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Financial market instability and CO2 emissions

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Abstract

Capital markets may be an important tool in the reduction of pollution emissions. Indeed, they provide firms with an incentive to maintain a good environmental record (or at least, a good reputation) in order to maximize the value of their equity shares. Also, efficient capital markets may facilitate financing of environmentally friendly projects and reduce problems resulting from asymmetric information. In this paper, I use a panel of 36 countries between 1981 and 2007 to study the impact of financial market instability on CO_2 emissions at the national level. According to my results, higher financial stability is beneficial for the environment.

Keywords: CO_2 emissions; financial stability; dynamic panel data model.

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1 Introduction

Capital markets may be an important tool in the reduction of pollution emissions because they may facilitate the financing of environmentally-friendly investment projects. Also, they provide investors with a channel through which they can punish firms with bad environmental records and reward those with good records, thus creating an incentive for firms to have a good environmental performance.

There is a rather large body of empirical evidence to the effect that financial markets provide firms with an incentive to be environmentally responsible. Most of it consists of event studies, that is, statistical estimation of the impact of some event or news concerning a given firm on the returns of the firm's stock. For example, Muhoghalu, Robison and Glascock (1990) use announcements of environment-related lawsuits and case settlements (that involve fines) between 1977 and 1986 in the United States and find that lawsuit announcement cause a market value loss of 1.2%. Similar results in advanced economies are presented by, among others, Shane and Spicer (1983), Lanoie and Laplante (1994), Hamilton (1995), Lanoie, Laplante and Roy (1998) and Khanna, Quimio and Bojilova (1998) and in emerging economies by Dasgupta, Laplante and Mamingi (2001), Gupta and Goldar (2005) and Dasgupta, Hong, Laplante and Mamingi (2006). Interestingly, according to these latter papers, the reaction of markets to bad news is greater in developing countries.

Financial markets also seem to be able to punish firms after environmental accidents such as oil spills or chemical explosions, see Salinger (1992), Rao (1996), White (1996), Herbst, Marchall and Wingender (1996), and Capelle-Blancard and Laguna (2010). On the other hand, a few papers find no relationship between environmental accidents and firms' market values, for instance, Jones and Rubin (2001). Though event study is the most widely used method in this literature, it is not the only one. For example, Konar and Cohen (2001) use a decomposition of firms' market value technique with a sample of S and P 500 firms. They find a positive relationship between a firm's environmental performance and the value of its intangible assets.

Furthermore, financial markets appear to be able to reward good firms. Indeed, Klassen and McLaughlin (1996) find, using United States data, that firms earning an environmental-performance award between 1985 and 1991 saw their market value increase by an average of 0.82% after the announcement. As well, financial market punishment does not appear to be in vain. According to Konar and Cohen (1997), firms that get punished for bad events tend to reduce their pollution emissions more than other firms in the same industrial sector.

These papers have shown that bad (good) environmental performances lead to decreases (increases) of stock market share values, presumably through a mechanism which requires an efficient financial market to operate. Indeed, the extent to which this mechanism of punishment and reward works is evidently function of the capacity of the financial market to make it work. For example, the loss of market value of a delinquent firm may depend on the importance investors give to environmental issues (or the level of the fine they expect it will have to pay in the future) but their capacity to influence the firm's value depends on their capacity to act on financial markets. In turn, the capacity of agents to act on financial markets greatly depends on the quality of the financial markets. Thus, it is possible that a given country's level of pollution is related to the state of its financial markets.

Some recent empirical studies investigate this point by focussing on the impact of financial development on pollutant emissions. For example, Tamazian, Chousa and Vadlamannati (2009) and Tamazian and Rao (2010) estimate the link between several financial development indicators and CO_2 emissions and find that greater financial sector development and openness helps reduce pollution.

The question investigated in this paper is that of the impact of episodes of financial instability on CO_2 emissions. The justification is similar to that which justifies a link between financial development and pollution, namely that information asymmetry tends to increase during financial crisis periods. This may cause identification of environmentally good firms to be difficult, which might render their financing more arduous and make the punishment and reward mechanism described above more difficult. In addition, firm managers are faced with a moral hazard problem with regards to their decision of respecting or not environmental regulations. This problem is very likely to increase in periods of financial hardships, when reliable information may be harder to obtain and incentives to cheat are greater. It is therefore not unreasonable to expect that environmental pressures on firms should be stronger (weaker) when financial markets are stable (unstable).

In this paper, I use an indicator called the Financial Stress Index (FSI) as a measure of capital markets instability. A panel of 16 developed and 20 developing countries observed between 1981 and 2005 is used to test the hypothesis that financial stress periods are related to periods of increased aggregate per capita CO_2 emissions. Table 1 gives the list of countries used. Results based on OLS and Arellano-Bond type dynamic panel data models suggest that financial stress may have a positive impact on CO_2 emissions.

As will be seen in the next section, the FSI measures the overall short term state of a country's financial market, which may be quite different from the level of financial market development. Thus, the results of the paper should not be interpreted as providing evidence of a link between financial markets development and pollution, but only between financial instability and pollution.

2 The data

The Financial Stress Index was first developed for advanced economies by Cardarelli, Elekdag and Lall (2009) and adapted for emerging economies by Balakrishna, Danninger, Elekdag and Tytell (2009). The Advanced Economies Financial Stress Index (AE-FSI) and Emerging Markets Financial Stress Index (EM-FSI) are built on the principle that financial stress occurs when the financial system cannot perform its intermediation role adequately. The FSI attempts to measure the level of financial stress in an economy through its manifestation within three markets: the banking sector, the securities market (stock markets returns, stock markets volatility and bonds yield spread) and foreign exchanges (currency exchange rate and currency reserves). The AE-FSI of Cardarelli et al. (2009) is the sum of seven elements:

$$AE\ FSI_t = \beta_t + TED\ spread_t + Inverted\ terms\ spread_t + Corporate\ debt\ spread_t$$

$$+ Stock\ market\ return_t + Stock\ market\ volatility_t + Exchange\ market\ volatility_t,$$

where β_t is the banking sector's β as estimated in a standard CAPM, *TED spread* is the spread between commercial papers and government short term rate, *Inverted terms spread* is the spread between short and long term government rates and *Corporate debt spread* is the spread between corporate bonds yields and government long term rates. Stock market returns is minus 1 times the country's stock market index returns. Finally, stock and exchange markets volatilities are obtained with GARCH(1,1) models. The EM-FSI is somewhat different:

$$EM\ FSI_t = \beta_t + Stock\ market\ return_t + Stock\ market\ volatility_t$$

$$+ Exchange\ market\ volatility_t + EMPI_t$$

where $EMPI$ is a measure of currency depreciation and foreign currency reserves decreases and the other elements are as above. The differences between the two indexes mainly result from data availability and some choices by the authors. For instance, the bond market was excluded from the EM-FSI because of its relatively small importance in these economies, see Balakrishna et al (2009) for details. Notice that, by construction, large positive (negative) values of the indexes correspond to periods of financial instability (stability).

Table 1 presents descriptive statistics for the EM-FSI and AE-FSI. As may be seen, there are much fewer observations available for emerging economies than there are for developed ones. This, of course, results from data availability. Emerging economies have slightly higher average FSI than developed ones, especially when excluding Czech Republic, Egypt and Pakistan (entry "EM-FSI ex"), for which the small number of observations available coincides with a period of general financial market stability.

Because they are not built in the exact same manner, it is hazardous to make any direct comparison between the AE-FSI and EM-FSI. In the following sections, I estimate models where these differences are ignored, that is, I pool emerging and developed economies and pretend that the AE-FSI and EM-FSI are of identical construction. I later estimate models for emerging and developed countries separately and find similar results in both cases.

Data on CO_2 emissions were downloaded from the World Resources Institute website (www.wri.org) and are measured in metric tons per capita. All other data series were obtained from either the World Bank's World Development Indicators database or from the International Monetary Fund's IFS database. These variables, along with their description and some basic statistics, are listed in table 2.

The purpose of these variables is to act as controls in the models estimated in the next section. Each of them has been used in past studies and we now give some motivation for their inclusion here. First and foremost is per capita GDP, which is expected to have, at least up to a certain point, a positive impact on pollution through increased consumption and production activities. Yet, it is possible that after a given level of per capita GDP is passed, the relation would become negative because, for instance, of preferences for a clean environment. This phenomenon is known as the Environmental Kuznets Curve (EKC) and, though it appears to manifests itself with some regularity with certain pollutants, it's existence in the CO_2 case is still the subject of a debate (see the surveys of Dasgupta et al., 2002 and Dinda, 2004).

It is particularly important to control for per capita GDP in the present context because financial stress periods tend to coincide with periods of low or negative GDP growth. Assuming a positive correlation between per capita GDP and CO_2 emissions, omitting to control for per capita GDP might bias downwards the estimated effect of financial stress on pollution.

The other variables are controls for the possible effects of the composition of each country's population and economy on CO_2 emissions. The shares of the industrial, agriculture and service sectors in total GDP aim to capture the possibility that some countries achieve lower pollution levels by concentrating their activities in the cleaner services sector. Among the authors who considered this possibility are York et al. (2003), Friedl and Getzner (2003) and Egli (2002). The share of international trade over GDP is included to take into account a possible relationship between international trade and pollution (see, among others, Antweiler et al, 2001). For example, some countries may improve their environmental record by importing rather than producing pollution intensive goods. Population variables are also included to account for the possibility that sparsely populated countries may have higher per capita emissions because of greater transportation distances or that rapid urbanization may lead to increased pollution (Vincent, 1997). Finally, increased petroleum prices may cause emissions to decrease.

Figure 1 shows a scatter plot of CO_2 emissions and FSI over the entire sample. According to this figure, there appears to be a slightly negative relationship between the FSI and CO_2 emissions. This result is, however, not robust to further statistical modeling, as will be seen in the next section.

3 Regression models

3.1 Static models

The first step of the analysis consists of the estimation of some linear regression models. These are simple error component models with both country and period specific effects:

$$E_{i,t} = \alpha + \delta_i t + y_{i,t}\beta_1 + y_{i,t}^2\beta_2 + y_{i,t}^3\beta_3 + fsi_{i,t}\gamma + X_{i,t}\Pi + v_i + e_t + \varepsilon_{i,t}, \qquad (1)$$

where the indexes i and t refer to the country and time period respectively and $E_{i,t}$ is per capita CO_2 emissions, $y_{i,t}$ is per capita GDP, $fsi_{i,t}$ is the Financial Stress

Index, $X_{i,t}$ is a vector of control variables, v_i is the country specific effect, e_t is the period specific effect and $\varepsilon_{i,t}$ is an error term. Notice that the model allows for each country to have its own trend parameter. This is done to avoid forcing every country to be on the same deterministic emission path and is a common specification, see Perman and Stern (2003) for an example. The control variables are those described in section 2.

Estimation results are presented in table 3. Obviously, country and time specific effects are very important and their omission yields several counter-intuitive results such as a U-shaped relationship between per capita income and pollution in models 1 and 2. The country specific trend specification is preferred in both models, with F tests' P values of 0.0000 when this model is tested as an alternative to the null of a single trend. Model 3 as a specification similar to that of model 2 except that the country effects are random. The Hausman test statistic takes a value of 33.57 with a P value of 0.0008, which clearly rejects the random effects specification in favor of fixed effects.

Models 4 and 5 include period in addition to country fixed effects and appear to provide the best specification. The F tests for the nonsignificance of country and period fixed effects in these models both have P values of 0.0000, so that both appear to be important. The FSI has a positive and statistically significant impact on CO_2 emissions according to these two models. This means that, as postulated, increased financial stress leads to higher levels of pollution.

According to the Durbin Watson test and a simple t statistic in a AR(1) model of the residuals, the models have serially correlated residuals. This may indicate omitted dynamics or that some nonlinearity has not been modeled properly. In any case, all standard errors reported for models 1 through 5 are robust to autocorrelation of unknown form.

3.2 Dynamic models

If omitted dynamics is the problem, then adding the first lag of CO_2 emissions to the regressor set is a potential solution. The presence of country specific fixed effects complicates the estimation of such a model and necessitates a rather large number of observations in the time dimension to provide accurate estimates. Precisely, the OLS estimator, henceforth LSDV, for least squares dummy variables, is consistent as $T \to \infty$ and $N \to \infty$, but not as $N \to \infty$ if T is fixed. In the present case, we posses 25 observations for each of the 16 developed countries, except for

Norway, Sweden and Switzerland for which there are 22, 22 and 24 observations each. The number of observations for emerging economies ranges from 2 to 9. Whether this is enough for the LSDV estimator to provide accurate inference in a dynamic model is unsure. Nevertheless, LSDV estimates provide an interesting benchmark and the results of the best fitting model are presented as model 6 in table 4.[1] It can be seen that the FSI still has a positive and statistically significant parameter estimate. The AR(1) autocorrelation test indicates that the residuals are no longer correlated, which suggests that missing dynamics were indeed the problem. Figure 2 shows a scatter plot of the relation between the FSI and per capita emissions after all the regressors in model 6 (including the country and period fixed effects) have been taken into account. It can be seen that the relationship indeed appears to be positive, although not very strong, as the models thus far suggested.

Consistent GMM estimation is performed using the technique proposed by Arellano and Bond (1991).[2] Estimation results for the best fitting model are reported in the second column of table 4 under the heading model 7. The FSI parameter is very similar to that obtained with simple LSDV, and is statistically significant.

Under the assumption that the errors of the dynamic model in levels are not serially correlated, the error at time t of the difference-based model used here should be correlated with the error at time $t-1$, and this correlation should be -0.5.[3] Because of this, the parameters estimates' standard errors were computed using an autocorrelation-robust covariance matrix estimator. A regression of the residuals at time t on the residuals at time $t-1$ yielded a correlation estimate of $\hat{\rho} = -0.46$, not statistically different from -0.5 (a test of this hypothesis yielded a P value of 0.3604).

The residuals AR(1) and AR(2) tests proposed by Arellano and Bond have P values of 0.0247 and 0.2864 respectively, which suggests that the first lag of CO_2 emissions appropriately captures the equation's dynamics. On the other hand, the overidentifying restrictions test has a P value of 0.000, which suggests some misspecification.

It is not perfectly clear whether the results from this GMM estimation should

[1] All the models in table 4 were also estimated by excluding Czech Republic, Egypt and Pakistan because of the very low number of observations available. This did not have much impact on the estimated parameters.

[2] That is to say that country specific effects are eliminated through first differentiation of the model and lags of CO_2 emissions as well as of the explanatory variables are used as instruments.

[3] See Wooldridge, 2002, chapter 10.

be regarded as accurate in the present situation. Indeed, when T is small, this estimator is consistent as $N \to \infty$ (Arellano and Bond, 1991). In the present case, the number of cross section units is 33, (Czech Republic, Egypt and Pakistan had to be dropped from the sample for all dynamic GMM models because of the small number of observations available) which may be considered as rather small. This may result in somewhat inaccurate GMM estimates.

Kiviet (1995) derives asymptotic expressions for the bias of the LSDV estimator in dynamic panel data models. Based on these, he proposes a bias corrected estimator, denoted LSDVc, which often, but not always, outperforms GMM estimators in the bias and MSE senses. While the simulations in Kiviet (1995) aim at representing typical microeconomic situations, (small T and large N) those in Judson and Owen (1999) are more relevant for macroeconomic modeling. In particular, they consider situations similar to the present one ($T = 20$ or 30 and $N = 20$) and find that GMM estimates have larger bias and MSE than LSDVc estimates. Bruno (2005) adapts the LSDVc estimator of Kiviet (1995) to unbalanced panels. His simulations indicate that his procedure provides excellent bias correction.

The third column of table 4 shows the results from estimating a dynamic model using this bias corrected estimator with country and period fixed effects and country specific trends. The estimated parameters are very similar to those obtained from the other dynamic models. In particular, the FSI is once more positive and statistically significant.

4 Some robustness checks

This section provides some robustness checks of the results presented in the previous section. More detailed results are available from the author on request.

4.1 Functional form

It has been argued by some authors that a third degree polynomial may not be sufficient to trace out the form of the relation between per capita GDP and CO_2 emissions (see He and Richard, 2010 among others). The static and dynamic models are therefore reestimated as partially linear models, that is

$$E_{i,t} = \alpha + \delta_i t + \beta E_{i,t-1} + \mu(y_{i,t}) + fsi_{i,t}\gamma + X_{i,t}\Pi + v_i + e_t + \varepsilon_{i,t}, \tag{2}$$

where $\mu(y_{i,t})$ is an unspecified continuous function. Estimation is carried out semi-parametrically as suggested by Robinson (1988) using a gaussian kernel and cross-validation. Results are presented in table 5 and indicate that financial stress has a positive and statistically significant impact on CO_2 emissions.

I also reestimated the dynamic model in a log-linear form. The results of LSDV estimation of this model are reported in the fifth column of table 4. Notice that the FSI is not transformed into logs because it often takes negative values. As can be seen, the results are qualitatively identical to those of the linear dynamic models. A similar exercise was carried-out for the LSDVc and GMM estimators and resulted in similar conclusions.

Finally, I have also reestimated model 7 under the assumption that per capita GDP (as well as its square) and the FSI are endogenous variables. GMM estimation was carried out using the second (and higher when possible) lags of all these variables as instruments. The results are reported in the last column of table 4, under the heading "GMM endo". As can be seen, the FSI still has a positive and statistically significant parameter estimate around 0.02.

4.2 Advanced vs emerging economies

This subsection checks whether similar results arise in subsamples containing only advanced economies or emerging economies. Recall from the introduction that researchers using event studies have found statistically significant links between environmental performances and stock values in both advanced and emerging economies and that there is some evidence to the effect that this link may be stronger in emerging markets. These results alone justify the separate studies carried out below. Further, since the EM-FSI and AE-FSI are not entirely identical, the separate sample estimations may be considered as some kind of robustness check.

4.2.1 Advanced economies

Restricting the analysis to advanced economies yields a sample of 393 observations. The results of the best fitting models estimated with LSDV, GMM and LSDVc are reported in the first three columns of table 6. The FSI parameter is positive in each cases and around 0.02. It is statistically significant according to 5% or 10%

tests with LSDV and at 10% with GMM. The P value of the LSDVc estimator is 0.1249. Thus, there is evidence of a positive effect of financial stress on CO_2 emissions in advanced economies.

4.2.2 Emerging markets

The sample of emerging market economies is composed of 20 countries and a total of 154 observations. Estimation results of the best fitting models using LSDV, GMM and LSDVc are reported in the last three columns of table 6. The estimated FSI parameter is around 0.015 and statistically insignificant at a 10% nominal level in all three cases. There is therefore only weak evidence of a positive link between financial stress and CO_2 emissions in developing economies.

4.3 Non-stationarity

Some authors have remarked that pollutant emissions time series are likely I(1) processes.[4] Because most macroeconomic time series typically utilized in studies such as the present one are also likely I(1) processes, cointegration analysis becomes an interesting strategy. Table 7 presents panel unit root test results for CO_2 emissions, FSI and GDP using the tests proposed by Levin, Lin and Chu (2002), Im Pesaran and Shin (2003) and Hadri (2000). While CO_2 emissions and GDP are almost certainly unit root processes, results for the FSI are somewhat mixed. This is quite possibly due to the rather small sample size, so that it is difficult to make any kind of reliable inferences about this series' order of integration.

In any case, it might be a good idea to reestimate our models in first differences so that all variables are certainly I(0). The first column of table 8 gives the results of estimating the best fitting first difference model. The FSI once more has a statistically significant coefficient around 0.02. Notice that the first lag of $\Delta E_{i,t}$ did not turn out as being statistically significant but that the residuals nevertheless do not appear to be serially correlated.

The tests of the null of no cointegration suggested by Pedroni (1999) Kao (1999) and Larsson, Lyhagen and Lothgren (2001) were conducted and revealed the possible presence of a cointegrating vector (all tests had a P value of 0.0000). Estimation

[4]See, for example, Perman and Stern (2003) who investigate the Environmental Kuznets Curve hypothesis using cointegration.

results for the best fitting error correction model are reported in the second column of table 8. Once again, the first difference of the FSI has a statistically significant positive coefficient with a value around 0.02.

5 Conclusion

Static and dynamic panel data models indicate that financial stress is positively related to CO_2 emissions, especially in advanced economies. This finding is robust to several modeling strategies. Although reduced form models do not allow to directly infer that financial stability leads to lower pollution levels, the results obtained here are nevertheless consistent with that hypothesis.

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6 Tables

Table 1. List of countries.

	Average	Median	Standard dev.	Maximum	Minimum	Observation
Austria	-0,3929	-0,6719	2,6915	5,5628	-5,4819	1981-2005
Belgium	-0,6634	-0,7520	2,0724	4,9165	-4,0722	1981-2005
Canada	-0,4863	-0,3244	1,5916	3,9644	-3,7971	1981-2005
Denmark	-0,3747	-0,5907	1,6721	2,9366	-3,6773	1981-2005
Finland	0,0615	0,0235	1,8183	4,1928	-2,5819	1981-2005
France	0,07456	-0,0679	3,0294	8,5779	-4,1313	1981-2005
Germany	-0,3904	-0,1313	2,3146	3,6204	-4,6676	1981-2005
Italy	-0,1177	-0,5239	2,2664	5,1414	-3,8578	1981-2005
Japan	-0,1815	-0,0724	1,8865	3,4517	-3,6310	1981-2005
Netherlands	-0,4860	-0,4721	1,9392	3,7653	-4,6180	1981-2005
Norway	-0,3816	-0,4990	2,0422	4,3437	-4,3623	1984-2005
Spain	0,0207	0,0352	1,9500	4,6709	-2,5419	1981-2005
Sweden	-0,0626	-0,1434	2,5116	6,4399	-4,5948	1984-2005
Switzerland	-0,3376	-0,5122	2,2873	4,3279	-3,9587	1982-2005
Great Britain	-0,4747	-0,5097	1,7472	2,3578	-3,8171	1981-2005
USA	-0,5096	-0,7294	2,2235	3,3433	-3,8443	1981-2005
AE-FSI	-0,2949	-0,3746	2,1279	8,5779	-5,4819	-
Argentina	0,3955	-0,2466	1,6907	3,8912	-1,7354	1997-2005
Brazil	0,1276	0,1020	1,2953	2,5008	-1,5505	1997-2005
Chile	-0,3857	-0,4262	1,9791	2,7654	-2,6696	2000-2005
China	0,1734	-0,1282	1,9934	3,8746	-1,9465	1997-2005
Colombia	0,0576	0,7797	2,1635	3,3066	-2,4505	1997-2005
Czech Republic	-1,4564	-1,4564	0,3146	-1,2338	-1,678920208	2004-2005
Egypt	-0,8279	-0,8006	1,1926	0,5976	-2,3079	2002-2005
Hungaria	-0,9210	-1,0254	1,2948	1,0335	-2,7907	1999-2005
Korea	0,3448	0,0681	1,9865	3,2695	-2,7456	1998-2005
Morocco	0,7434	0,5486	2,2691	5,5111	-2,2227	1997-2005
Mexico	-0,3877	0,0341	1,9401	2,6618	-2,71405	1997-2005
Malaysia	-0,3226	-0,1439	0,9773	0,9594	-1,7857	1997-2005
Pakistan	-1,8452	-1,8592	0,2397	-1,5386	-2,1237	2002-2005
Peru	0,3058	0,6903	1,8835	2,7227	-2,4316	1997-2005
Philippine	0,6911	0,7954	1,2150	2,3833	-1,0636	1998-2005
Poland	0,0652	-0,0156	1,2743	1,4910	-2,4010	1997-2005
Russia	0,0925	-0,8332	2,3385	4,8399	-1,6181	1998-2005
South Africa	0,1256	0,3272	2,0537	2,9633	-2,0841	1997-2005
Thailand	0,5433	-0,4848	2,7204	5,3645	-1,9603	1998-2005
Turkey	0,0899	0,4054	1,9501	2,6368	-2,7221	1997-2005
EM-FSI	0,0219	-0,1853	1,8023	5,5111	-2,7907	-
EM-FSI ex	0,1179	-0,0160	1,8128	5,5111	-2,7907	-

Table 2. Data and descriptive statistics.

Series	Description	Average	Median	Std. dev.	Max	Min
GDP per capita	PPP constant 2005 dollars	21672,90	23553	9924,83	47305	1937,42
Poil	USD / barrel	23,82	20,37	9,05	53,35	13,07
Urban population	millions	44,70	24,22	71,24	52,67	28,70
Population density	People per sqr. km	1237,23	100,7	5078,81	28249	2,74
adult share	Aged 15-64 / total population	64,14	65,47	4,52	71,82	51,87
Industry share	Share of GDP	31,73	30,92	5,25	49,71	20,68
Service share	Share of GDP	63,59	64,85	7,21	77,03	34,17
Agriculture share	Share of GDP	4,69	3,45	4,01	23,36	0,8
Trade share	Share of GDP	66,34	58,85	35,89	220,41	15,84

Table 3. Static models.

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	-17.0191	-0.7113	-4.3661	-6.1612	3.4694
	(14.2020)	(10.8741)	(5.8758)	(12.5279)	(2.6872)
gdp	-0.0012*	-2.61E-05	0.0004	0.0001	0.0003*
	(0.0006)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
gdp^2	5.45E-08*	7.79E-09	-8.45E-09	3.11E-09	-3.35E-09
	(2.99E-08)	(1.07E-08)	(1.05E-08)	(9.98E-09)	(2.66E-09)
gdp^3	-5.62E-13	-1.29E-13	6.16E-14	-9.35E-14	-
	(4.01E-13)	(1.23E-13)	(1.19E-13)	(1.15E-13)	-
poil	0.0059	-0.0006	-0.0063	-	-
	(0.0138)	(0.0044)	(0.0048)	-	-
ind	-0.0965	0.0342	0.0721	0.0211	-
	(0.0841)	(0.0347)	(0.0380)	(0.0377)	-
agri	-0.1570	0.0081	-0.0574	-0.0176	-
	(0.1189)	(0.0230)	(0.0478)	(0.0193)	-
popdens	7.55E-05	7.91E-05	0.0001	8.62E-06	-
	(0.0001)	(0.0001)	(6.99E-05)	(0.0001)	-
urban/totalpop	5.87E-06*	1.75E-05	6.10E-06	1.09E-05	-
	(3.49E-06)	(1.82E-05)	(2.82E-06)	(1.89E-05)	-
trade	-0.0191	-0.0097	-0.0016	-0.0088	-
	(0.0209)	(0.0065)	(0.0076)	(0.0077)	-
adlt	0.5165**	-0.0314	0.0518	0.0877	-
	(0.2310)	(0.1005)	(0.1048)	(0.1260)	-
fsi	-0.1100**	-0.0057	-0.0067	0.0349**	0.0333**
	(0.0312)	(0.0136)	(0.0265)	(0.0139)	(0.0146)
Country effects	no	fixed	random	fixed	fixed
Period effects	no	no	no	fixed	fixed
R^2_{adj}	0.9023	0.9909	0.2694	0.9917	0.9916
DW test stat	0.1599	1.0302	0.4973	0.9863	0.9636
AR(1) (P value)	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4. Dynamic models.

	Model 6 (LSDV)	Model 7 (GMM)	Model 8 (LSDVc)	Model 9 (LSDVc)	Log linear	GMM (endo)
Constant	0.1766**	-	-2.4961	-1.0555	-23.2314***	-
	(1.6472)	-	(2.6046)	(0.6544)	(8.5455)	-
gdp	0.0003**	0.0003***	0.0004***	0.00027***	4.6296***	0.00014**
	(0.0001)	(0.0001)	(0.0001)	(7.3976e-005)	(1.7936)	(0.00007)
gdp^2	-3.91E-09**	-4.38e-09**	-1.0055e-008 *	-3.9746e-009***	-0.2199***	-1.31e-09
	(1.78E-09)	(1.76e-09)	(5.3718e-009)	(1.3285e-009)	(0.0944)	(1.32e-09)
gdp^3	-	-	7.0228e-014	-	-	-
	-	-	(5.7196e-014)	-	-	-
ind	-	-	0.0066	-	-	-
	-	-	(0.0056)	-	-	-
agri	-	-	-0.0190	-	-	-
	-	-	(0.0180)	-	-	-
popdens	-	-	2.9072e-006	-	-	-
	-	-	(0.0001)	-	-	-
urban	-	-	-2.8941e-006	-	-	-
	-	-	(2.7567e-006)	-	-	-
trade	-	-	0.0014	-	-	-
	-	-	(0.0034)	-	-	-
adlt	-	-	0.0030	-	-	-
	-	-	(0.0369)	-	-	-
fsi	0.0247**	0.0293**	0.0263**	0.0232**	0.0030**	0.0230*
	(0.0124)	(0.0136)	(0.0104)	(0.0102)	(0.0014)	(0.0131)
$CO2_{t-1}$	0.5255***	0.5069***	0.5951***	0.5918***	0.5211***	0.5068***
	(0.0510)	(0.0433)	(0.0326)	(0.0318)	(0.0472)	(0.0411)
Country	fixed	differenced	fixed	fixed	fixed	differenced
Period	fixed	fixed	fixed	fixed	fixed	fixed
R^2_{adj}	0.9938	-	0.9989	0.9989	0.9969	-
AR(1)	0.2325	-	0.9774	0.8511	0.2491	-

Table 5. Partially linear models.

	Static PLM	Dynamic PLM
FSI	0.0167***	0.0110**
	(0.0059)	(0.0053)
popdens	0.2945**	0.2175*
	(0.1609)	(0.1268)
ind	0.0466**	0.0364*
	(0.0198)	(0.0204)
agri	-0.0146	-0.0149
	(0.0153)	(0.0146)
trade	0.0897**	-0.0088
	(0.0351)	(0.0318)
$E_{i,t-1}$	-	0.5212***
	-	(0.0472)

Table 6. Dynamic models (advanced vs. emerging economies).

	AE LSDV	AE GMM	AE LSDVc	EM LSDV	EM GMM	EM LSDVc
Constant	1.8725	-	5.1483**	-1.5437	-	-2.1724*
	(2.5193)	-	(1.9905)	(1.4709)	-	(1.1367)
gdp	0.0002	0.0002*	0.0002	0.0006**	0.0004**	0.0005**
	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
gdp^2	-2.05E-09	-2.70e-09	-2.076e-009	-1.76E-08	-1.39E-08*	-1.632e-008
	(2.42E-09)	(2.19e-09)	(2.150e-009)	(1.12E-08)	(9.03E-09)	(9.929e-009)
fsi	0.0251**	0.0298*	0.0241	0.0182	0.0130	0.0161
	(0.0125)	(0.0161)	(0.0157)	(0.0214)	(0.0179)	(0.0135)
$CO2_{t-1}$	0.5283***	0.5067***	0.5615***	0.4884***	0.4957***	0.5754***
	(0.0420)	(0.0489)	(0.0488)	(0.0909)	(0.0746)	(0.1069)
Country effects	fixed	differenced	fixed	fixed	differenced	fixed
Period effects	fixed	fixed	fixed	fixed	fixed	fixed
R^2_{adj}	0.989	-	0.998	0.998	-	0.999
AR(1) (P value)	0.2118	0.0336	0.4214	0.0207	0.0102	0.0032
AR(2) (P value)	-	0.2000	-	-	0.4151	-

Table 7. Panel unit root tests (P values).

	GDP	CO2	FSI
test (individual constant)			
Levin, Lin and Chu (common root)	1.0000	0.1841	0.0001
Im, Pesaran and Shin (individual roots)	1.0000	0.7307	0.2022
Hadri (H_0: no common unit root)	0.0000	0.0000	0.0000
test (individual constant and trend)			
Levin, Lin and Chu (common root)	0.9872	0.0000	0.0000
Im, Pesaran and Shin (individual roots)	0.9964	0.6619	0.0051
Hadri (H_0: no common unit root)	0.0000	0.0000	0.0000

Table 8. First difference and cointegration model.

	First diff	ECM
Constant	-0.0771**	-0.0285
	(0.0390)	(0.0285)
Δgdp	0.0004***	0.0003***
	(9.49E-05)	(9.85E-05)
Δgdp^2	-4.45E-09***	-3.76E-09***
	(1.41E-09)	(1.44E-09)
$\Delta adlt$	0.1525*	-
	(0.0866)	-
$\Delta popdens$	0.0001***	-
	(3.83E-05)	-
Δfsi	0.0196**	0.0182***
	(0.0067)	(0.0064)
$\Delta co2$	-	0.1729***
	-	(0.0664)
Error correction	-	-0.5481***
	-	(0.0546)
Country effects	Differenced	Differenced
Period effects	Fixed	Fixed
R^2_{adj}	0.1510	0.3191
DW	2.1211	1.9795
AR(1) (P value)	0.1328	0.9907

Figure 1. Scatter plot FSI-CO_2.

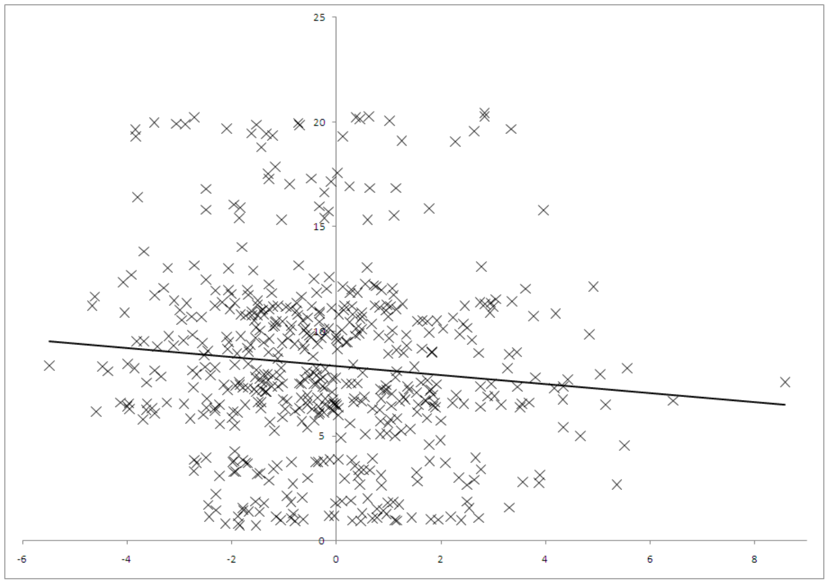

Figure 2. Scatter plot FSI-CO_2 after controls.