Does Trade Foster Institutions? An Empirical Assessment

Marcella Nicolini[1] and Alessia Paccagnini[2]

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[1]Fondazione Eni Enrico Mattei (FEEM) - Corso Magenta, 63 - 20123 Milano - email: marcella.nicolini@feem.it

[2]Università "L.Bocconi" -Dipartimento di Economia - Via Roentgen, 1 - 20136 Milano - email: alessia.paccagnini@unibocconi.it

Abstract

The causal relationship between trade and institutions has largely been debated in the theoretical literature. More recently, the focus has been on the role of contract enforcement on trade. Anderson (2007) suggests that the causal relationship may go in the opposite direction: trade may enhance contract enforcement. The aim of the present paper is to provide some empirical evidence on the causal relationship between contract enforcement and trade flows. We have a bilateral trade flows panel that covers 29 years. We present a Granger causality test. The issue of zero flows of trade is handled using a panel Poisson Pseudo-Maximum Likelihood estimator.

1 Introduction

The causal relationship between institutions and trade flows has been largely debated. On one side, a number of papers show theoretically, and demonstrate empirically, that better institutions foster trade flows. On the other side, the well-known issue of the endogeneity of institutions suggests that they could be determined by the openness of a country.

Recently, the literature has focused on a specific aspect of institutional quality as a determinant of trade flows: contract enforcement. Anderson has demonstrated both theoretically and empirically that overall trade is positively affected by good institutions. Other authors have instead inspected the role of contract enforcement as a determinant of comparative advantages. Although different in spirit, these two streams of literature suggest that institutional quality positively affects trade flows.

Nonetheless, a recent paper by Anderson (2007) suggests that the causal relationship is unclear, and that trade itself may induce traders to improve contract enforcement. Therefore, some empirical evidence seems necessary to shed light on this controverted issue. Using a database on bilateral trade flows for the period 1976-2004, we show that the causality runs from trade to institutions, and viceversa. The reminded of this paper is organized as follows: section 2 discusses the theoretical literature, section 3 presents the empirical model, and discusses the econometric specification, section 4 describes the data. Section 5 presents the results, and section 6 concludes.

2 Review of the Literature

The issue of the causal relationship between institutions and trade has been widely debated. More recently, the literature has focused on the role of contract enforcement as a possible determinant of trade flows.

The main contributor to this field of literature is Anderson. In a paper with Young (2000), he shows that the rule of law is not always preferred by all traders. The model determines the necessary and sufficient condition to ensure that all traders prefer the rule of law regime to the anarchy regime. Under anarchy contracts are not enforced, and agents match randomly. As there is an unequal number of buyers and sellers, trade is inefficient. Contracts are preferred by the scarce side of the market, while the excess side faces a trade off between power in bargaining and risk of not matching. They predict that, as institutions require a long time in order to develop, private institutions that insure contract enforcement may emerge. This finds a confirmation in the monopolistic trading institutions, like guilds, that characterized European history. They predict that monopolistic traders may obstruct the rise of the rule of law regime in order to protect their rents. In a subsequent paper, Anderson and Young (2002) demonstrate that multiple equilibria are possible: anarchy is a local optimum, perfect contract enforcement a local minimum, and imperfect contract enforcement a global optimum. Their model thus explains why for some countries imperfect contract enforcement is the optimal choice.

Anderson and Young (2006) develop a model that predicts that a poor level of contract enforcement reduces trade volume. The search for a counter part in the spot market, instead of the contract market, is inefficient, and this reduces trade volume.

Under risk neutrality, imperfect contract enforcement is equivalent to a tariff. This is a model of demand for contract enforcement with a focus on institutions that enforce international contracts.

In their seminal article, Anderson and Marcouiller (2002) affirm that trade expands when supported by good institutions, that ensure the enforcement of contracts. Instead, in presence of low quality of institutions trade is reduced, as insecurity rises the price of traded goods. Insecurity (corruption) acts as a hidden tax on trade. In a previous version of this paper (1999), the authors show that two types of insecurity can generate price markups: on one side, predation,[1] on the other, poor contract enforcement. Institutional quality explains why trade among high income countries is so high. High income countries are expected to trade less, as they have similar factor endowments. Large trade flows are explained by the fact that high income countries all have good institutions, which lower trade costs. The focus of the paper is on importer's institutions. Bad policies and poor legal system constraint trade as much as tariffs. They estimate a gravity model, using measures for institutional quality form the World Economic Forum.

Kaufmann and Wei (1999) consider the impact of corruption on trade. The efficient grease theory suggests that a firm may find bribes helpful to reduce the effective red tape it faces. They find evidence that corruption does not improve exchanges. Instead, if corruption is widespread, time spent with bureaucrats and regulatory burden are high.

[1] Anderson and Marcouiller (1998) present a general equilibrium model of predation, in which agents allocate their labour across productive and predatory activities. The probability of a successful shipment is endogenously determined.

More recently, several authors have demonstrated, both theoretically and empirically, that institutional quality may be a source of comparative advantage. Levchenko (2007) presents a model in which three goods are produced: two goods are produced using only one factor of production, while the third is produced using both factors. This good requires the interaction of two factors of production, and is therefore the more institutionally dependent. If contracts are not perfectly enforced, the buyer of the inputs may "hold-up" the supplier by reneging on the initially agreed price. The supplier anticipates the possibility of an opportunistic behavior and will underinvest. This leads to a suboptimal level of investment, which in turn raises the costs of production. Thus, the country with better contract enforcement is able to produce the mixed-good at a lower price. He provides empirical evidence that countries with better institutional quality have a comparative advantage in the production of complex goods. Nunn (2007) shows empirically that institutional quality is a source of comparative advantage in the production of goods for which relationship-specific investments are most important, where relationship-specificness is determined using Rauch's (1999) classification. Costinot's (2005) models suggests the quality of institutions interacts multiplicatively with human capital of workers. Finally, Acemoglu, Antràs, Helpman (2006) develop a model of contract incompleteness with varying degrees of technological complementarities, and draw implications, among others, on the pattern of trade.[2] Better contract enforcement has greater effect on investment decisions when there are greater technological complementarities. They thus

[2] A previous version of this paper (2005) focuses on the complementarity between tasks. It is thus closer to Costinot's model. This paper and its previous version share the same implications on comparative advantage.

derive that good institutional quality gives an endogenous comparative advantage in more contract-dependent sectors, which in this case are the sectors with greater technological complementarity.

On the other side, Anderson (2007) raises the doubt that trade may foster contract enforcement. Also Baier and Bergstrand (2001) affirm that trade liberalization, transport improvements and other developments of the last fifty years leave unexplained a large positive residual growth in world trade. This implies positive knock-on effects travelling from trade to institutions.

Thus, it is interesting to investigate empirically if there is any causal relationship between contract enforcement and trade, and vice versa.

3 The Empirical Model

So far, the literature has no presented research works in which this relationship between contract enforcement and trade is tested. Understanding if the contract enforcement implies the trade or viceversa could be a very interesting point in this field. To solve this dilemma, the time-series econometrics literature proposes a specific test, the Granger causality test (1969). In our framework, this test could be very useful to hightlight the possible presence of a causality in only sense or in two-way. The data used in our empirical analysis are not simply time-series, but show a panel dimension. Moreover, they have a missing value problem. Consequently, the empirical evidence is affected by all these characteristics and we need to use an appropriate econometric tool to fit these data. In this section, we present a brief description of the simple Granger causality test applied to a Pooled Ordinary Least Square estimator, then we present the recent research about the use of the Granger causality test in case of a Fixed Effect Panel Data. We conclude this discussion, presenting briefly Poisson Pseudo-Maximum Likelihood (PPML) estimator in case of a POLS and of a panel data and we apply the Granger causality test in case of this specific estimator.

3.1 The Granger Causality test (1969) in case of the POLS

The main purpose of the simple Granger Causality test (1969) is to check whether a (stationary) variable, called x_t, causes another (stationary) variable, called y_t, considering linear autoregressive data generating process. This procedure is useful not only to evidence how much of the current value of y_t can be explained by its past values, but also to see whether adding lagged values of x can improve the explanation. In this way, y_t is said to be Granger-caused by x_t if x_t helps in the prediction of y_t, or equivalently if the coefficients on the lagged x_t's are statistically significant.

For example, we suppose a bivariate system:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + ... + \alpha_N y_{t-N} + \beta_1 x_{t-1} + ... + \beta_N x_{t-N} + \epsilon_t \tag{1}$$

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + ... + \alpha_N x_{t-N} + \beta_1 y_{t-1} + ... + \beta_N y_{t-N} + u_t \tag{2}$$

Once we decide how many lags are involved in this system[3], the next step in

[3] To check the number of lags to use in the Granger test, it is possible to run a regression of Δy_t

the Granger test is set the joint null hypotheses tested by using F-statistics which are, in this case, the Wald statistics. Both for the first and the second equation, $H0 : \beta_1 = ... = \beta_N = 0$, i.e. y is not to be Granger-caused by x and viceversa. The alternative hypothesis is that at least one β_i is different from zero.

3.2 The Granger Causality test in the Panel Data Fixed Effect

There are several papers in which they discuss the possibility to apply the Granger Causality test in case of a Panel Data. The interest to apply the standard causality test to the panel data model is stressed out by Granger (2003). For example in macroeconomic research, the relationship between the real economy and the money (Sims, 1972) could be taken into consideration in both the time and in the country dimension, by using appropriate panel data model. An important paper in which there is a discussion about the use of the causality test in case of a heterogenous panel data model is Hurlin and Venet (2003). In this paper, they define some properties to take into consideration the causality in presence of heterogenous, presenting an application to the link between financial deepening and economic growth for sub-Saharian countries over around 30 years. The theoretical assumptions presented in this research work have been also considered in another empirical paper, (Lu, Chen and Wang (2006)) in which a causality test is implemented to investigate the relationship between R&D and productivity growth. In Hurlin (2005) and Hurlin

on its Δy_t 's lagged values and on Δx_t' s lagged values, taking into account t-tests and p-value. Obviously, viceversa if x_t is the variable explained by its lags and y_t's lags.

(2007), there is a complete theoretical analysis about the assumptions one should consider in case of using the Granger Causality test in case of a heterogenous fixed panel data. The necessity to be careful while using the usual causality test is also stressed out in Granger (2003), where the author puts in evidence that the simple causality test in case of a panel data framework asks *"if some variable, say x_t causes another variable, say y_t, everywhere in the panel [...]. This is rather a strong null hypothesis."*

The crucial point is how to implement the simple Granger Causality test. The extension of the standard causality test for the panel data implies to test cross-sectional linear restrictions on the coefficients of the model. As usually, considering the cross-sectional information could be useful to extend the information set on the causality from a given variable to another. Actually, the use of the cross-sectional information allows to take into account the heterogeneity across individuals defying the causal relationship.

Considering Hurlin (2007), we suppose to consider two generic variables, x and y, observed on T periods and on N individuals. For each individual $i = 1, ..., N$ at time $t = 1, ..., T$, the following linear model is taken into consideration:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \varepsilon_{i,t} \tag{3}$$

with $K \in \mathbb{N}^*$and $\beta_i = \left(\beta_i^{(1)}, ..., \beta_i^{(K)}\right)'$. α_i represent the fixed individual effects. Initial conditions $(y_{i,-K}, ..., y_{i,0})$ and $(x_{i,-K}, ..., x_{i,0})$ of both individual processes $y_{i,t}$ and $x_{i,t}$ are given and observable. The lag orders K are identical for all crosssection units of the balanced panel. The autoregressive parameters $\gamma_i^{(k)}$ and regression coefficients slopes $\beta_i^{(k)}$are constant and could differ across groups.

Hurlin (2007) defines four kinds of the causality relationships which could be occur in a panel data model with heterogeneity.

The first kind, called Homogenous Non-Causality (HNC) hypothesis, implies that there does not exist any individual causality relationships from x and y. The second case is the opposite one, called Homogenous Causality (HC) hypothesis. In this situation there exist N causality relationships and the individual predictors of y, obtained conditionally to the past values of y and x are identical. The third hypothesis is called Heterogenous Causality (HEC) hypothesis. As in the previous case, there exist N causality relationships, but the dynamics of y is heterogenous. However, the heterogeneity does not affect the causality result. The fourth case is the Heterogenous Non Causality (HENC) hypothesis, in which there exists a subgroup of individuals for whom there is a causal relationship from x to y.

In Hurlin (2005) and Hurlin (2007), a HNC hypothesis is proposed. Under the alternative, he allows there exists a subgroup of individuals with no causality relations and a subgroup of individuals for whom the variable x Granger causes y.

The null hypothesis of HNC is defined as:

$$H0 : \beta_i = 0 \ \forall i = 1, ..., N$$

Under the alternative hypothesis, β_i is allowed to differ across groups. Hurlin (2005, 2007) allows for some, but not all, of the individual vectors to be equal 0 (called non causality assumption). He assume under $H1$, there are $N_1 < N$ individual process with no causality from x to y.

The alternative hypothesis is:

$$
\begin{aligned}
H1 &: \beta_i = 0 \forall i = 1, ..., N_1 \\
H1 &: \beta_i \neq 0 \forall i = N_1 + 1, ..., N
\end{aligned}
$$

where N_1 is unknown but satisfies the condition $0 \leq N1/N \leq 1$. The fraction $N1/N$ is necessarily inferior to one since if $N_1 = N$ there is no causality for all the individual of the panel, and then we get the null hypothesis HNC. In case $N_1 = 0$, there is causality for all individual of the sample. The structure of this test is similar to the unit root test in case of a heterogenous panel data proposed by Im, Pesaran and Shin (2002). If the null hypothesis is not rejected, the variable x does not Granger cause the variable y for all the individuals of the panel and we obtain an homogenous result. In real data, the Data Generating Process (DGP) may be not homogenous, but the causality relations are observed for all individuals. In case $N_1 > 0$, the causality relations are different according to the individuals of the sample.

Hurlin (2005,2007) proposes the use of the average of individual Wald statistics associated to the test of the non causality hypothesis for units $i = 1, ..., N$.

$$
W_{N,T}^{HNC} = \frac{1}{N} \sum_{i=1}^{N} W_{i,T} \tag{4}
$$

He derives the asymptotic distribution of this statistic when T and N tend sequentially to infinity. He provides MonteCarlo experiments in order to describe this individual Wald statistics which have not a standard $\varkappa^2$ distribution.

3.3 The Granger Causality test with Poisson Pseudo-Maximum Likelihood

We follow the recent literature which proposes the use of the Poisson Pseudo-Maximum Likelihood, (Santos Silva and Tenreyro, 2006), when there is a problem of zeros in OLS estimator. Considering the example reported in Santos Silva and Tenreyo (2006), a stochastic model formulated as:

$$y_i = \exp(x_i\beta) + \varepsilon_i \tag{5}$$

with $y_i \geq 0$ and $E\left[\varepsilon_i|x\right] = 0$.

If we want to log-linearize the previous equation and estimate β by using OLS, we obtain some problems. First of all, y_i can be zero, consequently the log-linearization is not feasible. Second, even if all observations of y_i are only positive, the expected value of the log-linearized error depends on the covariance term and OLS estimator is not consistent.

Rewriting the previous equation in the following way:

$$y_i = \exp(x_i\beta)\eta_i \tag{6}$$

where $\eta_i = 1 + \varepsilon_i/\exp(x_i\beta)$ and $E\left[\eta_i|x\right] = 1$.

We assume that y_i is positive, the model is made in linear format in the parameters by taking logarithms of both sides of the equation:

$$\ln(y_i) = x_i\beta + \ln(\eta_i) \tag{7}$$

If $E\left[\ln\left(\eta_i\right)|x\right]$ does not depend on x_i, we can get a consistent estimator of the slope parameters by using OLS.

However, this does not happen since we need some statistical conditions on ε_i which results heteroskedastic and the $V\left[y_i|x\right]$ is not proportional to $\exp(2x_i\beta)$ and OLS provides inconsistent estimates of β.

To solve this problem, a non-linear model should be taken into account.

The Non-Linear least Squares (NLS) estimator of β is defined as:

$$\widehat{\beta} = \arg\min_b \sum_{i=1}^{n} \left[y_i - \exp(x_i b)\right]^2$$

which implies the following first order conditions:

$$\sum_{i=1}^{n} \left[y_i - \exp(x_i\widehat{\beta})\right] \exp(x_i\widehat{\beta})x_i = 0$$

Santos Silva and Tenreyro (2006) stress the possibility to obtain an estimator that is more efficient than the standard (NLS) without considering the nonparametric regression, following McCullagh and Nelder (1989). The alternative is to estimate the parameters using a pseudo-maximum likelihood estimator based on some assumptions on the functional form of $V\left[y_i|x\right]$.

Under the assumption $E\left[y_i|x\right] = \exp(x_i\beta) \propto V\left[y_i|x\right]$ and β is estimated by solving the following set of first order conditions:

$$\sum_{i=1}^{n} \left[y_i - \exp(x_i \widetilde{\widehat{\beta}}) \right] x_i = 0 \tag{8}$$

This estimator is numerically equal to the Poisson pseudo-maximum likelihood (PPML) estimator used for count data. In this case, this estimator can be used under the correct specification of the conditional mean, $E\left[y_i|x\right] = \exp(x_i\beta)$.

Van Ophem et al. (2001) investigate the relationship between R&D expenditures and number of patents acquired. They use a Poisson PML estimator since the patent are distributed following a Poisson.

The main difference between the application of the traditional Granger causality in case of using an OLS estimator is the presence of a non-linear estimator approximated by using PPML. In this way, it could be interesting to consider Baghli (2006), which proposes a causality testing procedure robust to the presence of potential nonlinearities

3.4 The Granger Causality test with Poisson Pseudo-Maximum Likelihood in a Panel Data Fixed Effect

The contribution of our paper is to imply the use of the Granger Causality test in case a of Poisson Pseudo-Maximum Likelihood estimator applied to a Panel Data Fixed Effect Model. In this case, we take into consideration the characteristic discussed in case of the application of the Granger causality test with a panel data model. The main difference is the use of a Poisson Pseudo-Maximum Likelihood estimator instead of an OLS estimator.

4 The Data

In order to investigate the causal relationship between trade and contract enforcement, we employ data taken from the Trade, Production and Protection Database, maintained by the World Bank. It contains information on bilateral trade flows classified by ISIC (International Standard Industrial Classification), Revision 2. As we are not interested in the sectorial dimension, we consider overall bilateral trade flows. This leads to an unbalanced panel with 403,135 observations on trade between 197 countries and 243 partner countries, that covers the period 1976-2004 (29 years). Assuming that missing observations correspond to zero flows of trade, we balance our database, obtaining a final database with 1,388,259 observations. As 985,124 zero flows observations have been created in order to balance the panel, we need to take into account this characteristic of our dependent variable.

The measures of institutional quality, $inst_{ct}$, are taken from the Freedom House Database, which provides information on political rights and civil liberties for 204 countries since 1976. The index on political rights is based on measures on electoral process; political pluralism and participation and functioning of government. The measure of civil liberties takes into account four different aspects: freedom of expression and belief; associational and organizational rights; rule of law and personal autonomy and individual rights. As it refers directly to rule of law, this is our preferred measure. These indicators are measured on a one-to-seven scale, with one representing the highest degree of freedom and seven the lowest. They have been rescaled in the interval [0,1] with increasing values associated with highest economic freedom. Freedom House Database. Table 1 shows some descriptive statistics.

5 The Empirical Evidence

In this section we present the application of the Granger Causality test in the different econometric frameworks discussed above.

We apply the Granger Causality test, considering first a Pooled Ordinary Least Square estimator. By using this kind of estimation, we do not consider the time dimension in the right panel data context. However, we use the lagged values of the variables involved in the bivariate system. Our purpose is to understand if there is causality implication between contract enforcement and trade flows (exports and imports), consequently, we regress trade flows (both export and import) on their lags and on the lagged values for the civil liberties variable which is the variable we use to proxy for contract enforcement. In this way, we want to test if export or import flow is caused by the civil liberties.

$$trade\_flow_t = \alpha_0 + \alpha_1 trade\_flow_{t-1} + ... + \alpha_N trade\_flow_{t-N} + \beta_1 civ\_lib_{t-1} + ... + \beta_N civ\_lib_{t-N} + \epsilon_t \tag{9}$$

Viceversa, we regress the civil liberties on their lags and on the lagged values for the trade flows.

$$civ\_lib_t = \alpha_0 + \alpha_1 civ\_lib_{t-1} + ... + \alpha_N civ\_lib_{t-N} + \beta_1 trade\_flow_{t-1} + ... + \beta_N trade\_flow_{t-N} + u_t \tag{10}$$

The next step regards the implementation of the Granger Causality test by testing that $H0 : \beta_1 = ... = \beta_N = 0$.

Our first attempt to investigate the causal relationship between trade and contract enforcement is shown in Table 2. Using ordinary least squares, we regress the logarithm of trade flows on past values of the dependent variable, and of the proxy for contract enforcement. Then, we repeat the same exercise using institutional quality as dependent variable. We show the results using four lags for our variables. Column 1 in Table 2 shows that past values of export flows and institutional quality are all significant in explaining export behavior. The joint F test rejects the null hypothesis that all the coefficients for the lagged values of institutional quality are equal to zero. Therefore, we find evidence that exports are Granger caused by institutional quality. We could imagine a similar effect of institutional quality on imports. Good contract enforcement facilitates trade, in both directions. As expected, we observe an analogous result for import flows. Again, the F test suggests that past values of institutional quality explain import flows: imports are Granger caused by contract enforcement.

Moving to the issue of the causal effect of institutions on trade, we repeat the same exercise using institutional quality as dependent variable. The coefficient estimates of lagged values of both exports and imports are significant, and the F test shows that the null hypothesis that these coefficients are jointly equal to zero has to be rejected. Thus, we observe that trade Granger causes institutional quality.

The second application regards the use of the simple Granger Causality test in the presence of a Panel Data Fixed Effect. Remembering the general specification,

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \varepsilon_{i,t} \tag{11}$$

we consider, as mentioned in the case of the POLS, the investigation of the causality in two-way, using both export and import as trade flows and civil liberties as before.

In this case, we assume the Homogenous Non-Causality hypothesis with the following null and alternative hypothesis:

$$H0 : \beta_i = 0 \ \forall i = 1, ..., N$$

$$\begin{aligned} H1 &: \beta_i = 0 \forall i = 1, ..., N_1 \\ H1 &: \beta_i \neq 0 \forall i = N_1 + 1, ..., N \end{aligned}$$

in which N_1 is equal to zero, in this way we do not take into account the heterogenous result, simplifying the framework. Results are reported in Table 3. The inclusion of country pair fixed effects does not change our results. Moreover, fixed effects are statistically significant. We still observe that Granger causality runs in both directions.

These estimates are obtained using the logarithm of trade flows. Although this is common practice in trade literature, it has been recently proven by Santos Silva and Tenreyro (2006) that the log-linearization of the dependent variable, estimated by OLS, produces inconsistent estimates in presence of heteroskedasticity. The Breusch

Pagan test for heteroskedasticity. rejects the null hypothesis of constant variance, therefore we are forced to move to a different estimation technique. Following Santos Silva and Tenreyro (2006), we adopt the pseudo-maximum likelihood estimator. When using PPML, we should take into consideration the presence of nonlinearities, but for simplicity we assume there is not difference in application of the Granger Causality test with a linear or no linear assumption. Hence, the only difference between the first empirical evidence is the use of this specific technique. Table 4 reports the results. When looking at the impact of lagged values of institutional quality of import and export flows, we observe that the coefficient estimates are always statistically significant. The F test suggests that trade flows are Granger caused by institutional quality. Thus, we can affirm that institutional quality Granger causes trade, and this results hold with OLS and PPML.

Again, to take into account the heterogeneity of country pairs, we repeat the exercise with a panel Poisson estimation, which includes country pair fixed effects. In this case, the use of the Granger Causality test is again simplified without the assumption of heterogeneity and non-linearity. The inclusion of the fixed effects does not change the results.

Our results do not depend on the number of lags included in the analysis. Tables A.1-A.4 reported in the appendix show that our results are robust also when using only one lag.

6 Conclusions

The causal relationship between institutional quality and trade has been debated at length. As the theory suggests that the causality could work in both directions, we implement a Granger causality test in order to inspect this relationship. We use trade data on export and import between 197 countries with 243 partners over the period 1976 to 2004. Given the nature of our data, after a preliminary analysis with OLS and fixed effects, we move to Poisson pseudo-maximum likelihood. We find that causality runs in both directions. Our results are robust across different estimators.

Next step in our research agenda is the refinement of the econometric setup of the use of Granger causality test under assumptions of heterogeneity and non-linearity. Moreover, we could investigate if the causal relationships found hold for different country sub groups .

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Tables

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
imp_tv_tot	1388259	59206.51	1211176	0	1.99E+08
exp_tv_tot	1388259	58992.21	1194743	0	1.99E+08
limp_tv_tot	1388259	1.760383	3.567373	0	19.1078
lexp_tv_tot	1388259	1.763042	3.630452	0	19.10718
cpr01	1196289	0.5118661	0.36883	0	1
ccl01	1196289	0.5073295	0.3169446	0	1
ppr01	1026961	0.4962114	0.3738599	0	1
pcl01	1026961	0.4939734	0.3236571	0	1

limp_tv_tot=ln(imp_tv_tot+1)

Table 1: Descriptive statistics

	lexport	inst	limport	inst
	(1)	(2)	(3)	(4)
inst[-1]	0.146***	0.952***	0.191***	0.953***
	(0.017)	(0.00098)	(0.019)	(0.00098)
inst[-2]	0.134***	0.00857***	0.0184	0.00862***
	(0.024)	(0.0013)	(0.026)	(0.0013)
inst[-3]	0.215***	-0.0452***	0.0877***	-0.0451***
	(0.023)	(0.0013)	(0.026)	(0.0013)
inst[-4]	-0.245***	0.0489***	-0.0485***	0.0499***
	(0.017)	(0.00097)	(0.019)	(0.00096)
lexport[-1]	0.649***	0.000724***		
	(0.00100)	(0.000057)		
lexport[-2]	0.212***	-0.000551***		
	(0.0012)	(0.000068)		
lexport[-3]	0.0580***	0.000326***		
	(0.0012)	(0.000069)		
lexport[-4]	0.0473***	0.000332***		
	(0.0010)	(0.000058)		
limport[-1]			0.631***	0.000585***
			(0.0010)	(0.000052)
limport[-2]			0.201***	-0.000184***
			(0.0012)	(0.000062)
limport[-3]			0.0600***	0.0000310
			(0.0012)	(0.000063)
limport[-4]			0.0632***	0.000129**
			(0.0010)	(0.000054)
constant	0.0582***	0.0238***	0.0831***	0.0234***
	(0.0027)	(0.00015)	(0.0030)	(0.00015)
Observations	1028376	1028133	1028376	1028133
R^2	0.87	0.93	0.83	0.93
Joint F-test	788.70	328.62	582.27	156.16
	(0.000)	(0.000)	(0.000)	(0.000)

Notes: OLS estimates. * significant at 10%, ** significant at 5%, *** significant at 1%

Table 2: Granger Causality Test with OLS, four lags

	lexport	inst	limport	inst
	(1)	(2)	(3)	(4)
inst[-1]	0.345***	0.885***	0.461***	0.885***
	(0.017)	(0.0010)	(0.019)	(0.0010)
inst[-2]	0.153***	0.00558***	0.0533**	0.00545***
	(0.023)	(0.0013)	(0.026)	(0.0013)
inst[-3]	0.207***	-0.0488***	0.0819***	-0.0487***
	(0.023)	(0.0013)	(0.025)	(0.0013)
inst[-4]	0.122***	0.0188***	0.333***	0.0193***
	(0.017)	(0.00099)	(0.019)	(0.00099)
lexport[-1]	0.555***	0.00148***		
	(0.0010)	(0.000059)		
lexport[-2]	0.170***	-0.000152**		
	(0.0012)	(0.000068)		
lexport[-3]	0.0361***	0.000559***		
	(0.0012)	(0.000068)		
lexport[-4]	0.0158***	0.000584***		
	(0.0010)	(0.000059)		
limport[-1]			0.535***	0.00140***
			(0.0010)	(0.000054)
limport[-2]			0.157***	0.000219***
			(0.0012)	(0.000062)
limport[-3]			0.0328***	0.000304***
			(0.0012)	(0.000062)
limport[-4]			0.0231***	0.000401***
			(0.0010)	(0.000054)
constant	0.148***	0.0725***	0.146***	0.0727***
	(0.0050)	(0.00029)	(0.0056)	(0.00029)
Observations	1028376	1028133	1028376	1028133
Number of countrypairs	42039	42039	42039	42039
R^2 within	0.54	0.76	0.49	0.76
R^2 overall	0.87	0.93	0.83	0.93
Joint F-test	1819.33	716.40	1806.50	687.54
	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Panel estimates with country pairs fixed effects. * significant at 10%, ** significant at 5%, *** significant at 1%

Table 3: Granger Causality Test with Fixed Effects, four lags

	export	import
	(1)	(2)
inst[-1]	2.230***	1.978***
	(0.000062)	(0.000061)
inst[-2]	0.192***	0.287***
	(0.000083)	(0.000082)
inst[-3]	-1.073***	-1.062***
	(0.000081)	(0.000080)
inst[-4]	2.284***	2.170***
	(0.000060)	(0.000059)
export[-1]	0.0000000721***	
	(0)	
export[-2]	-0.0000000101***	
	(0)	
export[-3]	1.63e-10***	
	(0)	
export[-4]	-0.0000000160***	
	(0)	
import[-1]		0.0000000761***
		(0)
import[-2]		-0.0000000289***
		(0)
import[-3]		0.0000000442***
		(0)
import[-4]		-0.0000000439***
		(0)
constant	8.654***	8.846***
	(0.000014)	(0.000013)
Observations	1028376	1028376
Log likelihood	-2.281e+11	-2.293e+11
Joint F-test	4.8e+10	4.4e+10
	(0.000)	(0.000)

Notes: Poisson estimates. * significant at 10%, ** significant at 5%, *** significant at 1%

Table 4: Granger Causality Test with Pooled Poisson, four lags

	export	import
	(1)	(2)
inst[-1]	1.502***	1.471***
	(0.000071)	(0.000072)
inst[-2]	-0.121***	0.0484***
	(0.000089)	(0.000090)
inst[-3]	-0.283***	-0.500***
	(0.000092)	(0.000091)
inst[-4]	0.658***	0.651***
	(0.000071)	(0.000071)
export[-1]	0.0000000242***	
	(0)	
export[-2]	-1.21e-09***	
	(0)	
export[-3]	-1.65e-09***	
	(0)	
export[-4]	-1.40e-09***	
	(0)	
import[-1]		0.0000000298***
		(0)
import[-2]		-7.17e-09***
		(0)
import[-3]		1.54e-09***
		(0)
import[-4]		-4.20e-09***
		(0)
Observations	628017	721759
Number of countrypair	25460	29377
Log likelihood	-1.553e+10	-1.568e+10
Joint F-test	1.6e+09	1.5e+09
	(0.000)	(0.000)

Notes: Panel Poisson estimates with country pair fixed effects. * significant at 10%, ** significant at 5%, *** significant at 1%

Table 5: Granger Causality Test with Panel Poisson with Fixed Effects, four lags

Appendix

	lexport	inst	limport	inst
	(1)	(2)	(3)	(4)
inst[-1]	0.452***	0.963***	0.413***	0.964***
	(0.0047)	(0.00025)	(0.0050)	(0.00025)
lexport[-1]	0.924***	0.000924***		
	(0.00039)	(0.000021)		
limport[-1]			0.906***	0.000681***
			(0.00043)	(0.000021)
constant	0.0112***	0.0235***	0.0578***	0.0231***
	(0.0026)	(0.00014)	(0.0029)	(0.00014)
Observations	1154493	1154250	1154493	1154250
R^2	0.85	0.93	0.81	0.93
Joint F-test	9330.93	1861.15	6823.74	1017.92
	(0.000)	(0.000)	(0.000)	(0.000)

Notes: OLS estimates. * significant at 10%, ** significant at 5%, *** significant at 1%

Table A.1: Granger Causality Test with OLS, one lag

	lexport	inst	limport	inst
	(1)	(2)	(3)	(4)
inst[-1]	0.813***	0.873***	0.851***	0.874***
	(0.0084)	(0.00047)	(0.0092)	(0.00047)
lexport[-1]	0.722***	0.00164***		
	(0.00063)	(0.000036)		
limport[-1]			0.697***	0.00163***
			(0.00067)	(0.000034)
constant	0.219***	0.0670***	0.232***	0.0671***
	(0.0044)	(0.00025)	(0.0048)	(0.00025)
Observations	1154493	1154250	1154493	1154250
Number of countrypair	42039	42039	42039	42039
R^2 within	0.56	0.76	0.51	0.76
R^2 overall	0.85	0.93	0.81	0.93
Joint F-test	9427.38	2111.50	8608.53	2267.11
	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Panel estimates with country pairs fixed effects. * significant at 10%, ** significant at 5%, *** significant at 1%

Table A.2: Granger Causality Test with Fixed Effects, one lag

	export	import
	(1)	(2)
inst[-1]	3.654***	3.390***
	(0.000016)	(0.000016)
export[-1]	0.0000000498***	
	(0)	
import[-1]		0.0000000519***
		(0)
constant	8.530***	8.728***
	(0.000014)	(0.000013)
Observations	1154493	1154493
Log likelihood	-2.395e+11	-2.410e+11
Joint F-test	4.9e+10	4.5e+10
	(0.000)	(0.000)

Notes: Poisson estimates. * significant at 10%, ** significant at 5%, *** significant at 1%

Table A.3: Granger Causality Test with Pooled Poisson, one lag

	export	import
	(1)	(2)
inst[-1]	1.625***	1.565***
	(0.000039)	(0.000039)
export[-1]	0.0000000221***	
	(0)	
import[-1]		0.0000000225***
		(0)
Observations	707343	813128
Number of countrypair	25574	29499
Log likelihood	-1.945e+10	-1.979e+10
Joint F-test	1.8e+09	1.6e+09
	(0.000)	(0.000)

Notes: Panel Poisson estimates with country pair fixed effects. * significant at 10%, ** significant at 5%, *** significant at 1%

Table A.4: Granger Causality Test with Panel Poisson with Fixed Effects, one lag