even though Bai (2009) showed that the IPC estimator becomes consistent as $N,T \to \infty$, the IPC estimator may not be efficient for finite samples due to the use of the inconsistent WG estimator as the initial value.

Therefore, we combine the merits of the IPC and PPC estimators as GHS (2012) suggested. In the first stage, we use the PPC estimator to obtain consistent regression residuals. In the second stage, we apply the IPC estimator. Asymptotically, this combined estimator shares the same limiting distribution as the IPC estimator. We call this estimator the modified PPC estimator (see Appendix A2 for a more detailed explanation).

3 Specific Application to the Impact of Terrorism on Economic Growth

In this section, we illustrate our methods and the differences that they make by considering terrorism as a potential determinant of economic growth. Past studies on this issue have applied dynamic panel analysis without a concern for Nickell bias or cross-sectional dependence.

Table 1 provides a brief summary of the recent empirical studies of the impact of terrorism on per-capita income growth. In Table 1, the leftmost column indicates the study; the second column displays the terrorist data source; the third column denotes the sample; the fourth column depicts the studies' time period; the fifth column indicates the type of analysis; the sixth column lists some key (select) controls other than a measure of terrorism; and the rightmost column highlights the influence of various measures of terrorism on per-capita income growth. Two studies—Blomberg, Hess, and Orphanides (2004) and Tavares (2004)—used a world sample. The other studies, including the latter half of Blomberg, Hess, and Orphanides (2004), analyzed regional samples. All previous studies utilized panel data; three of these studies performed additional cross-sectional analysis. Blomberg, Hess, and Orphanides (2004) and Blomberg, Broussard, and Hess (2011) found a significant negative impact of terrorism on per-capita income growth in their cross-sectional estimates for the world and an African sample, respectively. For their panel estimates, Blomberg, Hess, and Orphanides (2004) found mixed results for their regional samples—for

[3]Only Greenaway-McGrevy, Han, and Sul (2012) explicitly discussed their estimator in a dynamic panel regression framework; however, the CCE and IPC estimators are easily extended to this framework.

Table 1 A summary of the past literature on the impact of terrorism on per-capita income growth

Study	*Data*	*Sample*	*Period*	*Type of analysis*	*Select controls*	*Findings*
Blomberg, Hess, and Orphanides (2004)	ITERATE	World; World; Regions	1968–2000	Cross sectional	$\ln y_{it-1}$	(–)*
				Panel Data	I/Y, open, conflict	(–)* mixed
Tavares (2004)	IPIC	World	1987–2001	Panel Data	Terrorism × political rights	(–)*
Gaibulloev and Sandler (2008)	ITERATE	18 Western European	1971–2004	Cross sectional	$\ln y_{it-1}$	(–)
	TWEED			Panel Data	I/Y, open	
				Total (Trans + Dom)		(–)*
				Trans		(–)*
				Dom		(–)
Gaibulloev and Sandler (2009)	ITERATE	42 Asian	1970–2004	Panel Data	$\ln y_{it-1}$	(–)*
					I/Y, open, conflict	
Gaibulloev and Sandler (2011)	ITERATE	51 African	1970–2007	Panel Data	$\ln y_{it-1}$	
	GTD			Trans	I/Y, open, conflict	(–)*
				Dom		(–)
Blomberg, Broussard, and Hess (2011)	ITERATE	46 sub-Saharan African	1968–2004	Cross sectional	$\ln y_{it-1}$	(–)*
				Panel Data	I/Y, open, conflict	(–)*

Note. ITERATE stands *for International Terrorism: Attributes of Terrorist Events* (Mickolus et al. 2011); IPIC indicates International Policy Institute for Counterterrorism; TWEED denotes *Terrorism in Western Europe*: *Event Data* (Engene 2007); and GTD represents *Global Terrorism Database* (START 2011). ITERATE contains just transnational terrorist incidents (Trans), whereas the other two data sets contain domestic (Dom) and transnational terrorist incidents. Enders, Sandler, and Gaibulloev (2011) partitioned GTD into domestic and transnational terrorist incidents. y_{it-1} is lagged per-capita income for country i; I/Y is ratio of investment to GDP; open is a measure of trade openness; and conflict includes internal conflict and external wars. * denote the 5% level of significance.

example, terrorism did not have a significant negative impact on growth in the Middle East. Some studies distinguished between transnational (Trans) and domestic (Dom) terrorism, whereas others (e.g., Tavares 2004) did not. Studies that relied on terrorism data drawn from *International Terrorism: Attributes of Terrorist Events* (ITERATE) used just transnational terrorist events, since this data set does not include domestic incidents. Most of the previous studies found that one or more measures of terrorism had a negative and significant impact on per-capita income growth regardless of the choice of empirical specifications, regions, and types of terrorism. Gaibulloev and Sandler (2008) found a negative and significant impact of total and transnational terrorism on Western European per-capita income growth.

3.1 *Data*

Terrorism comes in two forms. Transnational terrorism occurs when an incident in one country involves perpetrators, victims, institutions, governments, *or* citizens of another country. The data on transnational terrorist events come from ITERATE (Mickolus et al. 2011). Among other variables, ITERATE records the incident's date and its country location, which we use for the number of incidents for each country during 1970–2009. For domestic terrorist events, the perpetrators and victims are all from the host or venue country. We draw our data on domestic terrorism from the *Global Terrorism Database* (GTD), maintained by the National Consortium for the Study of Terrorism and Responses to Terrorism (START 2011). We identify domestic terrorist incidents for 1970–2009 by applying a breakdown procedure of GTD incidents into transnational and domestic attacks, devised by Enders, Sandler, and Gaibulloev (2011). Because we have more confidence in ITERATE's tally of transnational terrorist events, we rely on ITERATE for runs using just these attacks. We also use the total number of terrorist incidents, which is the sum of transnational and domestic terrorist incidents obtained from GTD.

We obtain PPP-converted real GDP per capita at 2005 constant prices, investment share of per capita real GDP, and population from *Penn World Table Version 7.0* (Heston, Summers, and Aten 2011). The investment share is converted into 2005 international dollars using per-capita real GDP.

Our world sample covers ninety-nine countries during 1970–2009. Using World Bank definitions, we construct five regional balanced panel data sets. Appendix B presents the list of sample countries by regions. The important consideration for choosing a particular country for our sample is data availability. Our main econometric method—the factor-augmented panel estimator—requires a balanced panel data set. Therefore, we do not include countries with missing information over the sample period. We focus at the regional level to ensure that the number of years is sufficiently larger than the number of countries, essential for a proper econometric specification.

We believe that using regional balanced panel data does not drive the differences between our results and those in the literature. First, five of the six studies, listed in Table 1, performed regional investigations of the impact of terrorism on economic growth. Each of these five articles emphasized the importance of regional analysis in isolating terrorism's impact on growth because, in part, each region had unique and essential considerations. Second, we compare the conventional method and our method using the same regional samples to show that the results still differ and that this difference is driven by methodology, not by the data. Third, we replicate a specific study from the literature to demonstrate the sensitivity of its findings to ignoring the econometric concerns raised here.

3.2 *Impact of Nickell Bias on Point Estimates*

Previous panel regression studies of terrorism and growth are based on the following augmented Solow growth regression model:

$$\Delta \ln y_{it} = a_i + \psi \ln y_{it-1} + \beta \tau_{it} + \mathbf{z}_{it}\gamma + u_{it}, \tag{8}$$

which can be written as

$$\ln y_{it} = a_i + \rho \ln y_{it-1} + \beta \tau_{it} + \mathbf{z}_{it}\gamma + u_{it}, \tag{9}$$

where $\Delta \ln y_{it}$ indicates the ith country's per-capita real GDP growth rate at time t; $\ln y_{it-1}$ is the log of lagged per-capita income for country i; τ_{it} denotes the ith country's terrorist events at time t; $\mathbf{z}_{it}$ is a vector of control variables for country i at time t; and u_{it} is an error term. The a_i is a country-specific intercept; ψ and β are coefficients for log of lagged per-capita income and terrorism, respectively; and $\boldsymbol{\gamma}$ is a vector of parameters for the control variables. In equation (9), $\rho = 1 + \psi$.

For now, we exclude control variables, $\mathbf{z}_{it}$. Section 2 shows that $\hat{\beta}$ associated with equations (8) and (9) is inconsistent. This inconsistency is dependent on the true value of ρ and the correlation between the lagged dependent variable and regressors (see equation (4)). As ρ approaches unity, the inconsistency becomes more serious. A typical solution is to use the GMM/IV method as long as ρ is not near unity (Section 2). Christopoulos and Tsionas (2004) found that the log of per-capita GDP follows an I(1) process; hence, we are not able to utilize the GMM/IV approaches to correct for Nickell bias.

When the dependent and independent variables are I(1), the cointegration approach has been used (e.g., Christopoulos and Tsionas 2004). However, Enders and Sandler (2005) and Enders, Sandler, and Gaibulloev (2011) found that the number of terrorists attack is stationary, so that cointegration analysis is not germane for the study of the impact of terrorism on growth. Instead, we impose a nonstationary restriction of $\rho = 1$ on equations (8) and (9), and use the first difference of the log of per-capita GDP (i.e., economic growth) as the dependent variable. By imposing the unit root restriction, we avoid Nickell bias.[4] Our specification is

$$\Delta \ln y_{it} = a_i + \beta \tau_{it} + \theta_t + u_{it}, \tag{10}$$

where θ_t is the time FE.

Table 2 shows the empirical results based on equations (8) and (10). We also control for time FE in equation (8)—see conventional specification in Table 2. We consider two measures of terrorism—the total number of terrorist attacks divided either by one thousand or by population—and perform separate regressions for total (domestic and transnational), domestic, and transnational terrorism. We report estimates for the whole sample and for the regional subsamples. To the right of the column for the samples, the first three columns of Table 2 report the point estimates of β in equation (8). The boldface coefficients indicate that they are significantly different from zero at the 5% level (see supplementary tables for p-values). Consistent with previous empirical studies (Table 1), these point estimates are generally negative, including for the regional subsamples. When per-capita terrorism data are used, the t-statistics become larger in absolute value. The second three right-hand columns show the point estimates of β in equation (10), and the last three columns display the difference between the estimates of β in equations (8) and (10). Since equation (10) is free of Nickell bias, the difference between the β coefficients in equations (8) and (10) represents the Nickell bias in equation (8). Evidently, the unit root restriction usually produces smaller point estimates of β in absolute value so that the bias is positive in absolute terms. Moreover, the absolute values of the t-statistics (p-values) become generally smaller (larger); hence, there are many fewer statistically significant cases with the unit root restriction in equation (10) than in equation (8).

Interestingly, imposing the unit root restriction does not always reduce the point estimates, because the inclusion of common time effects or time FE does not properly control for cross-sectional dependence. With cross-sectional dependence, Phillips and Sul (2007) showed that Nickell bias becomes random even when N is very large. If the time FE properly controlled for cross-sectional dependence, the point estimate in equation (10) would have always been smaller than that in equation (8). More important, we cannot rely on the conventional critical value for the t-statistics (Section 2).

[4]The log of per-capita GDP has an upward deterministic trend, whereas the terrorism data do not. Therefore, equation (9) becomes unbalanced. By imposing the unit root restriction, we can avoid the unbalanced regression problem.

Table 2 Impact of Nickell bias on point estimates of current level terrorism

	Conventional equation (8)			*Unit Root Restriction equation (10)*			*Equation (8) − equation (10)*		
	Total	*Dom*	*Trans*	*Total*	*Dom*	*Trans*	*Total*	*Dom*	*Trans*
Terrorism is divided by 1000									
World (99)	−0.025	−0.034	0.274	−0.012	−0.021	0.304	−0.013	−0.013	−0.030
America (22)	−0.062	−0.072	**−0.612**	−0.052	−0.061	−0.551	−0.010	−0.011	−0.061
Asia (21)	−0.018	−0.025	0.355	0.042	0.034	0.517	−0.060	−0.059	−0.162
ME & NA (13)	−0.045	−0.072	**1.353**	0.061	0.044	**1.320**	−0.106	−0.116	0.033
S.S. Africa (24)	**−0.284**	**−0.207**	−1.232	**−0.239**	−0.164	−1.032	−0.045	−0.043	−0.200
W. Europe (19)	−0.010	−0.008	−0.012	−0.012	−0.008	−0.055	0.002	0.000	0.043
Terrorism is divided by population (in thousands)									
World (99)	**−1.055**	**−1.179**	1.905	**−1.057**	**−1.155**	1.520	0.002	−0.024	0.385
America (22)	**−1.054**	**−1.059**	**−12.84**	−1.036	−1.036	**−13.18**	−0.018	−0.023	0.338
Asia (21)	−1.670	−1.613	12.48	−1.011	−0.837	14.65	−0.659	−0.776	−2.168
ME & NA (13)	0.106	−1.748	**4.802**	0.371	−0.910	**3.747**	−0.265	−0.838	1.055
S.S. Africa (24)	−2.827	−1.791	**−8.689**	−2.475	−1.395	−7.518	−0.352	−0.396	−1.171
W. Europe (19)	−1.370	−0.779	**−5.945**	−1.231	−0.514	**−5.764**	−0.139	−0.265	−0.181

Conventional: $\Delta \ln y_{it} = a_i + \psi \ln y_{it-1} + \beta\tau_{it} + \theta_t + u_{it}$.
Unit Root Restriction: $\Delta \ln y_{it} = a_i + \beta\tau_{it} + \theta_t + u_{it}$.
Note. Boldface numbers are significantly different from zero at the 5% level. Panel robust standard errors are used. The numbers in parentheses stand for the number of countries.

3.3 *Factor-Augmented Approach*

Before applying the factor-augmented approach, we address further specification issues. First, per-capita income growth rates are possibly serially correlated. To account for serial correlation, we include the lagged dependent variable, $\Delta \ln y_{it-1}$, as an extra regressor, so that

$$\Delta \ln y_{it} = a_i + \alpha\Delta \ln y_{it-1} + \beta\tau_{it} + u_{it}, \tag{11}$$

where α stands for the autocorrelation between the GDP growth rates, which is different from ψ in equation (8). The regression model in equation (11) has been widely used in the empirical growth literature (Levine 2005); however, this specification does not reveal the true causal relationship between past terrorism and current economic growth. In other words, the empirical evidence of $\beta \neq 0$ does not imply that $E(\tau_{it}\Delta \ln y_{it+k}) \neq 0$ for any $k \geq 1$. To appreciate this insight, without loss of generality, consider the following VAR(1) model:

$$\begin{aligned} \Delta \ln y_{it} &= a_{i1} + \alpha_{11}\Delta \ln y_{it-1} + \alpha_{12}\tau_{it-1} + u_{it}, \\ \tau_{it} &= a_{i2} + \alpha_{21}\Delta \ln y_{it-1} + \alpha_{22}\tau_{it-1} + v_{it}, \end{aligned} \tag{12}$$

where we assume that the innovation of economic growth, u_{it}, is contemporaneously correlated with the innovation of terrorism, v_{it}; that is, $u_{it} = \delta v_{it} + \varepsilon_{it}$. We also assume that $\alpha_{12} = \alpha_{21} = 0$, so that there is no causal relationship between terrorism and economic growth. Furthermore, for simplicity, let $\alpha_{22} = 0$. Economic growth can then be rewritten as

$$\Delta \ln y_{it} = (a_{i1} - \delta a_{i2}) + \alpha_{11}\Delta \ln y_{it-1} + \delta\tau_{it} + \varepsilon_{it}. \tag{13}$$

Based on equations (11)–(13), $\beta = \delta$ when $\alpha_{12} = \alpha_{21} = \alpha_{22} = 0$. Hence, even in the absence of any causal relationship, economic growth can still be correlated with current terrorism as long as $\delta \neq 0$. This is why recent empirical studies (e.g., Chambers and Guo 2009; Cieślik and Tarsalewska 2011) considered dynamic panel regressions with lagged explanatory variables. Therefore, our specification becomes

$$\Delta \ln y_{it} = a_i + \alpha\Delta \ln y_{it-1} + \beta\tau_{it-1} + u_{it}. \tag{14}$$

We address Nickell bias by only estimating regional panels for which the biggest N is 24, whereas T is 40; hence, T is always greater than N. To overcome cross-sectional dependence, we initially applied a sieve nonparametric bootstrapping method to compute the t-statistics using various measures of terrorism. The impact of terrorism is statistically significant only in a few cases and the statistical significance is sensitive to the choice of terrorism measure.[5] Such nonrobust results may arise due to possible correlation between the common factors of regressors and those of the regression error, which results in invalid bootstrapped critical values. Therefore, we implement the factor-augmented panel regression to accommodate cross-sectional dependence. Combining the causal relationship with common factors yields

$$\Delta \ln y_{it} = a_i + \alpha \Delta \ln y_{it-1} + \beta \tau_{it-1} + \lambda_i' \mathbf{F}_t + \varepsilon_{it}. \tag{15}$$

We apply the modified PPC method to estimate equation (15), as discussed in Section 2.2. The maximum number of common factors is set at five, and the convergence criterion for the iterative procedure is 0.0001. The estimated factor numbers are slightly different across the regions; for most of the cases, the estimated factor numbers are between one and two. We also use Pesaran's CCE estimation and find that our conclusion still holds.[6]

Table 3 shows the factor-augmented panel regression results. Separate analysis is performed for total, domestic, and transnational terrorism. Furthermore, terrorism is measured as the number of terrorist incidents divided by one thousand and, alternatively, as the number of terrorist incidents divided by population. We report empirical results with both level and first-differenced terrorism. The boldface and italic numbers indicate the rejection of the null hypothesis that the parameter of interest is zero at the 5% and 10% level of significance, respectively. Moreover, the total number of countries for each region differs—see Appendix B. The domestic GTD sample for Western Europe does not include Iceland, whereas the ITERATE sample does not include Macau (Asia), Morocco (Middle East and North Africa), and Finland (Western Europe). We excluded these countries because they had no terrorist incidents over the sample period, which does not allow us to perform the factor-augmented panel regression. In terms of magnitudes, the terrorism estimates in Table 3 are mostly smaller than the terrorism estimates from equation (8) in Table 2. Notably, there is no statistically significant impact of terrorism on economic growth, which holds across all cases. Even though we do not report their p-values except in supplementary tables, most of them are far from 0.5, so that the terrorism coefficients are not significant even at the 50% level. In our estimates, the common factor is explaining the variation of the dependent variable in equation (15). Notice that the significant regional terrorism coefficients in Table 2 become insignificant when we account for cross-sectional dependence and Nickell bias in Table 3. This strongly suggests that the results from the previous literature are sensitive to model specification.

3.4 *Robustness Checks*

So far we did not include any control variables in the dynamic panel regressions. We check the sensitivity of our results to the inclusion of control variables by including the first difference of log investment ($\Delta \ln I$) and population growth rates (Δn) as additional regressors in equation (15). The empirical results with alternative measures of terrorism are reported in Table 4. Evidently, the inclusion of other key growth variables in equation (15) does not impact our main conclusion. The point estimates on the terrorism coefficients vary in their magnitude and, sometimes, their sign, but there are no consistent patterns to these changes. Most importantly, all terrorism estimates remain statistically insignificant. To conserve space, we do not report the point estimates in Table 4 on lagged economic growth and other control variables (some of which are significant); these results are available upon request.

[5]These bootstrapping results are available on the *Political Analysis* Web site in supplementary tables.
[6]These CCE estimates are available on the *Political Analysis* Web site in supplementary tables.

Table 3 Factor-augmented dynamic panel regression

Dependent: $\Delta \ln y_{it}$	*Explanatory variables*					
	$\Delta \ln y_{it-1}$			τ_{it-1}		
	Total	Dom	Trans	Total	Dom	Trans
Terrorism/1000						
America	0.233	0.233	0.235	−0.053	−0.054	−0.027
Asia	0.161	0.162	0.156	−0.078	−0.080	−0.012
ME & NA	−0.060	−0.060	0.023	0.034	0.046	0.186
S.S. Africa	0.113	0.113	0.111	−0.091	−0.065	−1.172
W. Europe	**0.446**	**0.366**	*0.270*	0.0001	−0.0002	0.0102
Terrorism/population						
America	0.227	0.228	0.222	−0.509	−0.497	−5.162
Asia	0.171	0.173	0.146	−1.802	−0.800	−27.70
ME & NA	−0.063	−0.064	0.018	0.658	1.099	1.224
S.S. Africa	0.113	0.114	0.107	−1.854	−1.769	−11.82
W. Europe	**0.447**	**0.376**	0.256	0.234	0.656	−2.051
	$\Delta \ln y_{it-1}$			$\Delta\tau_{it-1}$		
Terrorism/1000						
America	0.236	0.236	0.240	−0.004	−0.010	0.338
Asia	0.172	0.172	0.160	0.015	0.021	0.196
ME & NA	−0.043	−0.044	0.022	0.132	0.143	−0.010
S.S. Africa	0.113	0.113	0.115	−0.066	−0.006	−2.233
W. Europe	**0.445**	**0.360**	0.267	−0.048	−0.043	−0.033
Terrorism/population						
America	0.236	0.235	0.236	−0.314	−0.360	1.135
Asia	0.169	0.174	0.160	1.102	1.577	−14.36
ME & NA	−0.051	−0.054	0.020	1.394	1.346	1.646
S.S. Africa	0.113	0.114	0.116	−1.840	−1.540	−12.94
W. Europe	**0.447**	**0.373**	0.267	0.336	0.625	−0.748

Regression: $\Delta \ln y_{it} = a_i + \alpha\Delta \ln y_{it-1} + \beta\tau_{it-1} + \lambda_i^{'}\mathbf{F}_t + \varepsilon_{it}$ or $\Delta \ln y_{it} = a_i + \alpha\Delta \ln y_{it-1} + \beta\Delta\tau_{it-1} + \lambda_i^{'}\mathbf{F}_t + \varepsilon_{it}$.
Note. ME & NA represent Middle East and North Africa, S.S. Africa is Sub-Saharan Africa, and W. Europe is Western Europe. Boldface and italic numbers are significantly different from zero at the 5% and 10% level, respectively.

We also examine alternative partitioning of the data based on per-capita income in US dollars and on the number of terrorist attacks. In particular, we split our sample into three subsamples of countries with average per-capita GDP of less than \$3000 (thirty countries), between \$3000 and \$15,000 (twenty-eight countries), and over \$15,000 (twenty-three countries), respectively. For all estimates, terrorism is never a statistically significant determinant of growth. We also re-estimate Table 3 for the thirty most attacked sample countries for 1970–2009, based on the number of total, transnational, and domestic terrorist attacks, respectively. Additionally, we analyze a panel of the thirty most attacked sample countries (in terms of total terrorism) with average per-capita GDP of less than \$15,000, and a panel of the thirty most frequently attacked sample countries based on the number of years of at least one terrorist attack. For all factor-augmented dynamic panels, terrorism is never a significant determinant of growth (estimates available upon request).

Finally, we have chosen a data set used by Gaibulloev and Sandler (2008) to further show that econometric specification issues are behind the differences between our results and those of the previous literature. Their original data covered eighteen Western European countries for 1971–2004 and satisfied the $N < T$ condition. We dropped Finland, since it had no terrorism over the sample period. Gaibulloev and Sandler (2008) used trade openness and investment as control variables, and found that total and transnational terrorism reduced economic growth. We are able to replicate their results. However, when we revise their model specification and apply the factor-augmented

Table 4 Factor-augmented dynamic panel regression with control variables

	τ_{it-1}		
	Total	Dom	Trans
Terrorism/1000			
America	–0.056	–0.061	–0.084
Asia	–0.038	–0.035	0.142
ME & NA	–0.006	–0.009	0.402
S.S. Africa	–0.124	–0.107	–0.891
W. Europe	0.020	0.017	–0.014
Terrorism/population			
America	–0.503	–0.522	–3.628
Asia	–2.689	–2.268	–9.526
ME & NA	0.341	0.523	1.838
S.S. Africa	–1.950	–1.953	–12.696
W. Europe	–0.070	0.819	–2.046
	$\Delta\tau_{it-1}$		
Terrorism/1000			
America	–0.030	–0.039	0.231
Asia	0.031	0.037	0.435
ME & NA	0.048	0.051	0.016
S.S. Africa	–0.090	–0.025	–2.413
W. Europe	–0.024	0.003	–0.031
Terrorism/population			
America	–0.489	–0.572	–0.161
Asia	–0.583	0.715	0.728
ME & NA	–0.152	0.233	0.979
S.S. Africa	–1.984	–1.590	–15.526
W. Europe	–0.152	0.397	0.068

Regression: $\Delta \ln y_{it} = a_i + \alpha\Delta \ln y_{it-1} + \beta\tau_{it-1} + \beta_1 \Delta \ln(I)_{it} + \beta_2\Delta n_{it} + \lambda_i^{'}\mathbf{F}_t + \varepsilon_{it}$
or $\Delta \ln y_{it} = a_i + \alpha\Delta \ln y_{it-1} + \beta\Delta\tau_{it-1} + \beta_1 \Delta \ln(I)_{it} + \beta_2\Delta n_{it} + \lambda_i^{'}\mathbf{F}_t + \varepsilon_{it}$.
Note. Boldface and italic numbers imply that they are significantly different from zero at the 5% and 10% level, respectively.

dynamic panel regression, the terrorism coefficients are no longer statistically significant (estimates available upon request).

4 Concluding Remarks

For dynamic panel analysis, this article highlights inconsistency and invalid statistical inference that arise from Nickell bias and cross-sectional dependence. These concerns are particularly relevant for dynamic panel studies in international political economy, where $N > T$ and countries' variables are driven by common factors. These econometric concerns are also germane to dynamic panels in other fields of political science. We begin with a straightforward explanation for why Nickell bias may result in inconsistent estimates. Although a large number of time periods can ameliorate the inconsistency concern, Nickell bias may still be associated with invalid statistical inference owing to biased t-statistics. Cross-sectional dependence can also cause invalid statistical inference and inconsistency. As cross-sectional correlation with the regression error increases, the true critical value of the t-statistic becomes larger in absolute value, so that the proper critical value is not known. Inconsistency arises when common factors in the error term are correlated with the regressors.

We show practical ways of avoiding Nickell bias in dynamic panel regression. For many international political economy applications, this may necessitate running regional rather than global dynamic panels to ensure that the number of periods, T, exceeds the number of sample countries, N. Other fixes are discussed. To address cross-sectional dependence, we put forward factor-augmented regressions, where common factors are explicitly taken into account to eliminate inconsistency worries.

The importance of our exercise is illustrated by applying our methods to the study of the impact of various forms of terrorism on economic growth. In so doing, we provide estimates of dynamic panel regressions for five regional conglomerates. Even though the extant literature found a negative and significant effect of terrorism on economic growth for these regional aggregates, our factor-augmented regressions do not find any such significant impact. Our specific application highlights that avoiding Nickell bias and correcting for cross-sectional dependence may yield much different dynamic panel findings than those in the literature. This may also be true for other dynamic panel applications, especially when cross-country dependence looms large.

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Appendix A: Derivations

A.1 Nickell Bias and Inconsistency of the WG Estimator

The WG estimator requires the following WG transformation of equation (2) to eliminate the fixed effects, a_i:

$$y_{it} - \frac{1}{T}\sum_{t=1}^{T} y_{it} = \rho\left(y_{it-1} - \frac{1}{T}\sum_{t=1}^{T} y_{it-1}\right) + \varepsilon_{it} - \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{it},$$

or

$$\tilde{y}_{it} = \rho\tilde{y}_{it-1} + \tilde{\varepsilon}_{it}. \tag{A1}$$

The probability limit of the WG estimator, as $N \to \infty$ with a fixed T, is

$$\begin{aligned}\mathrm{plim}_{N\to\infty}(\hat{\rho} - \rho) = {} & \mathrm{plim}_{N\to\infty}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} y_{it-1}\varepsilon_{it}\right)\left(\sum_{i=1}^{N}\sum_{t=1}^{T} \tilde{y}_{it-1}^{2}\right)^{-1} \\ & - \mathrm{plim}_{N\to\infty}\frac{1}{T}\left[\sum_{i=1}^{N}\left(\sum_{t=1}^{T} y_{it-1}\right)\left(\sum_{t=1}^{T}\varepsilon_{it}\right)\right]\left[\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{y}_{it-1}^{2}\right]^{-1}.\end{aligned} \tag{A2}$$

The first term on the right-hand side of equation (A2) becomes zero, since $E(y_{it-1}\varepsilon_{it}) = 0$; that is,

$$\mathrm{plim}_{N\to\infty}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} y_{it-1}\varepsilon_{it}\right)\left(\sum_{i=1}^{N}\sum_{t=1}^{T} \tilde{y}_{it-1}^{2}\right)^{-1} = 0 \cdot \sigma_{\varepsilon}^{2}/\left(1-\rho^{2}\right) = 0.$$

The second right-hand term in equation (A2) becomes

$$\mathrm{plim}_{N\to\infty}\frac{1}{T}\left[\sum_{i=1}^{N}\left(\sum_{t=1}^{T} y_{it-1}\right)\left(\sum_{t=1}^{T}\varepsilon_{it}\right)\right]\left[\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{y}_{it-1}^{2}\right]^{-1} = (1+\rho)T^{-1} + O\left(T^{-2}\right), \tag{A3}$$

since for any t

$$E\left(\frac{1}{N}\sum_{i=1}^{N} y_{it}\varepsilon_{it}\right) = \sigma_\varepsilon^2 \text{ and}$$

$$E\frac{1}{N}\sum_{i=1}^{N}\left(\sum_{t=1}^{T} y_{it-1}\right)\left(\sum_{t=1}^{T}\varepsilon_{it}\right) = \frac{\sigma_\varepsilon^2}{1-\rho} + O\left(T^{-1}\right),$$

where $O(\bullet)$ represents the order of magnitude. In fact, the dominant bias in equation (A3) is $(1+\rho)T^{-1}$, so that the bias term can be expressed as $O\left(T^{-1}\right)$, which means that the bias vanishes at a rate proportional to T. Equation (A2) reduces to

$$\text{plim}_{N\to\infty}(\hat{\rho}-\rho) = -\frac{1+\rho}{T} + O\left(T^{-2}\right). \quad \textbf{(A4)}$$

Hence, the WG estimator becomes inconsistent as $N \to \infty$.

We can rewrite $\hat{\rho} - \rho$ as

$$(\hat{\rho}-\rho) = \left(\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} y_{it-1}\varepsilon_{it}\right)\left(\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{y}_{it-1}^2\right)^{-1} + O_p\left(T^{-1}\right),$$

or

$$\sqrt{NT}(\hat{\rho}-\rho) = \left(\frac{1}{\sqrt{NT}}\sum_{i=1}^{N}\sum_{t=1}^{T} y_{it-1}\varepsilon_{it}\right)\left(\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{y}_{it-1}^2\right)^{-1} + O_p\left(N^{1/2}T^{-1/2}\right), \quad \textbf{(A5)}$$

where $O_p(\bullet)$ stands for the order in probability. For example, $O_p\left(T^{-1}\right)$ implies that the term goes to zero in probability as $T \to \infty$. The first right-hand term in (A5) has the limiting distribution of $N\left(0,1-\rho^2\right)$, whereas the second right-hand term becomes purely random and depends on an N/T ratio (Alvarez and Arellano 2003). If $T > N$, then the N/T term becomes small, so that the second term can be ignored. However if $N > T$, then the limiting distribution of $\hat{\rho}$ cannot be defined. In other words, the ordinary t-statistic for $\hat{\rho}$ becomes large in absolute value as $N,T \to \infty$ but $N/T \to \infty$.

A.2 Factor-Augmented Regression

The CCE estimator is obtained by running the following regression with simple augmented cross-sectional averages (Pesaran 2006):

$$y_{it} = a_i + \rho y_{it-1} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_{1i}\bar{y}_t + \delta_{2i}\bar{y}_{t-1} + \mathbf{X}_t\delta_{3i} + e_{it}, \quad \textbf{(A6)}$$

where $\bar{y}_t$, $\bar{y}_{t-1}$, and X_t are cross-sectional averages of y_{it}, y_{it-1}, and X_{it}, respectively.

The IPC estimator is obtained as follows (Bai 2009):

1. Estimate the regression in equation (1), $y_{it} = a_i + \theta_t + \rho y_{it-1} + \mathrm{X}_{it}\boldsymbol{\beta} + u_{it}$, and obtain the residuals, $\hat{u}_{it} = y_{it} - \hat{a}_i - \hat{\rho} y_{it-1} - \mathrm{X}_{it}\hat{\boldsymbol{\beta}}$.
2. Obtain the (estimated) common factors $\hat{\mathbf{F}}_t^u$ from the residuals $\hat{u}_{it}$ by the principal component analysis.
3. Run the following regression: $y_{it} = a_i + \rho y_{it-1} + \mathrm{X}_{it}\boldsymbol{\beta} + \lambda_i'\hat{\mathbf{F}}_t^u + e_{it}$.
4. Repeat steps 1–3 until $\hat{\boldsymbol{\beta}}$ converges.

The original PPC estimator is obtained by running the following regression:

$$y_{it} = a_i + \rho y_{it-1} + \mathrm{X}_{it}\boldsymbol{\beta} + \lambda_{xi}'\hat{\mathbf{F}}_t^x + \lambda_{yi}'\hat{\mathbf{F}}_t^y + \lambda_{y_{-1}i}'\hat{\mathbf{F}}_{t-1}^y + e_{it}, \quad \textbf{(A7)}$$

where $\hat{\mathbf{F}}_t^x$, and $\hat{\mathbf{F}}_t^y$ are principal component estimators obtained from X_{it} and y_{it}, respectively.

The modified PPC estimator is derived as follows: After obtaining PPC estimators, construct the PPC residuals, $\hat{u}_{it} = y_{it} - \hat{a}_{\mathrm{ppci}} - \hat{\rho}_{\mathrm{ppc}} y_{it-1} - \mathrm{X}_{it}\hat{\boldsymbol{\beta}}_{\mathrm{ppc}}$. The subscript ppc stands for the PPC estimators from equation (A7). The factor-augmented regression is then estimated using $\hat{\mathbf{F}}_t^u$. The iterative procedure is repeated until convergence.

Appendix B: Sample Countries

Table B1 List of sample countries by region

America	*Asia*	*ME & NA*	*Sub-Saharan Africa*	*W. Europe*
Argentina	Afghanistan	Algeria	Angola	Austria
Bolivia	Bangladesh	Bahrain	Burundi	Belgium
Brazil	Cambodia	Cyprus	Chad	Denmark
Canada	China	Egypt	Congo (Brazzaville)	Finland
Chile	Hong Kong	Iran	Congo (Kinshasa)	France
Colombia	India	Iraq	Ethiopia	Germany
Costa Rica	Indonesia	Israel	Ivory Coast	Great Britain
Cuba	Japan	Jordan	Kenya	Greece
Dominican Republic	Laos	Lebanon	Lesotho	Iceland
Ecuador	Macau	Morocco	Mali	Ireland
El Salvador	Malaysia	Syria	Mozambique	Italy
Guatemala	Maldives	Tunisia	Namibia	Luxembourg
Haiti	Nepal	Turkey	Niger	Malta
Honduras	Pakistan		Nigeria	Netherlands
Mexico	Philippines		Rwanda	Norway
Nicaragua	Singapore		Senegal	Portugal
Panama	South Korea		Sierra Leone	Spain
Peru	Sri Lanka		Somalia	Sweden
Puerto Rico	Taiwan		South Africa	Switzerland
United States	Thailand		Sudan	
Uruguay	Vietnam		Togo	
Venezuela			Uganda	
			Zambia	
			Zimbabwe	

Note. ME & NA stands for Middle East and North Africa and W. Europe denotes Western Europe.

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