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DEGREE OF STRINGENCY MATTERS: REVISITING THE POLLUTION HAVEN HYPOTHESIS BASED ON HETEROGENEOUS PANELS AND AGGREGATE DATA

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Empirical studies on the trade-environment nexus that use panel data face two simultaneous challenges. One is associated with the potential presence of unobserved cross-country heterogeneity, while the other is due to the use of aggregate data. In this paper, we apply both the dynamic fixed effects and iterative empirical Bayes estimators to show first that when country heterogeneity is accurately accounted for in the estimation, it is possible to obtain significant impacts of trade variables on the environment, even though we use aggregate data. Second, using both the empirical Bayes parameter estimates and indicators of stringency of environmental regulations, we show that at low levels of stringency, the probability of having pollution-intensive foreign direct investments (FDIs) increases with a decrease in stringency. However, at high levels of regulatory stringency, more stringent regulations may lead to more pollution-intensive FDIs. This implies that pollution havens may exist only if environmental regulations are very lax or nonexistent.

Keywords: Foreign Direct Investment, Pollution Haven, Regulatory Stringency, Bayesian Shrinkage Estimator

1. INTRODUCTION

This paper presents an empirical framework for studying the relationship between international trade flows, air pollution, and environmental regulations. In

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particular, we focus on the strategy of estimation of the parameters of an equation describing this relationship, which is one of the most extensively studied economic relationships in the field of environmental and development economics. However, a host of methodological problems plague this literature. Levinson and Taylor (2008) distinguish three main problems, namely, unobserved heterogeneity, unobserved foreign regulation, and aggregation bias. Unobserved heterogeneity results from unobserved differences and comparative advantages at the industry or economy-wide level. Unobserved foreign environmental regulations affect pollution abatement costs in the home country. Aggregation bias may arise from the fact that national economies are a heterogeneous mix of industries having different pollution intensities and abatement costs. This last point was previously underlined by Grether and De Melo (2003) who indicated that the relationship between the location decisions of multinational firms and the environmental conditions of host countries is very likely to disappear when aggregate data are used in the empirical work. As a result, when aggregate data are used, "the pollution haven hypothesis may be a popular myth" [Grether and De Melo (2003, pp. 5)].

Nevertheless, using disaggregate data is not free of problems. As indicated by Brunnermeier and Levinson (2004), some industries may share unobservable characteristics (such as fossil fuel intensities) that make them immobile. By considering only such industries, not only there would be a significant loss of variation in the data, but also only the least geographically footloose industries would be included in the empirical analysis, and this will therefore very likely bias the results against finding pollution havens.

With this background, this paper proposes an alternative method to study the trade-environment nexus. The analysis follows three steps. We begin by investigating whether there exists a global trade–environment relationship. Using aggregate data for a panel of 55 countries, we employ the dynamic fixed effects (DFE) estimator [Pesaran et al. (1996, 1999)] to estimate an econometric model that includes gross domestic product (GDP), trade openness, and inward foreign direct investment (FDI) as the explanatory variables of carbon dioxide (CO_2) emissions. This estimator imposes the homogeneity assumption for all parameters of the trade–environment relationship except for the country fixed effects (FE).

Second, we estimate the same model, but this time, by means of the iterative empirical Bayes estimator in order to relax this homogeneity assumption. As it will be discussed later, the advantage of this estimator is that it allows us to analyze the cross-country dispersions in the trade-environment nexus while considering at the same time, common dynamics of international trade, and pollution that may affect each country's pattern. These first two steps enable us to investigate whether, by switching from the DFE estimator to the iterative empirical Bayes estimator, significant impacts of trade, and inward FDI on the environment can be detected when aggregate trade data are used and country heterogeneity is accounted for simultaneously. In the perspective that we suggest in this paper, although countries undergo different sequences and patterns of economic, social, and institutional changes, they face the same global circumstances, and therefore

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this may involve some degree of similarity on a variety of dimensions, including, but not limited to, economic growth, trade, FDI, and polluting emissions.

Third, based on the estimated parameters from the iterative empirical Bayes procedure, we study the pollution haven hypothesis. More specifically, we investigate whether the fact that FDI increases emissions in some countries can be explained by the level of stringency of environmental regulations. For this purpose, in the framework of a logit regression, we use indicators of stringency of environmental regulations in the countries under consideration along with the estimated parameters associated with the variable of FDI to examine whether and how the probability of having pollution-intensive FDI varies with stringency of environmental regulations. No study that we are aware of approaches this research question from the empirical strategy that we have in this paper.

The remainder of the paper is organized as follows. Section 2 presents the related literature and theoretical background that guide our empirical analysis. Section 3 outlines first the model to be estimated and the data used in this paper, and then presents the preliminary results from the DFE estimation. Section 4 describes the advantages of the iterative empirical Bayesian procedure for heterogeneous panel and provides the results that it produced. Section 5 presents logit regression results and discusses the main findings of the study. Finally, Section 6 concludes the paper.

2. LITERATURE AND THEORETICAL BACKGROUND

Theoretically, there are three effects that contribute to the overall environmental impact of trade [Grossman and Krueger (1992)]. The first one is the scale effect. More economic activity means, *ceteris paribus*, more environmental degradation and also more income. The income–environment relationship may follow an inverted U-shaped curve. This situation, known also as the environmental Kuznets curve (EKC) hypothesis [Grossman and Krueger (1992)], suggests that increasing income cannot be always invoked as the driving force of environmental degradation.

The second effect is called technique effect. As indicated by the endogenous growth theories [Romer (1990)], human capital accumulation and technological innovation are the main drivers of economic growth as they increase factor productivities. At this point, FDI and international trade serve as crucial channels for transfer of knowledge-based assets, and they can decrease pollution per output. We will return to this point shortly.

Finally, trade can affect environmental quality by means of a composition effect. This effect stems from the theory of comparative advantages, according to which, countries specialize in the production and trade of "clean" or "dirty" goods depending on their comparative advantages.

Since the three effects that we mentioned here may be of opposite signs and counteract, to study the net environmental impact of trade a number of studies extended the basic framework of trade–environment relationship to account for

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other factors that might influence the impact of trade on the environment. One of the directions that have been pursued is on the so-called pollution haven hypothesis [Copeland and Taylor (1994)], which postulates that pollution intensive industries tend to be relocated in the countries where environmental regulations are lax, if not nonexistent. To avoid such an industrial relocation (called also as carbon leakage), governments may choose to adopt less stringent environmental policies than they would have chosen without the threat of pollution havens.[1] In the end, successive deregulations may lead to sub-optimal environmental policies and create a "race to the bottom effect" [see List and Co (2000)].

Against the pollution haven hypothesis, it might be argued that intercountry differences in factor endowments determine comparative advantages, and that, as a result, pollution-intensive industries are more likely to be relocated as inward FDI in capital-intensive developed countries and not in the developing world. Another argument that is made against the pollution haven hypothesis is that inward FDI and trade bring to host countries more efficient and environmentally friendly technologies, equipment, products, and management. As a result of this process, which is what the pollution halo hypothesis postulates, international trade and FDI can provide significant environmental benefits for developing countries [see Zarsky (1999)].

Despite the growing body of work devoted to the aforementioned investigations, the current state of empirical research is still controversial.[2] A small number of country-specific studies have used time series analysis to investigate the relationships between FDI inflows and pollution [e.g. Lau et al. (2014)]. Studies that have employed panel data techniques to analyze the trade–environment nexus for a given group of countries are also scarce [e.g. Omri et al. (2014)]. The common point of these country-specific and panel data studies is that they use aggregate data on trade or FDI flows and environmental indicators. On the other hand, a more abundant literature uses disaggregated data and estimates mostly gravity or input–output models of bilateral trade flows to study trade–environment nexus [see, for instance, Hubbard (2014)].

Clearly, the above discussion suggests that in the trade–environment relationship, some degree of country heterogeneity may arise from different factors, and that this may be an important missing part of the equation in the empirical literature. In what follows, we provide a framework through which we can explore this heterogeneity issue, and in turn, the pollution haven hypothesis.

3. MODEL, DATA, AND PRELIMINARY RESULTS

3.1. Model and Theoretical Framework

Since the objective of this paper is to analyze the impacts of FDI and international trade on environmental degradation, the empirical model that we plan to test is based on the following relationship:

$$\mathrm{CO}_{2i,t} = \mu_i + \beta_{1i}\mathrm{GDP}_{i,t} + \beta_{2i}\mathrm{GDP2}_{i,t} + \beta_{3i}\mathrm{FDI}_{i,t} + \beta_{4i}\mathrm{OPEN}_{i,t} + \varepsilon_{i,t}, \quad (1)$$

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where μ_i is the unobserved effect, $\varepsilon_{i,t}$ is the error term for the ith country in period t, respectively ($i = 1, 2, \ldots, N$, and $t = 1, 2, \ldots, T$), and β_{ji} are the coefficients to be estimated with $j = 1, \ldots, 4$. As is standard in the related literature, environmental degradation is measured by per capita CO_2 emissions. To test for the EKC hypothesis, per capita real GDP and its square (GDP2) are involved in the model. The variable FDI represents the value of inward FDIs as percentage of GDP by following the studies of Duttaray et al. (2008), Gurgul and Lach (2014), and Kar and Majumdar (2016). The variable OPEN represents trade openness, which is calculated as the total sum of exports and imports divided by GDP.[3]

From the estimation of equation (1), depending on the significance and the sign of the estimated β parameters, we are able to distinguish three effects. First, the income effect can be captured by the parameters β_1 and β_2. The income–emissions nexus follows an inverted U-shaped pattern (i.e. EKC) if $\beta_1 > 0$ and $\beta_2 < 0$. Some countries in the panel may experience such a pattern for at least three reasons. First, there may be a structural transformation in the composition of economic activities, which modifies energy intensity and carbon intensity of the economy. Second, increase in environmental awareness and knowledge (or increasing demand by consumers for environmentally friendly products) leads to a reduction in environmental degradation. Third, establishment of strict environmental regulations helps to reduce the level of pollutant emissions.

The second effect is the inward FDI effect that can be given by the estimated sign of β_3. A positive β_3 suggests that inward FDI contributes to the development of a pollutant sector. In such a situation, pollution havens or factor endowments hypotheses may be put forward. If β_3 is found to have a negative sign, the technique effect should be advanced. Then it might be concluded that inward FDI allow financing (for developed countries) or distribution of (for developing countries) more efficient production technologies that can curb pollution emissions.

Finally, the last effect that can be deduced from equation (1) is called openness effect and it can be examined by the estimated sign of β_4. If all three effects of Grossman and Krueger (1992) that we discussed above (i.e. scale, technique, and composition effects) are present, the sign of β_4 depends on which effect outweighs the others.

3.2. Data

In this study, we consider a balanced panel of 55 countries over the period from 1970 to 2013. The time period is chosen to be as large as possible so that the estimators provide robust results. Annual data on CO_2 emissions [in millions tones of CO_2 (MtC)] are taken from British Petroleum [BP (2014)]. Data on GDP, population, inward FDI, as well as exports and imports (which are used to calculate trade openness) are obtained from the United Nation's database [UNCTAD (2015)]. Population data are expressed in thousands of people, while data on the economic variables are in millions US dollars at constant (2005) prices and exchange rates.

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TABLE 1. Data coverage

	CO_2	GDP	FDI	Exports	Imports	Population
Sample	0.88	0.93	0.78	0.89	0.89	0.75
ROW	0.12	0.07	0.22	0.11	0.11	0.25

Notes: Values are calculated and presented as percentage of total (2013). ROW stands for rest of the world. *Data sources*: BP (2014) and UNCTAD (2015).

The FDI data include three components, namely, equity capital, reinvested earnings, and intracompany loans, while the trade data include merchandise exports and imports (excluding services).

We selected 55 countries based on the availability of the data.[4] Our sample excludes essentially most of the sub-Saharan African countries and former Soviet republics, for which there are no reliable reconstructed data before 1990. As shown in Table 1, our sample covers at least three quarters of the worldwide total of the variables used in this analysis. However, it should be noted that our analysis may still suffer, to some extent, from the fact that Russia is excluded and that Africa and Eastern Europe are underrepresented. Another notable feature of the data is that among the countries involved in the analysis there is important heterogeneity.[5]

3.3. Preliminary Analysis

We begin our empirical analysis by employing panel data techniques to estimate equation (1). First, we examine the stationarity properties of the variables by using a battery of panel unit root tests. All tests unanimously indicate that FDI is a stationary process [i.e. I(0)], while the remaining variables are integrated of order one [i.e. I(1)].[6]

Since the variables involved in our analysis are a mixture of I(0) and I(1) processes, ordinary least squares (OLS) estimation of equation (1) may yield inconsistent results. To overcome this problem, we follow Pesaran et al. (1999) and estimate a panel auto-regressive distributed lag (ARDL) model. This method not only allows for dynamics but also yields consistent estimates if the variables are either I(1) or I(0) [Pesaran et al. (1996)]. As a result, to study the relationship given in equation (1), we estimate the following model:

$$\Delta CO_{2i,t} = \Phi(CO_{2i,t-1} - \theta X_{i,t}) + \sum_{j=1}^{q} \eta_j \Delta CO_{2t-j} + \sum_{j=0}^{p} \delta_j \Delta X_{t-j} + \mu_i + \varepsilon_{i,t}, \quad (2)$$

where Δ is the first difference operator, Φ stands for the error-correcting speed of adjustment to the long-run relationship, $X_{i,t}$ is the vector of explanatory variables given in equation (1), which are GDP, GDP2, FDI, and OPEN, and the vector θ contains the long-run coefficients associated with these variables. On the other hand, η_j and δ_j are coefficient vectors capturing short-run dynamics, μ_i represents

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TABLE 2. Estimation results for the panel autoregressive distributed lag (ARDL) model

Long-run coefficients	GDP	GDP2	FDI	OPEN
	0.90812***	−0.01128***	−0.01262	−0.02586
	(0.214)	(0.002)	(0.101)	(0.032)
Speed of adjustment	Φ			
	−0.093**			
	(0.046)			

Notes: Robust standard errors are in parentheses. ** and *** indicate significance at the 5% and 1% levels, respectively.

the FE as in equation (1), p and q denote lag orders, and $\varepsilon_{i,t}$ is the disturbance term ($i = 1, 2, \ldots, \text{N}$, and $t = 1, 2, \ldots, \text{T}$).

To estimate the ARDL specification given in equation (2), we use the within regression estimator which is simply a pooled OLS estimator based on time-demeaned variables [see Greene (2008)]. This yields a standard DFE estimation that allows the intercepts to differ across countries but imposes complete homogeneity of all slope coefficients of the vector θ. The estimation results are given in Table 2.

The first conclusion to be drawn from Table 2 is that the EKC hypothesis is validated for the whole panel. Furthermore, based on the first derivative of equation (1), the maximum level of the variable CO_2 (i.e. the global turning point of income) is reached when GDP is equal to $-\beta_1/2\beta_2$, that is 40,253 US dollars. We find that 13 out of 55 countries have already reached this threshold.[7] We also find that inward FDI and trade openness have no significant effect on per capita emissions. That is to say, since in the ARDL framework the slope coefficients are assumed to be equal across countries, the trade–environment nexus does not hold.[8] Having this useful information, we now proceed with the iterative empirical Bayes estimation, which permits us to relax the assumption of equality of the slope coefficients across countries, thus enabling us to investigate whether the trade–environment nexus holds when the cross-sectional heterogeneity is accounted for.

4. IS THERE HETEROGENEITY IN THE TRADE–ENVIRONMENT RELATIONSHIP?

As we described above, there is a considerable degree of heterogeneity among the countries in terms of CO_2 emissions and economic development levels, as well as FDI flows and trade openness. This means that estimations that do not take into account such heterogeneity may lead to incorrect conclusions on the trade–environment relationship. To deal with this issue of heterogeneity, we propose the use of the iterative empirical Bayes estimator, which is briefly described next.

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4.1. The Iterative Empirical Bayes Estimator

In the recent empirical panel studies that consider cross-country heterogeneity, the hypothesis of homogeneity in the slope parameters is often rejected in favor of heterogeneous regressions [Baltagi and Kao (2000), Baltagi et al. (2003, 2008)]. Indeed, in the panel data analysis, the observations are often pooled by including or excluding individual-specific dummies. While in the FE models, these dummies are assumed to be fixed, in the random-effects (RE) framework, the REs allow to model the cross-country heterogeneity through the regression residual term. More specifically, in the FE models, the intercept (unobserved effect) is allowed to differ among individuals in order to account for special characteristics of each individual unit. In the RE models, the intercept gives the mean value of all the cross-sectional intercepts, and individual differences with respect to the intercept values of each individual are incorporated in the individual-specific error component. In the FE models, the unobserved effect may be correlated with the regressors, while in the RE models the regressors are assumed to be uncorrelated with the unobserved effect. The similarity between these two approaches is that both the FE and RE models assume a complete homogeneity of the slope coefficients. In this respect, Hsiao (2003) shows that in case where the true model's intercept and slopes are all heterogeneous, an estimation using individual intercepts with common slopes may lead to a wrong conclusion that the estimated relation is curvilinear. In order to avoid the assumption of common slopes, a model can be estimated separately for each country, which would provide distinct estimates for the slope parameters. Indeed, in the time series analysis, all the coefficients are assumed to be different for each country.

According to Maddala et al. (1997), the true values of the parameters fall somewhere in between complete homogeneity and complete heterogeneity. "The parameters are not exactly the same, but there is some similarity between them. One way of allowing for the similarity is to assume that the parameters all come from a joint distribution with a common mean and a nonzero covariance matrix" [Maddala et al. (1997, p. 91)]. The parameter estimates are then given by the weighted average of the separate time-series estimates for each cross-section and the overall pooled estimate. More specifically, separate estimations are shrunk toward the overall pooled estimation, hence the name "shrinkage estimator." In the case of panel data models with coefficient heterogeneity, according to Maddala and Hu (1996), Maddala et al. (1997), Hsiao et al. (1999), and Trapani and Urga (2009), the shrinkage estimators are superior to the homogeneous and other heterogeneous estimators as far as predictive ability is concerned. Baltagi et al. (2008) compared the out of sample forecast performances of 11 heterogeneous and shrinkage Bayes estimators and 9 homogeneous panel data estimators. They concluded that the Bayes shrinkage estimator has the best performances, while the average heterogeneous estimators have the worst. Furthermore, another advantage of the empirical Bayes estimator framework is that, although the coefficients differ across countries, the number of parameters to be estimated is reduced, thanks to

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the random coefficients specification. In this framework, the OLS estimations are used in the initial iteration to obtain the prior distribution of parameters. The posterior distribution for the parameters is derived from the subsequent iterations, which are based on the iterative empirical Bayes estimator. The interested reader can find a more detailed and technical description of this estimation procedure in Appendix B.

Before we proceed with the estimation results, let us turn to the stationarity issue, but this time in the framework of shrinkage estimators. The bulk of the literature using macroeconomic variables is concerned with the nonstationarity issue in panel data. However, so far the unit root tests developed for panel data are based on individual time-series unit root tests. Typically, the statistics obtained in this type of tests are based on "combining the p-values of the individual unit root t-statistics" [Westerlund and Bacher (2008, p. 113)]. In the Bayesian framework, dynamic panel data models raise other problems than individual time series (such as a correct consideration of cross-country homogeneity or heterogeneity). This is the reason why the recent empirical literature on the estimation of dynamic panel data models argues in favor of shrinkage estimators that shrink the heterogeneous estimators toward the pooled homogeneous estimator. In the framework of dynamic panel, the problem of nonstationarity does not arise. For panel data (more specifically, for dynamic heterogeneous panels), the seminal article is that of Hsiao et al. (1999). In this paper, there is no question about the unit root problem. More recently, Hsiao and Pesaran (2008) get back on the same issue raised by the estimation of dynamic panel data models. Similarly, Baltagi et al. (2008) considered the dynamic version of the classical Tobin q investment model. Since their model is dynamic, they focus on pooled and some shrinkage estimators using as instruments some exogenous variables and their lagged values (without discussing about the potential nonstationarity of their panel data). All in all, the recent empirical literature on the estimation of dynamic panel data models shows that, unlike in time series analysis (where one of the most important problems is the nonstationarity), the inconsistent estimators are not caused by the nonstationary series but by the insufficient consideration of cross-country heterogeneity.

We now employ the iterative empirical Bayes estimator proposed by Maddala et al. (1997) in order to obtain heterogeneous (country by country) estimates for the trade–environment model given in equation (1). Recall that these estimates will allow us to study the pollution haven hypothesis in the next section.

4.2. Results

Employing the iterative empirical Bayes estimator, we obtained the results given in Tables C.1 and C.2 in Appendix C. To facilitate the interpretation of these results, we consider Table 3, which reproduces the information provided in Tables C.1 and C.2.

For a given country, if a parameter is nonsignificant at the 5% level in Tables C.1 and C.2, we state in Table 3 that the variable associated with that parameter has no

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TABLE 3. Summary of estimation results country by country

OPEN	FDI	GDP and GDP2 Neutral	Positive	Negative
Neutral	Neutral	AUT; CND; FND; POL; SAR; AFR; USA; VNZ; SPA	**ARG**; **GRC**; **IND**; **KWT**; **MLS**; **KOR**; **TWN**; **TRK**; **EMI**; IRN; PHL; *SWE*; TLD	**AUS (2003)**; **DNK (1983)**; **ISR (2012)**; **NZL (2003)**; **QTR (1997)**; FRA
	Positive		**NOR**; ECD; *JPN*; T&T	**SWZ (1979)**
	Negative		**PER**	
Positive	Neutral	IRL	**CHK**; **EGY**; **INS**; CHN	BLG
	Positive			
	Negative		**MXC**	GER (1970)
	Neutral		**CLM**; ALG	**ROM (1992)**
Negative	Positive	NLD	**PRT**; *BEL*; BRZ; CHL; *ITL*; PKS; SNG	GBR
	Negative			**HUN (1999)**

Notes: Countries shown in bold, italic, and underlined codes are those having inverted U-shape, U-shape, and linear relationship, respectively. Dates in parentheses refer to the turning point years.

impact on CO_2 emissions (i.e. neutral). On the other hand, if a country following an EKC pattern has not yet reached the turning point income, it is considered to be on the increasing part of the EKC (i.e. positive relationship between GDP and CO_2 emissions), and *vice versa* for a country having already reached its turning point. Here we should note that the countries that are found to have a U-shaped relationship are all on the increasing part of the curve.

At first glance, one conclusion that we can draw from Table 3 is that there is important country heterogeneity both for the EKC hypothesis and the impacts of international trade and inward FDI on emissions. For nine countries, there is no relationship. The EKC hypothesis is validated for 25 countries and only eight of them are beyond the turning point. These countries are either "rich" countries or former communist countries. For nearly half of the countries (28 countries), both inward FDI and trade openness have no impact on emissions. International trade does not affect emissions of countries that are located at the horizontal part of the EKC, the only exceptions being Ireland and the Netherlands. Trade openness and inward FDI simultaneously affect emissions for only 12 countries. In what follows, we use the results of this section to analyze whether and to what extent lax environmental regulations attract polluting FDI.

5. ENVIRONMENTAL REGULATIONS AND POLLUTING FDI

It is well known from the literature that environmental regulation is an important determinant of FDI [see, for instance, List and Co (2000)]. In order to study

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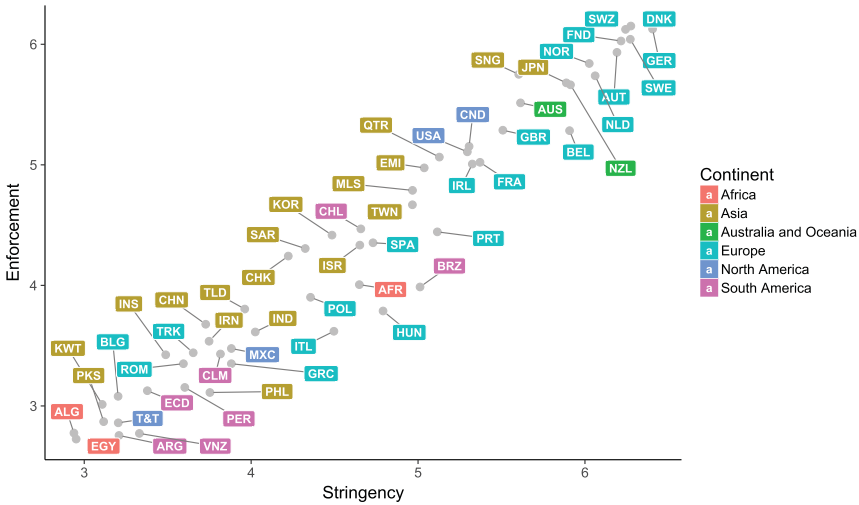


FIGURE 1. Stringency versus enforcement of environmental regulations. *Notes:* Average values, for period 2005 to 2014 are based on WEF (2015).

the impact of environmental regulations on relocation decisions of polluting productions, we use additional information provided by environmental regulation indicators obtained from the World Economic Forum's global competitiveness report series [WEF (2015)]. Based on the Executive Opinion Surveys [WEF (2015)], two indicators, namely, stringency of environmental regulations and enforcement of environmental regulations, rank countries on a scale of 1 to 7, where 7 denotes "very stringent" regulations while 1 denotes "very lax." In Figure 1, we plot the average index values for period 2005 to 2014. Not surprisingly, the two indicators are strongly correlated.

In order to assess whether stringency of environmental regulations have the potential to create pollution havens, we suggest employing logit regression models and using both the above-mentioned environmental regulatory stringency indicators and our empirical Bayes estimation results on the significance and sign of the coefficients associated with the variable FDI. Hence, we can assess the marginal effect of environmental regulations on the probability of having pollution-intensive FDI. In this framework, we construct a binary variable that equals one with a probability of success ϕ if the estimated coefficient is significantly positive for FDI, zero otherwise with probability of failure $(1 - \phi)$. In such a context, it is well known from the literature that OLS regressions produce inconsistent estimates [Long (1997)]. The logit model to be estimated takes the following form:

$$\log\left(\frac{\phi_i}{1-\phi_i}\right) = \alpha_0 + \alpha_1 \mathrm{Reg}_i + \alpha_2 \mathrm{Reg2}_i + \alpha_3 \mathrm{CoefGDP}_i + \varepsilon_i, \qquad (3)$$

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TABLE 4. Logit regressions

	Model specifications		
Independent variables	(1)	(2)	(3)
Reg	−0.215***	−0.919***	−2.136***
	(0.074)	(0.353)	(0.666)
	[0.806]	[0.398]	[0.118]
Reg2		0.143**	0.330***
		(0.069)	(0.113)
		[1.154]	[1.392]
CoefGDP			2.280**
			(0.959)
			[9.784]
Wald χ^2	8.43***	12.81***	15.36***
Likelihood-ratio (score) test		4.68**	7.53***
Percent correctly classified	74.6%	74.6%	80.0%
Goodness-of-fit tests			
Hosmer and Lemeshow χ^2	15.38*	12.78	8.49
Pearson χ^2	56.12	54.79	49.87

Notes: Robust standard errors are in parentheses. Odds ratios [exponential values of α coefficients associated with the explanatory variables given in equation (3)] are in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

where α_0 is the intercept and ε_i is the error term. Reg is the indicator for environmental regulation ranging from 1 to 7, Reg2 is the square of this indicator, and CoefGDP is a binary variable that equals one for countries for which GDP is found to increase CO_2 emissions and zero otherwise. $\frac{\phi_i}{1-\phi_i}$ is the odds ratio in favor of having CO_2-increasing FDI from the estimation results obtained in the preceding section. Put another way, it is the ratio of the probability that FDI increases significantly CO_2 emissions to the probability that FDI does not affect CO_2 emissions. Table 4 reports the results of the logit regressions in which the indicator Reg stands for the enforcement of environmental regulations.[9]

In all model specifications, the results show that there is a U-shaped relationship between environmental regulation and the probability of having CO_2-increasing FDI as both the level and quadratic terms associated with the regulation variable are significant. This result suggests that decreasing environmental stringency increases the likelihood of having pollution havens. In other words, countries with lax environmental regulations are more likely to receive pollution-intensive FDI. However, the direction of this relation may differ at different levels of regulation stringency as we have a U-shaped curve. The results are robust when we control for the significance of GDP variable in Table 3. Furthermore, the estimated odds ratio for this variable indicates that the likelihood of CO_2-increasing FDI is significantly higher for countries for which GDP is found to increase CO_2 emissions. A caveat is in order. In the preceding sections, data used to estimate the parameters of the

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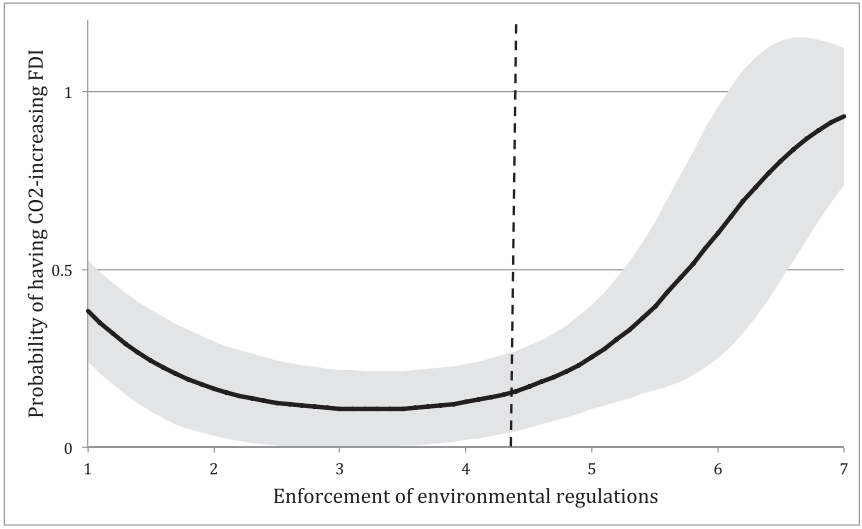


FIGURE 2. Adjusted predictive margins. *Notes:* Predictive margins are estimated at the means of other covariates. The shaded area indicates 95% confidence intervals and the vertical line indicates the median value of the enforcement variable.

CO_2 equation cover the period from 1970 to 2013. In this section, logit models are estimated using these parameter estimates with environmental regulation data, which, however, are obtained by taking the average index values over the period 2005–2014. Therefore, the results, although very significant and robust, may be affected by this incompatibility between the periods being compared.

Based on the estimation results given in Table 4, we plot the adjusted predictions (predictive margins) that show the probability of having significantly positive coefficient for FDI at different values of enforcement of environmental regulations index.

It follows from Figure 2 that stringency in environmental enforcement decreases the probability of receiving pollution-intensive FDI for only very low levels of stringency. This means that the pollution haven hypothesis may exist only when environmental regulations are very lax or unenforced. There is a turning point beyond which enforcement of environmental regulations has a positive effect on the probability of having a positive FDI coefficient. While this finding may seem counter-intuitive at first glance, it is not inconsistent with some of the arguments and findings of the earlier literature. Albrecht (1998) showed that while the strict environmental regulations implemented in the United States have increased environmental costs, the inward FDI for the group of dirty industries increased by 67.1% for period 1991 to 1995. To explain this result, the author argues that there is a regulatory uncertainty in less strict countries and that despite strict regulations in the United States, investors still opted for this country because of the stability of regulatory schemes that provide reliable rules. Another explanation that the

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author puts forward is that the dirty industries invest most intensively in research and development and that since strict environmental policies stimulate research and development, pollution-intensive FDI would locate in countries where these policies are implemented in order to take advantage of first-mover advantages. On the other hand, it should be noted that environmental costs represent only a small fraction of internal costs of industries (around 1% to 3% of GDP) even in heavy industries such as chemicals, metals, paper, etc. [Albrecht (1998), Neumayer, (2000)]. Moreover, improving environmental quality serves as a source of stabilization and lowers social costs, which can compensate environmental costs incurred by strict regulations [see, for instance, Tobey (1990), Low and Yeates (1992), Palivos and Varvarigos (2017)]. From another perspective, Sanna-Randaccio and Sestini (2012) show that when the market size of a country is large, increasing stringency of environmental regulations does not induce firms to relocate to other countries with lax environmental regulations. The market size effect is also indicated by Gray (1997) and Wilson et al. (2002), who suggest that firms tend to locate where the market size is large and that polluted areas may have shrinking markets.

Another explanation of this result may lie in the fact that the cost of capital can outweigh any benefit from lower environmental regulations [Antweiler et al. (2001)]. Cole and Elliott (2005) call this effect as "capital-labor hypothesis." The authors indicate that comparative advantages are determined by differences in both factor endowments and environmental regulations, and that countries with lax environmental regulations do not have the necessary capital stock to attract capital- and pollution-intensive FDI.

6. CONCLUSION

The use of the iterative empirical Bayes estimator allows dealing with the heterogeneity problem, while standard panel estimators may fall short of solving it. In this paper, the results obtained by using this method are indeed interpretable, which led us to identify countries for which international trade movements decrease pollution and those for which they increase it. Based on these results, we also showed in what direction and to what extent stringency of environmental regulations affect the probability of having pollution-intensive FDI.

All in all, our results imply that it is empirically unrealistic to believe in the existence of EKC that would solve the climate change problem once a certain level of development is reached. Furthermore, we found almost no evidence of pollution havens for CO_2 emissions.

In terms of future research, a number of extensions emerge. Since our results suggest that other factors (market size, uncertainty, factor endowments) may generate forces that oppose the pollution haven hypothesis, a natural extension is to examine to what extent these factors are significant determinants of pollution-intensive FDI inflows. In the same framework, instead of using CO_2 emissions, some local pollutants, such as sulfur dioxide, can also be considered. Another

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direction that can be pursued is to estimate similar models for each country at the sectoral level to control for composition effects depending on the degree of pollution in each sector. Finally, for countries in which legislations may differ from state to state (e.g. the United States), it would be more appropriate to conduct an analysis at the state level.

NOTES

1. For instance, the EU Emissions Trading System provides a differentiated treatment to the energy-intensive sectors, which are at significant risk of carbon leakage, in order to support their competitiveness.

2. We do not offer a detailed review of this literature. Brunnermeir and Levinson (2004) and Copeland and Taylor (2004) survey the earlier literature, and Shahbaz et al. (2015) review the newer studies.

3. It should be noted that ideally, one would estimate an augmented version of equation (1), which might have six explanatory variables (and a constant term), namely, GDP, GDP2, exports, imports, inward FDI, and outward FDI. Nevertheless, as we will take into account country heterogeneity, it would not be statistically optimal to estimate an equation with more than four explanatory variables. Because, every time we add a new variable, there are as many parameters to be estimated as countries [for instance, from equation (1), 275 parameters should be estimated for a panel of 55 countries].

4. The list of the countries included in the panel is provided in Table A.1 in Appendix A.

5. Let us give a few examples to illustrate this point. In the low-income countries, emissions are very low (e.g. 0.91 tonnes of CO_2 for Pakistan), for European countries, the emissions level increases to about 7 tonnes of CO_2, for North American countries it is nearing to 20 tonnes of CO_2, and for the Arabian Gulf countries it exceeds 30 tonnes of CO_2. Among the developed countries, those having the lowest trade openness are the United States and Japan (about 20% of GDP), while Hong Kong and Singapore are the most open countries with a degree of openness over 200%. The share of inward FDI in GDP is very low for Japan and Kuwait, while Belgium, Hong Kong, and Singapore have very high average levels (over 8% of GDP).

6. As first-generation tests, we use the LLC (Levin et al., 2002) and IPS (Im et al., 2003) unit root tests, and as a second-generation test, we use Pesaran's cross-sectional IPS (CIPS) test developed by Pesaran (2007) along with Pesaran cross-section dependence (CD) test (Pesaran, 2004). To conserve space, we do not provide a detailed description of these tests and their results, which are available from the authors on request.

7. Those countries are Australia, Denmark, Finland, Ireland, Kuwait, the Netherlands, Norway, Qatar, Sweden, Switzerland, United Arab Emirates, the United Kingdom, and the United States.

8. The results reported in Table 2 are obtained from an ARDL (1,1) specification (i.e. one lag for both the lagged dependent and explanatory variables). We also examined the sensitivity of our results to the order of the ARDL model, and found that the EKC hypothesis is clearly confirmed, and that our variables of interest FDI and OPEN remain non-significant.

9. The results for the stringency of environmental regulations are very similar and thus are suppressed for brevity. In an unreported regression, we also estimated a multinomial logit specification and verified that all of the results reported herein held when the dependent variable is categorical (negative, neutral, or positive FDI–CO_2 relationship) rather than binary. It should be also noted that the results from probit regressions (not presented but available upon request) were consistent with those found from logit regressions.

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APPENDIX A: LIST OF COUNTRIES AND COUNTRY CODES

TABLE A.1. Country codes used in tables and figures

Continent	Code	Country	Continent	Code	Country	Continent	Code	Country
Asia	CHK	China Hong Kong SAR	Africa	AFR	South Africa	Europe	AUT	Austria
	CHN	China		ALG	Algeria		BEL	Belgium
	EMI	United Arab Emirates		EGY	Egypt		BLG	Bulgaria
	IND	India	Australia and Oceania	AUS	Australia		DNK	Denmark
	INS	Indonesia		NZL	New Zealand		FND	Finland
	IRN	Iran	North America	CND	Canada		FRA	France
	ISR	Israel		MXC	Mexico		GBR	United Kingdom
	JPN	Japan		T&T	Trinidad and Tobago		GER	Germany
	KOR	South Korea		USA	United States		GRC	Greece
	KWT	Kuwait	South America	ARG	Argentina		HUN	Hungary
	MLS	Malaysia		BRZ	Brazil		IRL	Republic of Ireland
	PHL	Philippines		CHL	Chile		ITL	Italy
	PKS	Pakistan		CLM	Colombia		NLD	Netherlands
	QTR	Qatar		ECD	Ecuador		NOR	Norway
	SAR	Saudi Arabia		PER	Peru		POL	Poland
	SNG	Singapore		VNZ	Venezuela		PRT	Portugal
	TLD	Thailand					ROM	Romania
	TWN	Taiwan					SPA	Spain
							SWE	Sweden
							SWZ	Switzerland
							TRK	Turkey

APPENDIX B: ITERATIVE EMPIRICAL BAYES ESTIMATION PROCEDURE

In the framework of the random-coefficients model, the Bayesian approach for the basic model of trade–environment [see equation (1)] can be rewritten as

$$y_i = X_i \gamma_i + \varepsilon_i, \tag{B.1}$$

where y_i contains CO_2 time series, X_i is the matrix with explanatory variables, and γ_i are the slope coefficients. In the Bayesian framework, the *prior* distribution of γ_i is given by $\gamma_i \sim N(\mu, \Sigma)$. In this distribution, the parameters μ (mean of γ_i), Σ (variance of γ_i), and σ_i^2 (residual variance) are unknown. Consequently, some assumptions need to be made on prior specification of these parameters. Then we can derive the posterior distribution for the parameters γ_i. However, if they are all known, the posterior distribution of γ_i is normal and calculated by

$$\gamma_i{}^* = \left[\frac{1}{\sigma_i^{*2}} X_i' X_i + \Sigma^{*-1}\right]^{-1} \left[\frac{1}{\sigma_i^{*2}} X_i' X_i \hat{\gamma}_i + \Sigma^{*-1}\mu^*\right], \tag{B.2}$$

where $\hat{\gamma}_i$ is the OLS estimator of γ_i. The posterior distribution mean of γ_i and its variance can be obtained from equations (B.3) and (B.4), respectively, as follows:

$$\mu^* = \frac{1}{N}\sum_{i=1}^{N} \gamma_i{}^*, \tag{B.3}$$

$$V[\gamma_i{}^*] = \left[\frac{1}{\sigma_i^{*2}} X_i' X_i + \Sigma^{*-1}\right]^{-1}. \tag{B.4}$$

Since, in general, Σ and σ_i^2 are unknown, one needs to specify priors for these parameters. To do this, Smith (1973) suggested using the mode of the joint posterior distribution given by equations (B.5) and (B.6) as follows:

$$\sigma_i^{*2} = \frac{1}{T + \varsigma_i + 2}\left[\varsigma_i \lambda_i + (y_i - X_i \gamma_i{}^*)'(y_i - X_i \gamma_i{}^*)\right] \tag{B.5}$$

and

$$\Sigma^* = \frac{1}{T - k - 2 + \delta}\left[R + \sum_{i=1}^{N} (\gamma_i{}^* - \mu^*)(\gamma_i{}^* - \mu^*)'\right], \tag{B.6}$$

where the parameters ς_i, λ_i, δ, and R come from the specification of the prior distributions. Smith (1973) suggested also that these parameters can be approximated by choosing $\varsigma_i = 0$, $\delta = 1$, and R as a diagonal matrix having small positive entries (e.g., 0.001). By doing so, the estimators take the following forms:

$$\Sigma_i^{*2} = \frac{1}{T + 2}\left[(y_i - X_i \gamma_i{}^*)'(y_i - X_i \gamma_i{}^*)\right], \tag{B.7}$$

$$\Sigma^* = \frac{1}{T - k - 1}\left[R + \sum_{i=1}^{N} (\gamma_i{}^* - \mu^*)(\gamma_i{}^* - \mu^*)'\right], \tag{B.8}$$

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$$\gamma_i{}^* = \left[\frac{1}{\sigma_i^{*2}} X_i' X_i + \Sigma^{*-1}\right]^{-1} \left[\frac{1}{\sigma_i^{*2}} X_i' X_i \hat{\gamma}_i + \Sigma^{*-1}\mu^*\right], \tag{B.9}$$

and

$$\mu^* = \frac{1}{N}\sum_{i=1}^{N} \gamma_i{}^*, \tag{B.10}$$

$$V[\gamma_i{}^*] = \left[\frac{1}{\sigma_i^{*2}} X_i' X_i + \Sigma^{*-1}\right]^{-1}. \tag{B.11}$$

Then equations (B.7)–(B.11) should be solved iteratively. The initial iteration uses the OLS estimator $\hat{\gamma}_i$ to compute μ^*, Σ^*, and σ_i^{*2}; the second, and the following iterations are based on the empirical iterative Bayes estimator $\gamma_i{}^*$ which was first proposed by Maddala et al. (1997). The only difference compared to the Smith's (1973) estimator concerns the computation of the parameters σ_i^{*2} and Σ^*. Equations (B.7) and (B.8) become

$$\sigma_i^{*2} = \frac{1}{T-k}(y_i - X_i\gamma_i{}^*)'(y_i - X_i\gamma_i{}^*), \tag{B.12}$$

$$\Sigma^* = \frac{1}{N-1}\left[R + \sum_{i=1}^{N}(\gamma_i{}^* - \mu^*)(\gamma_i{}^* - \mu^*)'\right]. \tag{B.13}$$

The iterative procedure is stopped as soon as the standard deviation of the Bayesian estimators is sufficiently small. As suggested by Maddala et al. (1997), we use the heterogeneity matrix given in equation (B.13) to terminate the iteration process. Thus, the iterations are stopped when $[\sqrt{\sum *}]'[\sqrt{\sum *}] \leq 0.005$, that is, the heterogeneity of the estimators is sufficiently reduced, and the parameters are shrunk toward the overall pooled estimation.

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APPENDIX C: SHRINKAGE ESTIMATORS COUNTRY BY COUNTRY

TABLE C.1. Shrinkage estimators country by country

	Code	Coef.	Robust std error	Code	Coef.	Robust std error	Code	Coef.	Robust std error	Code	Coef.	Robust std error
μ	**AFR**	5.680**	1.538	**CHK**	−1.231*	0.718	**EMI**	−2.224	6.360	**INS**	−0.389**	0.059
β_1		0.495	0.396		0.352**	0.054		1.893	0.243		1.379**	0.054
β_2		−0.008	0.020		−0.004**	0.002		−0.021	0.002		−0.029**	0.012
β_3		0.006	0.023		0.010	0.006		−0.003	0.012		−0.015	0.011
β_4		0.003	0.013		0.017**	0.006		−0.003	0.015		0.004**	0.002
μ	**ALG**	−1.357**	0.444	**CHL**	0.353	0.244	**FND**	5.644**	2.328	**IRL**	1.775**	0.850
β_1		1.940**	0.193		0.588**	0.095		0.311*	0.162		0.095	0.089
β_2		−0.035*	0.019		−0.005	0.007		−0.005	0.003		0.000	0.001
β_3		−0.005	0.022		0.030**	0.010		0.009	0.011		−0.003	0.007
β_4		−0.024**	0.005		−0.010**	0.004		0.007	0.013		0.035**	0.008
μ	**ARG**	1.177**	0.339	**CHN**	0.954**	0.058	**FRA**	17.105**	2.744	**IRN**	0.095	1.078
β_1		0.696**	0.135		1.615**	0.074		−0.517**	0.207		1.609**	0.396
β_2		−0.029**	0.012		−0.019	0.016		0.006	0.004		−0.011	0.020
β_3		−0.011	0.012		−0.015	0.017		0.014	0.011		−0.002	0.023
β_4		0.002	0.003		0.008**	0.003		0.000	0.014		0.010	0.014
μ	**AUS**	−11.369**	2.307	**CLM**	0.689**	0.151	**GBR**	17.324**	1.536	**ISR**	−11.042**	1.827
β_1		1.668**	0.162		0.669**	0.097		−0.278**	0.110		1.881**	0.207
β_2		−0.024**	0.003		−0.049**	0.012		0.003	0.002		−0.041**	0.006
β_3		0.003	0.012		−0.006	0.012		0.033**	0.010		−0.011	0.011
β_4		0.010	0.014		−0.035**	0.006		−0.035**	0.012		0.004	0.010

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TABLE C.1. Continued

	Code	Coef.	Robust std error	Code	Coef.	Robust std error	Code	Coef.	Robust std error	Code	Coef.	Robust std error
μ	**AUT**	4.035**	1.450	**CND**	14.926**	3.436	**GER**	9.111**	1.724	**ITL**	8.593**	1.528
β_1		0.168*	0.092		0.146	0.249		0.423**	0.123		−0.166	0.132
β_2		−0.002	0.002		−0.002	0.004		−0.013**	0.002		0.006**	0.002
β_3		0.011	0.011		−0.003	0.011		−0.025**	0.009		0.037**	0.009
β_4		0.014	0.012		0.011	0.012		0.033**	0.009		−0.019**	0.009
μ	***BEL***	26.025**	3.320	**DNK**	5.041	4.695	**GRC**	−9.631**	2.736	**JPN**	14.378**	1.393
β_1		−0.757**	0.230		0.501**	0.253		1.606**	0.322		−0.502**	0.103
β_2		0.016**	0.004		−0.008**	0.003		−0.034**	0.009		0.011**	0.002
β_3		0.031**	0.008		0.019	0.011		−0.002	0.013		0.032**	0.010
β_4		−0.029**	0.009		−0.012	0.015		−0.001	0.014		−0.013	0.011
μ	**BLG**	6.436**	0.493	**ECD**	−1.248**	0.156	**HUN**	2.600**	1.046	**KOR**	−0.066	0.456
β_1		−0.538**	0.202		0.914**	0.096		1.244**	0.239		0.912**	0.049
β_2		−0.018	0.015		0.016	0.013		−0.070**	0.014		−0.009**	0.002
β_3		−0.012	0.016		0.044**	0.014		−0.053**	0.017		0.017*	0.009
β_4		0.025**	0.003		0.001	0.004		−0.013**	0.004		−0.006	0.007
μ	**BRZ**	0.111	0.135	**EGY**	−0.043	0.033	**IND**	0.126**	0.023	**KWT**	6.333	5.223
β_1		0.369**	0.059		1.622**	0.030		1.288**	0.146		0.873**	0.244
β_2		0.011	0.007		−0.015**	0.007		−0.031**	0.014		−0.008**	0.002
β_3		0.052**	0.007		−0.001	0.005		−0.013	0.015		0.010	0.012
β_4		−0.009**	0.003		0.005**	0.001		0.000	0.004		−0.010	0.015

Notes: Estimated equation: $CO_{2i,t} = \mu_i + \beta_{1i}GDP_{i,t} + \beta_{2i}GDP2_{i,t} + \beta_{3i}FDI_{i,t} + \beta_{4i}OPEN_{i,t} + \varepsilon_{i,t}$. Number of iterations is 15 (*, ** indicate significance at the 10% and 5% levels, respectively).

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TABLE C.2. Shrinkage estimators country by country

	Code	Coef.	Robust std error	Code	Coef.	Robust std error	Code	Coef.	Robust std error	Code	Coef.	Robust std error
μ	**MLS**	−1.492**	0.170	**PHL**	0.264**	0.071	**SAR**	10.930**	5.259	**TLD**	−0.619**	0.079
β_1		1.563**	0.137		0.311**	0.074		0.758	0.630		1.210**	0.102
β_2		−0.028**	0.013		−0.018	0.014		−0.031	0.018		0.014	0.015
β_3		−0.015	0.015		0.007	0.014		−0.023	0.020		0.027	0.016
β_4		0.002	0.002		0.003**	0.001		−0.003	0.015		0.005*	0.002
μ	**MXC**	−3.847**	0.653	**PKS**	−0.095**	0.027	**SNG**	7.795**	1.682	**TRK**	−1.554**	0.202
β_1		1.456**	0.193		1.416**	0.051		1.176**	0.125		0.978**	0.075
β_2		−0.065**	0.015		−0.002	0.009		−0.001	0.003		−0.034**	0.005
β_3		−0.047**	0.018		0.020**	0.007		0.019**	0.007		−0.013	0.008
β_4		0.009**	0.003		−0.004**	0.001		−0.021**	0.006		0.004	0.004
μ	**NLD**	15.271**	3.053	**POL**	12.273**	1.165	**SPA**	0.187	1.805	**TWN**	−0.826	0.866
β_1		−0.021	0.185		−0.193	0.326		0.378*	0.194		1.123**	0.095
β_2		0.003	0.003		−0.017	0.019		−0.003	0.005		−0.016**	0.004
β_3		0.023**	0.008		−0.004	0.023		0.022*	0.011		0.004	0.011
β_4		−0.023**	0.007		−0.003	0.014		0.003	0.013		0.002	0.009
μ	**NOR**	4.218**	0.945	**PRT**	−3.299**	1.058	**SWE**	32.269**	2.729	**USA**	20.650**	3.487
β_1		0.145**	0.034		0.906**	0.179		−1.279**	0.167		0.134	0.217
β_2		−0.001**	0.000		−0.017**	0.006		0.016**	0.003		−0.003	0.003
β_3		0.022**	0.010		0.029**	0.010		0.012	0.011		0.004	0.012
β_4		0.000	0.012		−0.028**	0.010		−0.008	0.013		−0.017	0.015
μ	**NZL**	−15.464**	4.003	**QTR**	−11.571	7.062	**SWZ**	−0.665	2.892	**VNZ**	4.530**	0.908
β_1		1.859**	0.356		2.991**	0.319		0.370**	0.121		0.265	0.228
β_2		−0.035**	0.007		−0.034**	0.004		−0.005**	0.001		−0.014	0.018
β_3		0.009	0.011		−0.015	0.013		0.023**	0.008		0.009	0.020
β_4		−0.005	0.012		0.003	0.015		−0.001	0.009		−0.003	0.009
μ	**PER**	−0.147	0.109	**ROM**	7.561**	0.928	**T&T**	−3.713	2.395			
β_1		0.613**	0.072		0.238	0.288		2.309**	0.409			
β_2		−0.041**	0.008		−0.041**	0.019		0.036*	0.018			
β_3		−0.018**	0.006		−0.003	0.022		0.049**	0.021			
β_4		−0.003	0.002		−0.035**	0.011		0.004	0.012			

Notes: Estimated equation: $CO_{2i,t} = \mu_i + \beta_{1i}GDP_{i,t} + \beta_{2i}GDP2_{i,t} + \beta_{3i}FDI_{i,t} + \beta_{4i}OPEN_{i,t} + \varepsilon_{i,t}$. Number of iterations is 15 (*, ** indicate significance at the 10% and 5% levels, respectively).