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Causal Link Between Bilateral Aid and Exports: The Swiss Case

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Abstract

This paper investigates the direction of Granger causality, if Granger causality there is, between Swiss bilateral official development aid and Swiss exports for a panel of 50 recipient countries over the period 1974-2013. To account for possible geographical effects, three specific group of recipient countries across the same period are considered, that is "Africa", "Latin America" and "Asia". To shed on light potential level effects, four other group of countries are considered according to the relative amount of aid, respectively exports, Switzerland has exchanged with a given recipient country across the all period. The former panel plus the seven specific group of countries and the fact that we test for Granger causality in both directions give us a total of 16 models. As a necessary first step, four different panel unit root tests are conducted on each series of all eight panels and results systematically indicate stationary series in levels. Then and to test for Granger causality, Dumitrescu-Hurlin Granger non-causality tests are conducted. Results indicate bidirectional Granger causality in all panels except for the "African" one where Granger causality seems to run only from exports to bilateral aid. This result is important in terms of policy implications, particularly for a donor country as Switzerland, since it implies that if aid towards a recipient country is cut, it is likely to cause Swiss export reductions to that same recipient country.

JEL Classification: C23, F35.

Keywords: Aid, exports, unit root, Granger causality, panel datasets.

1 Introduction

An important feature of today's economy is that nations increasingly trade with each other. Economically, this is a blessing as Ricardo's theory of comparative advantages proved two centuries ago: trade has the potential to make everyone better-off. It is precisely to promote trade that the OECD has put in place in 1961 a committee in charge of encouraging wealthy nations to assist "Least Developed Countries" (LDCs). This assistance is nowadays commonly known as the "Official Development Aid" (ODA) (hereafter aid).

Even if a purely altruistic behavior can not be excluded (see for instance Berthélemy, 2006) donor countries may conceal reasons to donate to a particular country. For instance, an hidden rationale, or at least not publicly admitted, to favor a country can be the current trade situation. It is indeed possible and understandable that donor countries will likely consider important trading partners first when allocating aid. We may thus expect causal links from exports to aid. On the other hand, causality from aid to export can also be expected due to, for instance, the creation of a long-standing relationship, referred to as "goodwill" in the literature (see for instance Arvin et al., 2000; Wagner, 2003; Martínez-Zarzoso et al., 2009) between the donor and the recipient country. The "goodwill" effect can be simplistically viewed as the fact that if you help someone one day, you may be helped back the following day. In their contribution Martínez-Zarzoso et al. (2009) also point out at two other reasons why giving aid may affect the donor exports, that is tied aid and habit-formation. Concerning the former effect it is basically the fact that the donor's aid consists in exporting its own goods towards the recipient country. Then, habit-formation is, in a sense, the continuity of the direct impact of tied aid. Indeed, having send your own goods may create a dependence/familiarity with that goods (see Djajić et al. (2004) for more details on habit-formation).

Switzerland is a very interesting country to analyze because tied aid and habit-formation effects are likely to be weak since this country is considered as one of the most altruistic donor country (i.e. untied aid). See for instance Berthélemy (2006) who categorizes 19 donor countries in terms of their behavior towards giving aid, that is, altruistic, average or egoistic donor. Switzerland is found by the author to be the most altruistic country. In addition, in the report of Clay et al. (2009), undertook under the auspices of the Secretariat for the Evaluation of the Paris Declaration and the OECD/DAC, Switzerland is classified as an highly altruistic country with an untied aid ratio in 2007 of 98.4%.¹ To summarize, out of the three economic explanations on why aid may create exports for the donor country, the most valid in the Swiss case is apparently the "goodwill" effect. Thus, the fact that we will focus on Switzerland in the present study is particularly innovative since we are analyzing the statistical link between aid and exports (and conversely) for a country with a very high proportion of untied aid.

Studies that test for any kind of causality between aid and exports and that focus on one donor country as we do, are rather scarce. To our knowledge, the only papers are Arvin et al. (2003) who use Italy as donor country and Lloyd et al. (2000) who use France, Germany, the Netherlands and the United Kingdom as donor countries. Both studies use the method developed by Granger (1969) to test for causality. The conclusion of Arvin et al. (2003) is that causality exists only towards some recipient countries. Lloyd et al.'s (2000) conclusion

 $^{^{1}}$ See Clay et al. (2009) Table 3.3 (page 12) for details on the untied aid ratio.

is less nuanced: a statistical link between aid and trade is an exception rather than the norm. The present study differs in two major ways: 1) it focuses on a country considered as highly altruistic in his way to allocate aid, that is Switzerland, 2) it uses current econometric tools to test for causality in an heterogeneous panel data set. To do so, four different unit root tests and the Dumitrescu-Hurlin Granger non-causality test are employed.

Although in the present study we will test for causality in both directions, that is exports towards aid and aid towards exports, it is this latter relation that may interest strong Swiss supporters of official development aid. Indeed, regardless the results we will obtain, the outcome will; or give them a strong argument to ask for an increase of the total amount of aid (or at least to not cut current amounts) or give them an opportunity to recall Switzerland is so altruistic that the aid they allocate does not influence their trade.

The rest of the paper is organized as follows. Section 2 discusses some literature on ODA and Granger causality tests. Section 3 presents the data used in the present study and describes the different groups of countries created. Section 4 details the panel unit root tests used (4.1) as well as the Granger causality test employed (4.2). Section 5 presents the results of all tests. Section 6 discusses some important issues and gives some limitations of the present study. Section 7 concludes and provides policy implications.

2 Literature review

Since its creation, ODA has been the subject of numerous studies, dealing with various issues, but in particular its impact on trade and/or growth. A large body

of literature focuses on recipient countries and is concerned with the degree of efficiency of such aid on their growth rate (see for instance Burnside and Dollar, 2000; Easterly, 2003) or on their trade capacity (see for instance Nowak-Lehmann et al., 2013). A striking feature of this literature is that results do not provide clear-cut evidence on the effective impact of ODA on recipient countries.

Then, some authors have started to look at the effects of aid on the donor countries. Among them stand the ones measuring the impact of aid on the donor country through trade. McCallum (1995) and then Anderson and van Wincoop (2003), have shown in their contributions that a good way to adequately compute aid's impact on trade is by using a modified/augmented trade gravity model. Since 2003, several authors have tried to measure the impact of ODA on the donor country's exports, all convinced that aid creates a "goodwill" which then becomes source of future partnerships. We believe this assumption constitutes the foundation for a possible statistical link between ODA and exports. Each contribution is of course unique due to its specific assumptions or methods but nearly all conclude that there is indeed a positive relationship between aid and exports in the donor country (see for instance recently Helble et al. (2012); Silva and Nelson (2012); Pettersson and Johansson (2013); Hühne et al. (2014) or Wagner (2003), one of the first using a gravity model in the present topic). These studies use databases with many donor countries and several recipient countries.

Studies analyzing thoroughly a single country (at least the ones using a gravity model) are scarce. We can still mention Martínez-Zarzoso et al. (2009), Nowak-Lehmann et al. (2009), Martínez-Zarzoso et al. (2010) or Martínez-Zarzoso et al. (2013) looking in detail at the German case or Skärvall (2012)

looking at the Swedish case. The present study does not aim at quantifying the impact of aid on trade (exports) but at determining the direction of Granger causality, if Granger causality there is, between aid and exports within an heterogeneous panel data set (see Arvin et al., 2003, for a similar approach in a time series framework).

Granger causality between two series is an old issue in time series but a relatively recent topic in panel data. Indeed, there is a growing availability of panel databases with not only a large number of individuals N but also a large number of time periods T. This shift from micro panels to macro panels implies that classical issues from times series extend to panel data, as spurious regressions due to unit roots, but also consequently implies that time series techniques can now also be used in panel data, as Granger causality. The term "Granger causality" refers to a specific form of causality that has been developed by Granger (1969, 1980). Although nearly fifty years old, the model and the technique proposed by Granger are still currently used in many recent studies, the present one being one of them. Again, even if the concept of Granger causality was born in a time series framework, it has been extended to panel data since already thirty years. The main difference between the two frameworks is that in panel there are as many coefficients as individuals N in the data set. Therefore, the different models adapting Granger causality in panel data will basically differ in the way they treat and test the individuals coefficients.

One of the first study in such framework is the one by Holtz-Eakin et al. (1988). The authors first difference their data in order to eliminate fixed effects and then, estimate the model by applying instrumental variables. Their model assumes a common coefficient on the independent variable for all individuals. To relax this strong assumption, Nair-Reichert and Weinhold (2001) have used Mixed Fixed and Random (MFR) models as first proposed by Hsiao et al. (1989) and then adapted to the present panel data framework by Weinhold (1996). A closely related approach is the one by Kónya (2006), who uses seemingly unrelated regressions (SUR) systems and Wald tests with country specific bootstrap critical values. Finally, in the same kind of framework but with a slightly different approach, Dumitrescu and Hurlin (2012) propose to test for Granger non-causality by basing their test on an averaged across individuals Wald statistic. This is the strategy we follow in this paper.

3 Data

The two variables of interest in the present study are Swiss bilateral aid² and Swiss exports (annual data). Regarding Swiss bilateral aid in Swiss francs $(CHF)^3$, data is available on the "Federal Department of Foreign Affairs" website under the "Swiss Agency for Development and Cooperation (SDC)" section. In the present study we will use Swiss bilateral aid from 1974 to 2013 and towards a total of 50 recipient countries.⁴ Concerning Swiss exports towards

²Bilateral aid is aid that is directly donated to a country. Multilateral aid is aid that is donated to international organizations that are active in several least developed countries. In our study only bilateral aid is considered since multilateral aid is difficult, if not impossible, to correctly spread across recipient countries. Together, bilateral aid and multilateral aid sum up to the so called "official development aid".

 $^{^{3}\}mathrm{In}$ 2016, 1 USD was equivalent to 0.985 CHF according to the OECD statistics website.

⁴Data on Swiss bilateral aid under the SDC website is available from 1960 to 2015 and towards 105 recipient countries but with an important number of missing values. Since some econometric tests used in this study do require a strongly balanced panel data set, only 50 countries are kept across 40 years (1974 to 2013). As mentioned 2014 and 2015 are also available but provisional and therefore not considered for the analysis.

the same 50 aid recipient countries and for the same period, data is collected on the UN Comtrade database. All data are directly available or converted into USD using annualized exchange rates from the OECD database.

The nature of the relationship between aid and export might differ across recipient countries. In order to investigate this issue, we will evaluate the causality between our series for various groups of countries. We will first consider geographical regions with the "African", "Latin American" and "Asian" group of countries. Then, to capture level effects, we have created the "high" and the "low" exports group of countries. In the former group stand the 25 countries with which Switzerland trades more (above the entire period average) and in the latter group stand the countries with which Switzerland trades less. The exact same procedure is used to create the two last group of countries, i.e. the "high" and the "low" bilateral aid groups. Appendix A enumerates the 50 countries kept and shows their classification into specific group of countries.

4 Tests

Non-stationarity is a well-known potential issue in time-series, and it could also arise in long panel datasets. Therefore, a necessary first step before testing causality is to test for the presence of unit roots. If the series contain unit roots, the issue of spurious regression arises and one has to employ cointegration techniques in order to ensure the identification of causal relationships. On the contrary, if the series follow a stationary process, then causality tests as developed by Granger (1969, 1980) are valid to detect the presence and the direction of a statistical link.

4.1 Unit root tests

Several panel unit root tests have been developed and this study will apply several of them. Four different tests are applied, the HT test (Harris and Tzavalis, 1999), the LLC test (Levin et al., 2002), the IPS test (Im et al., 2003) and the PESCADF test (Pesaran, 2007). Here below follow a brief description of the four unit root tests.

A general autoregressive panel equation serves as a basis to all tests:

$$\Delta y_{it} = \beta y_{i,t-1} + \alpha_{mi} d_{mt} + \mu_{it} \qquad i = 1, \dots, N; \ t = 1, \dots, T; \ m = 1, 2, 3 \tag{1}$$

where d_{mt} allows to implement different specifications, with $d_{1t} = \emptyset$ (empty set) which implies that there is no fixed effect and therefore an homogeneous panel is assumed, $d_{2t} = \{1\}$ which includes individual fixed effects and therefore allows for heterogeneity across individuals of the panel, and $d_{3t} = \{1, t\}$ which includes individual fixed effects as well as an individual time trend.

Although the tests all rely on the above general equation they still differ for instance, on the method used to estimate the coefficients, on the test statistic, on the assumption regarding the disturbances (μ_{it}) , i.e. cross-sectional dependence versus cross-sectional independence⁵ or, on the definition of the coefficient β , i.e. whether it is homogeneous across all individuals in the panel or not.

For instance, in their paper, Harris and Tzavalis (1999) test for unit roots based on the normalized pooled least square estimator of the autoregressive coefficient (that is corrected depending on the model used) coming from the pooled regression. They assume a fixed time dimension (T). The models they use are

⁵Serial correlation can also be an issue in panel data, but all tests except Harris and Tzavalis (1999) allow for serial correlation. We will therefore not further discuss this issue.

the ones from equation (1). The assumptions made by Harris and Tzavalis (1999) imply cross-sectional independence by design. The authors argue that one option to relax, or at least mitigate this assumption, is by subtracting the cross-section mean from the data. Their assumptions also imply serially uncorrelated errors.

Levin et al. (2002) propose a unit root test based on the t statistic (and not on the estimator itself as in Harris and Tzavalis (1999)) obtained from a pooled regression. Although the authors assume that all individuals in the panel have identical first-order partial correlation (i.e. β and not β_i), the test is based on the Augmented Dickey Fuller (ADF) method.⁶ The authors point as an important limit of their test the requirement of cross-sectional independence and add that sometimes subtracting the cross-sectional averages is not sufficient to remove contemporaneous correlation. By construction the authors' assumptions allow for serial correlation.

Im et al. (2003) propose a different approach to test for unit roots, they use a *t*-statistic based on ADF statistics averaged across individuals. Their test allows for serial correlation when T and N are sufficiently large. In addition to the change in the method used, the other observable dissimilarity between the HT and LLC procedures and the one proposed by Im et al. (2003) is that the first-order autoregressive parameter β_i can differ across countries in the latter, which implies that the interpretation of the alternative hypothesis differs substantially. Indeed in Im et al. (2003) if the null is rejected it is stated that

 $^{^6\}mathrm{See}$ the proposed three-step procedure in section 2.2 of Levin et al. (2002) for more details.

⁷As the authors write, it is not possible to identify the exact proportion of stationary individuals.

and Tzavalis (1999) and Levin et al. (2002) if the null is rejected it is stated that all individuals in the panel are stationary. As in HT and LLC, the IPS test does not deal with cross-sectional dependence but again, subtracting the cross-sectional averages may mitigate this issue.

Finally, Pesaran (2007) proposes a unit root test that allows for crosssectional dependence and serial correlation. To do so he uses an extended version of the standard augmented Dickey-Fuller regression. Concretely standard ADF regressions for the individuals series are augmented with current and lagged cross-section averages of all the series in the panel. As in Im et al. (2003) the alternative hypothesis has to be cautiously interpreted when the null is rejected.

4.2 Dumitrescu-Hurlin Granger non-causality test

This study uses the Dumitrescu-Hurlin Granger non-causality test recently developed by Dumitrescu and Hurlin (2012), which is a modified version of the well-known Granger test . The simple model developed by Granger (1969) with two series (that have to be stationary) is given by:

$$X_{t} = \sum_{j=1}^{m} a_{j} X_{t-j} + \sum_{j=1}^{m} b_{j} Y_{t-j} + \epsilon_{t}$$
$$Y_{t} = \sum_{j=1}^{m} c_{j} X_{t-j} + \sum_{j=1}^{m} d_{j} Y_{t-j} + \eta_{t}$$

where ϵ_t and η_t are two uncorrelated white-noise series. If some b_j or c_j are

not zero then Y_t is causing X_t or X_t is causing Y_t respectively. The two causal relationships are not mutually exclusive.

In a similar way we will do for the Dumitrescu-Hurlin model, Hsiao (1979, 1981, 1982) has proposed an augmented version of the above Granger causality test by allowing different lag length for each series and where the latter are chosen to minimize the Akaike (1969, 1970) final prediction error. The Hsiao version of the Granger causality test is thus based on the following equations:

$$X_{t} = \sum_{j=1}^{m} a_{j} X_{t-j} + \sum_{j=1}^{n} b_{j} Y_{t-j} + \epsilon_{t}$$
$$Y_{t} = \sum_{j=1}^{o} c_{j} X_{t-j} + \sum_{j=1}^{p} d_{j} Y_{t-j} + \eta_{t}$$

Then, Dumitrescu and Hurlin (2012) have proposed a modified version of the Granger causality test in order to use it in a heterogeneous panel datasets. As in Granger (1969) the test require two stationary series and the model is given by:

$$y_{i,t} = \alpha_i \sum_{k=1}^{K} \gamma_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \epsilon_{i,t}$$
(2)

with $K \in \mathbf{N}^*$ and $\beta_i = (\beta_i^{(1)}, ..., \beta_i^{(k)})'$. The lag order K is identical for all individuals of the panel. The authors do not discuss in their paper the optimal lag length to include in the model. The autoregressive parameters $\gamma_i^{(k)}$ and the coefficients $\beta_i^{(k)}$ can differ across individuals but are constant in time. The null and the alternative hypotheses associated with the model are given by:

 $H_0: \ \beta_i = 0 \ \forall i = 1, ..., N$ (non causality in all panels)

$$H_a = \begin{cases} \beta_i = 0 \ \forall i = 1, ..., N_1 \\\\ \beta_i \neq 0 \ \forall i = N_1 + 1, N_1 + 2, ..., N \end{cases}$$
 causality in some panels

where N_1 is unknown but satisfies the condition $0 \le N_1/N < 1$. This structure

is similar to the one proposed by Im et al. (2003) and Pesaran (2007) discussed above.⁸

Dumitrescu and Hurlin (2012) propose to associate the Wald statistics averaged across individuals to the test of the non causality hypothesis for individuals i = 1, ..., N:

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

where $W_{i,T}$ is the standard adjusted Wald statistic for individual *i* calculated over *T* periods.⁹ Although the individual Wald statistics converge to a chi-squared distribution with *K* degrees of freedom¹⁰ (where *K* stands for the number of lags), the authors show that the distribution of the average Wald statistic when $T \to \infty$ first and then $N \to \infty$, can be deduced from a standard Lindberg-Levy central limit theorem and thus infer that $W_{N,T}$ sequentially converges in distribution in the following way:

$$Z_{N,T} = \sqrt{\frac{N}{2K}} (W_{N,T} - K) \quad \xrightarrow{d}_{T,N \to \infty} \mathcal{N}(0,1)$$
(3)

In addition to this Z-statistic, Dumitrescu and Hurlin (2012) also propose the \tilde{Z} statistic allowing for a fixed T dimension (under the assumption of T > 5+2K).
Their standardized average \tilde{Z} is given by:

$$^{10}W_{i,T} \xrightarrow{d} \chi^2(K), \forall i = 1, ..., N.$$

⁸The alternative has to be read as, if we have 50 (= N) recipient countries in our panel, and 20 (= N_1) do not show causal link ($\beta_i = 0$), then 30 (= $N - N_1$) do show causal link ($\beta_i \neq 0$).

⁹See Dumitrescu and Hurlin (2012) page 1453 for the exact mathematical definition of $W_{i,T}$.

$$\tilde{Z}_N = \sqrt{\frac{N}{2K} \frac{(T - 2K - 5)}{(T - K - 3)}} \left[\frac{(T - 2K - 3)}{(T - 2K - 1)} W_{N,T} - K \right] \xrightarrow{d}{N \to \infty} N(0, 1) \quad (4)$$

This latter stat, i.e. \tilde{Z}_N , has been closely examined by Dumitrescu and Hurlin by running Monte-Carlo simulations. Their conclusion is that \tilde{Z}_N has very good properties even with small T and N. They also show that their standardized panel statistics have good small sample properties even in the presence of crosssectional dependence.

Finally, it is important noting that in such autoregressive models the optimal number of lags to include is often an issue. In the present study, we propose to select the optimal number of lags so as to minimize the Akaike Information Criteria (AIC) like in Hsiao (1979, 1981, 1982) or alternatively, the Bayesian Information Criteria (BIC). To do so model (2) is run using a Stata routine developed by Lopez and Weber (2017).

The results of both the unit root tests and the Dumitrescu-Hurlin Granger non-causality tests are presented below in, respectively, subsection 5.1 and 5.2.

5 Results

5.1 Unit root

The motivation for selecting the four tests discussed above is that they cover two major panel data issues. Indeed, whereas one test (HT) assumes serial uncorrelated errors, the others allow for serial correlation (LLC, IPS and PESCADF). Most tests assume cross-sectional independence although this issue can be mitigated (HT, LLC and IPS) but one allows for cross-sectional dependence (PESCADF).

Concerning the optimal lag length to include in the tests, it is based on the Akaike Information Criteria (AIC) for the LLC and IPS tests (with a restriction of a maximum of five lags in order to keep sufficient degrees of freedom). In the PESCADF test one lag is included. Finally, in the HT test, no lags are included.

With regard to the models, only the model specifications 2 and 3 presented in equation (1) are run. Indeed, model specification 1 assumes homogeneity of the panel, an assumption that does not hold in this study given the nature of our data. Then, as a second step, the HT, LLC and IPS tests are run with the option of subtracting the cross-sectional mean to mitigate eventual crosssectional dependence.

Furthermore, we sequentially apply these tests to aid and exports first for the overall panel of 50 countries, then to the "African", "Asian" and "Latin American" groups of countries, next to the so-called "high" and "low" exports and aid countries respectively.

Results are reported in tables 1 to 8 and are rather unambiguous. All series seem to follow a stationary process. There is no model, regardless of the set of countries considered, where all tests show unit root process. Demeaning does not seem to bring much information which tends to indicate crosssectional dependence is not a big issue in our data. This feeling is reinforced by the fact that the results of the PESCADF test, that allows for cross sectional dependence, are not different from the other tests' results. These results of stationary process in our series allow us to confidently run Dumitrescu-Hurlin Granger causality test in the next section.

Variable	Test	Ι		I + '	Г	I + T -	+ D
		stat	lags	stat	lags	stat	lags
AID	HT	.524***	-	.301***	-	.257***	-
	LLC	-7.7^{***}	1.52	-7.195^{***}	1.34	-11.823^{***}	1.18
	IPS	-6.979^{***}	1.52	-8.878^{***}	1.34	-14.506^{***}	1.18
	PESCADF	-2.788^{***}	1	-3.205^{***}	1	-	-
EXP	HT	.844***	-	.603***	-	.546***	-
	LLC	-3.779^{***}	.92	-5.281^{***}	.88	-6.994^{***}	1.02
	IPS	-2.315^{**}	.92	-6.879^{***}	.88	-10.001^{***}	1.02
	PESCADF	-2.437^{***}	1	-2.958^{***}	1	-	-

Table 1: Panel unit root tests

Note: $p^* < 0.10$, $p^* < 0.05$, $p^* < 0.01$. I = Intercept, T = Trend, D = Demean

Variable	Test	Ι		I + T	Г	I + T -	+ D
		stat	lags	stat	lags	stat	lags
AID	HT	.565***	_	.292***	-	.16***	-
	LLC	-6.353^{***}	1.77	-6.376^{***}	1.46	-9.645^{***}	.96
	IPS	-5.523^{***}	1.77	-6.069^{***}	1.46	-10.239^{***}	.96
	PESCADF	-2.657^{***}	1	-3.276^{***}	1	-	-
EXP	HT	$.746^{***}$	-	$.6^{***}$	-	.504***	-
	LLC	-2.932^{***}	.85	-3.34^{***}	1	-7.491^{***}	.65
	IPS	-3.05^{***}	.85	-5.158^{***}	1	-9.262^{***}	.65
	PESCADF	-2.633^{***}	1	-3.37^{***}	1	-	-

Table 2: Panel unit root tests "Africa"

Note: *p < 0.10, **p < 0.05, *** p < 0.01. I = Intercept, T = Trend, D = Demean

Variable	Test	Ι		I + '	Г	I + T -	+ D
		stat	lags	stat	lags	stat	lags
AID	HT	.574***	-	.449***	-	.449***	-
	LLC	-3.64^{***}	1.55	-3.865^{***}	1.36	-6.333^{***}	.82
	IPS	-3.087^{***}	1.55	-5.079^{***}	1.36	-6.296^{***}	.82
	PESCADF	-2.896^{***}	1	-3.084^{***}	1	-	-
EXP	HT	.936	-	$.587^{***}$	-	$.577^{***}$	-
	LLC	-2.927^{***}	1	-2.669^{***}	1	-3.091^{***}	1.64
	IPS	512	1	-3.974^{***}	1	-3.779^{***}	1.64
_	PESCADF	-2.392^{**}	1	-2.576	1	-	-

Table 3: Panel unit root tests "Asia"

Note: $p^* < 0.10$, $p^* < 0.05$, $p^* < 0.01$. I = Intercept, T = Trend, D = Demean

Variable	Test	Ι		I + '	Г	I + T	+ D
		stat	lags	stat	lags	stat	lags
AID	HT	.732***	-	.631***	-	.607***	-
	LLC	-3.051^{***}	.92	607	1.17	-3.686^{***}	1
	IPS	-3.178^{***}	.92	-2.687^{***}	1.17	-6.643^{***}	1
	PESCADF	-2.271^{**}	1	-2.757^{*}	1	-	-
EXP	HT	$.854^{***}$	-	.636***	-	$.594^{***}$	-
	LLC	255	1.08	-2.881^{***}	.58	-3.442^{***}	.58
	IPS	.091	1.08	-2.219^{**}	.58	-2.522^{***}	.58
	PESCADF	-2.237^{**}	1	-2.847^{**}	1	-	-

Table 4: Panel unit root tests "Latin America"

Note: *p < 0.10, **p < 0.05, ***p < 0.01. I = Intercept, T = Trend, D = Demean

Variable	Test	Ι		I + '	Г	I + T	+ D
		stat	lags	stat	lags	stat	lags
AID	HT	.736***	-	.609***	_	.568***	-
	LLC	-5.778^{***}	1.72	-4.536^{***}	1.6	-5.712^{***}	1.56
	IPS		1.72	-5.962^{***}	1.6	-8.626^{***}	1.56
	PESCADF	-2.65^{***}	1	-3.283^{***}	1	-	-
EXP	HT	$.839^{***}$	-	$.59^{***}$	-	$.532^{***}$	-
	LLC	-2.625^{***}	1.28	-2.952^{***}	1.12	-5.535^{***}	1.08
	IPS	-1.562^{*}	1.28	-4.369^{***}	1.12	-8.506^{***}	1.08
	PESCADF	-2.667^{***}	1	-3.206^{***}	1	-	-

Table 5: Panel unit root tests "High aid"

Note: $p^* < 0.10$, $p^* < 0.05$, $p^* < 0.01$. I = Intercept, T = Trend, D = Demean

Variable	Test	Ι		I + '	Г	I + T ·	+ D
		stat	lags	stat	lags	stat	lags
AID	ΗT	$.385^{***}$	-	.134***	-	.112***	-
	LLC	-5.146^{***}	1.32	-5.689^{***}	1.08	-7.783^{***}	1.08
	IPS	-4.749^{***}	1.32	-6.596^{***}	1.08	-8.56^{***}	1.08
	PESCADF	-2.744^{***}	1	-3.007^{***}	1	-	-
EXP	HT	.851***	-	.623***	-	$.564^{***}$	-
	LLC	-2.733^{***}	.56	-4.485^{***}	.64	-5.523^{***}	.76
	IPS	-1.714^{**}	.56	-5.365^{***}	.64	-6.37^{***}	.76
	PESCADF	-2.165^{**}	1	-2.825^{***}	1	-	-

Table 6: Panel unit root tests "Low aid"

Note: *p < 0.10, **p < 0.05, ***p < 0.01. I = Intercept, T = Trend, D = Demean

Variable	Test	Ι		I + '	Г	I + T -	+ D
		stat	lags	stat	lags	stat	lags
AID	HT	.453***	-	.203***	-	$.175^{***}$	-
	LLC	-4.839^{***}	1.36	-5.124^{***}	1.28	-8.3^{***}	1.32
	IPS	-3.941^{***}	1.36	-6.493^{***}	1.28	-10.186^{***}	1.32
	PESCADF	-2.774^{***}	1	-3.074^{***}	1	-	-
EXP	HT	.941	-	.679***	-	.661***	-
	LLC	-2.593^{***}	.96	-3.702^{***}	.88	-4.569^{***}	1.04
	IPS	.79	.96	-5.014^{***}	.88	-5.56^{***}	1.04
	PESCADF	-2.449^{***}	1	-2.762^{***}	1	-	-

Table 7: Panel unit root tests "High exports"

Note: $p^* < 0.10$, $p^{**} < 0.05$, $p^{***} < 0.01$. I = Intercept, T = Trend, D = Demean

Variable	Test	Ι		I + T	Г	I + T -	+ D
		stat	lags	stat	lags	stat	lags
AID	HT	.632***	-	.464***	_	.37***	-
	LLC	-5.993^{***}	1.68	-5.106^{***}	1.4	-6.995^{***}	1.4
	IPS	-5.924^{***}	1.68	-6.063^{***}	1.4	-10.228^{***}	1.4
	PESCADF	-2.63^{***}	1	-3.269^{***}	1	-	-
EXP	HT	$.714^{***}$	-	.575***	-	.484***	-
	LLC	-3.577^{***}	.88	-3.812^{***}	.88	-7.762^{***}	.64
	IPS	-4.066^{***}	.88	-4.714^{***}	.88	-9.699^{***}	.64
	PESCADF	-2.586^{***}	1	-3.431^{***}	1	-	-

Table 8: Panel unit root tests "Low exports"

Note: *p < 0.10, **p < 0.05, ***p < 0.01. I = Intercept, T = Trend, D = Demean

5.2 Dumitrescu-Hurlin Granger non-causality

The Dumitrescu-Hurlin Granger non-causality test explained above (see section 4.2) is run on each of the eight group of countries described earlier and in both directions, i.e. from exports towards aid and from aid towards exports. This give us 16 different models. The expected results are not obvious since one may expect causality from aid to exports due to the creation of a long standing relationship ("goodwill") between the donor and the recipient countries but, on the other hand, one may also expect causality from exports to aid since donor countries may consider trade when allocating the total amount of aid to be distributed.

Again, Dumitrescu and Hurlin (2012) propose two different statistics in their paper, i.e. $Z_{N,T}$ (see equation (3)) and \tilde{Z}_N (see equation (4)) depending on the size of T as explained earlier. Since in our case T is equal to 40, it is not clear what statistic should be use. Indeed, even if far from infinity, a T equal to 40 is sufficient according to table 1 in Dumitrescu and Hurlin (2012) to have a powerful panel Granger (non-)causality test. In this context, we have decided to compute both statistics.

Table 9 show the results of the Dumitrescu-Hurlin Granger non-causality test with one lag. Including one lag means that the test is based on the individual averaged Wald statistics from the model: $y_{i,t} = \alpha_i + \gamma_i y_{i,t-1} + \beta_i x_{i,t-1} + \epsilon_{i,t}$. The results are unambiguous (and similar whether we look at $Z_{N,T}$ or \tilde{Z}_N). Granger causality seems to run from exports to aid as well as from aid to exports and for all countries except for the African ones where there is Granger causality only from exports to aid. When the assumption on the number of lags is either by minimizing the Akaike's information criteria, or the Bayesian information criteria, conclusions remain unaltered despite the slight changes in $Z_{N,T}$ and \tilde{Z}_N (see tables 10 and 11). As for the unit root tests, we have set a maximum number of lags equal to 5 to avoid losing too many degrees of freedom.

To summarize, results show that causality is bidirectional. On the one hand, some amounts of aid may thus have been allocated on the basis of existing trade relationships. On the other hand, exports to a given country may have occured thanks to the existence of "goodwill" created by past amounts of aid.

	Direction	Zbar $(Z_{N,T})$	Zbar tilde (\tilde{Z}_N)	Lags
All panel	$\mathrm{Exp}\to\mathrm{Aid}$	13.083^{***}	11.590^{***}	1
All panel	$\mathrm{Aid} \to \mathrm{Exp}$	3.715^{***}	3.105^{***}	1
Asia	$\mathrm{Exp}\to\mathrm{Aid}$	10.236^{***}	9.084***	1
Asia	$\mathrm{Aid} \to \mathrm{Exp}$	2.570^{**}	2.141**	1
Africa	$\mathrm{Exp}\to\mathrm{Aid}$	6.459^{***}	5.729^{***}	1
Africa	$\mathrm{Aid} \to \mathrm{Exp}$	1.603	1.330	1
Latin America	$\mathrm{Exp}\to\mathrm{Aid}$	2.973^{***}	2.566^{**}	1
Latin America	$\mathrm{Aid} \to \mathrm{Exp}$	2.105^{**}	1.780^{*}	1
High exports	$\mathrm{Exp}\to\mathrm{Aid}$	11.457^{***}	10.193^{***}	1
High exports	$\mathrm{Aid} \to \mathrm{Exp}$	2.607^{***}	2.178^{**}	1
Low exports	$\mathrm{Exp}\to\mathrm{Aid}$	7.046^{***}	6.198^{***}	1
Low exports	$\mathrm{Aid} \to \mathrm{Exp}$	2.646^{***}	2.213^{**}	1
High aid	$\mathrm{Exp}\to\mathrm{Aid}$	9.236***	8.181***	1
High aid	$\mathrm{Aid} \to \mathrm{Exp}$	2.100^{**}	1.719^{*}	1
Low aid	$\mathrm{Exp}\to\mathrm{Aid}$	9.267^{***}	8.210***	1
Low aid	$\mathrm{Aid} \to \mathrm{Exp}$	3.154 ^{***}	2.673***	1

Table 9: Dumit
rescu-Hurlin Granger non-causality test with $1\ {\rm lag}$

Note: $p^* < 0.10$, $p^* < 0.05$, $p^* < 0.01$.

	Direction	Zbar $(Z_{N,T})$	Zbar tilde (\tilde{Z}_N)	Lags
All panel	$\operatorname{Exp} \to \operatorname{Aid}$	10.061***	7.598^{***}	5
All panel	$\mathrm{Aid} \to \mathrm{Exp}$	3.715^{***}	3.105^{***}	1
Asia	$\mathrm{Exp}\to\mathrm{Aid}$	3.294^{***}	2.220^{**}	5
Asia	$\mathrm{Aid} \to \mathrm{Exp}$	8.508^{***}	6.510^{***}	5
Africa	$\mathrm{Exp}\to\mathrm{Aid}$	12.069^{***}	9.612***	5
Africa	$\mathrm{Aid} \to \mathrm{Exp}$	1.603	1.330	1
Latin America	$\mathrm{Exp}\to\mathrm{Aid}$	4.061***	3.008^{***}	5
Latin America	$\mathrm{Aid} \to \mathrm{Exp}$	2.105^{**}	1.780^{*}	1
High exports	$\mathrm{Exp}\to\mathrm{Aid}$	10.488^{***}	8.149***	5
High exports	$\mathrm{Aid} \to \mathrm{Exp}$	2.607^{***}	2.178^{**}	1
Low exports	$\mathrm{Exp}\to\mathrm{Aid}$	3.740^{***}	2.596^{***}	5
Low exports	$\mathrm{Aid} \to \mathrm{Exp}$	2.427^{**}	1.763^{*}	3
High aid	$\mathrm{Exp}\to\mathrm{Aid}$	10.288^{***}	7.984^{***}	5
High aid	$\mathrm{Aid} \to \mathrm{Exp}$	8.451***	6.472^{***}	5
Low aid	$\mathrm{Exp}\to\mathrm{Aid}$	3.940^{***}	2.760^{***}	5
Low aid	$\mathrm{Aid} \to \mathrm{Exp}$	3.154***	2.673***	1

Table 10: Dumitrescu-Hurlin Granger non-causality test with AIC option for lags

Note: p < 0.10, p < 0.05, p < 0.05, p < 0.01.

	Direction	Zbar $(Z_{N,T})$	Zbar tilde (\tilde{Z}_N)	Lags
All panel	$\mathrm{Exp}\to\mathrm{Aid}$	8.507***	6.615^{***}	4
All panel	$\mathrm{Aid} \to \mathrm{Exp}$	3.715***	3.105^{***}	1
Asia	$\mathrm{Exp}\to\mathrm{Aid}$	3.995^{***}	2.959^{***}	4
Asia	$\mathrm{Aid} \to \mathrm{Exp}$	2.570^{**}	2.141**	1
Africa	$\mathrm{Exp}\to\mathrm{Aid}$	12.069^{***}	9.612***	5
Africa	$\mathrm{Aid} \to \mathrm{Exp}$	1.603	1.330	1
Latin America	$\mathrm{Exp}\to\mathrm{Aid}$	3.667***	2.817***	4
Latin America	$\mathrm{Aid} \to \mathrm{Exp}$	2.105^{**}	1.780^{*}	1
High exports	$\mathrm{Exp}\to\mathrm{Aid}$	8.324***	6.879***	3
High exports	$\mathrm{Aid} \to \mathrm{Exp}$	2.607***	2.178^{**}	1
Low exports	$\mathrm{Exp}\to\mathrm{Aid}$	3.772^{***}	2.779^{***}	4
Low exports	$\mathrm{Aid} \to \mathrm{Exp}$	2.646^{***}	2.213^{**}	1
High aid	$\mathrm{Exp}\to\mathrm{Aid}$	10.288^{***}	7.984^{***}	5
High aid	$\mathrm{Aid} \to \mathrm{Exp}$	2.100^{**}	1.719^{*}	1
Low aid	$\mathrm{Exp}\to\mathrm{Aid}$	3.196^{***}	2.567^{**}	2
Low aid	$\mathrm{Aid} \to \mathrm{Exp}$	3.154^{***}	2.673^{***}	1
N * 0.10 ³	** ***			

Table 11: Dumitrescu-Hurlin Granger non-causality test with BIC option for lags

Note: $p^{*} < 0.10$, $p^{**} < 0.05$, $p^{***} < 0.01$.

6 Discussion and limitations

As we have seen, there are different tests to check for unit roots in time-series and there are also different methods to test for causality. These differences arise because each method is based on particular hypotheses and therefore each has its own pro and cons. Two main issues discussed in the literature of unit root/panel non-causality tests are serial correlation and cross sectional dependence. In the present study, we have used four different unit root tests in order get robust results. Three of the four unit root tests allow for serial correlation and one allows for cross-sectional dependence. Concerning the latter issue, and to hopefully definitely discard the possibility of non-robust results due to cross-sectional dependence , we have run the three tests that do not not control for cross-sectional dependence with the specification of subtracting the cross-sectional means in order to mitigate this issue.

The same problem of cross-sectional dependence can potentially also alter the results obtained with the Dumitrescu-Hurlin Granger non-causality test. However, and as already mentioned, the authors have run Monte-Carlo simulations and their conclusion is that their statistics have good small sample properties even in the presence of cross-sectional dependence. That being said, and as Dumitrescu and Hurlin (2012) note in their section "further issues", an important further work would be to use so-called "second-generation" panel non-causality tests in order to take into account general forms of dependence among individuals of the panel.

Another topic of discussion is the bivariate model used in the present study to test for Granger causality (see equation (2)). Indeed, even if such bivariate model, that is a model with a single independent variable, is what is mainly used in studies testing for Granger causality, one could argue that additional variables may be included as exogenous and control variable (trivariate model). For instance, in our topic, we may want to account for trade agreements or Gross Domestic Product of the recipient country. Further work in this direction would be a clear improvement.

Then, a limitation specific to our study is that since the tests implemented require a strongly balanced panel dataset, we had to drop available observations. However, since remaining data is still large, we believe this issue does not affect the results. Finally, another limitation is the number of lags to include when running the Dumitrescu-Hurlin Granger non-causality tests. In their paper, the authors do not give any hint concerning how to select the number of lags. Lopez and Weber (2017) have proposed to select the number of lags by minimizing standard information criteria. In the panel data context, tests being based on individual-specific regressions, the information criteria have to be calculated as averages of individual statistics. This may lead to situations where the average information criteria are driven by a few individuals of the panel. There is probably still place for improvements here.

7 Conclusion

In this study, we investigate the causal relationships between bilateral aid and exports. Four different unit root tests, carefully selected to mitigate possible serial correlation and cross sectional dependence issues, have been implemented. Bilateral aid and exports are found to be stationary processes. This result allows us to use Dumitrescu-Hurlin Granger non-causality tests to investigate causality in a second step. The null hypothesis, of non-causality for all individuals, is systematically rejected except for the "African" countries in the direction from aid to exports. Thus, some amounts of aid may have been allocated due to past amounts of exports towards the recipient country. But, and as an interesting result for politicians, some exports to a given country seem to have been realized thanks to past amounts of bilateral aid. The political message that should go along with this result is that when bilateral aid is allocated, Switzerland gets some economic benefit later on, through its exports. This result basically means that when Switzerland gives 1CHF it is actually giving less than 1CHF since the 1CHF donated will bring back some revenues through Swiss exports. Two implications arise from this fact: 1) total aid allocated can be increased as a kind of investment since there is an economic return through exports, 2) if total aid allocated is cut, Switzerland should expect a drop in exports in the following years.

Aid allocation is always a topic of discussion in Switzerland and more generally in all donor countries. In 2015, Switzerland has disbursed as official development aid 3'404.4 millions of CHF. Even if this amount seems large it is equivalent to only 0.52% of the Swiss Gross National Income (GNI), which is still far from the 0.7% prescribed by the United Nation in 1970. Switzerland ranks 8th among the 29 member countries of the OECD Development Assistance Committee (DAC) but second in terms of the highest GNI per capita (Norway is first).¹¹ Together, this ascertainment and our results, should give Swiss politicians confidence to increase the total amount of official development aid.

The procedure proposed in this study can be applied to any donor country but with some modifications in particular when the unit root test show non-

 $^{^{11}\}mathrm{Data}$ comes from the World bank statistic portal.

stationary process in the series. Obviously, further work is still required in order to deal with some limitations such as cross-sectional dependence or absence of exogenous explanatory variables. However, we strongly believe the method employed here is a good starting point to analyze if there exists a statistical link between official development aid and trade.

Appendix A

Country	Continent	High/low exports	High/low aid
Algeria	Africa	Н	L
Angola	Africa	\mathbf{L}	\mathbf{L}
Bangladesh	Asia	Н	Н
Benin	Africa	L	Н
Bolivia	Latin America	L	Н
Brazil	Latin America	Н	L
Burkina Faso	Africa	L	Н
Burundi	Africa	\mathbf{L}	\mathbf{L}
Cameroon	Africa	\mathbf{L}	\mathbf{L}
Chad	Africa	\mathbf{L}	Н
Chile	Latin America	Н	L
Colombia	Latin America	Н	Н
Congo, Dem. Rep.	Africa	\mathbf{L}	\mathbf{L}
Costa Rica	Latin America	Н	L
Cote d'Ivoire	Africa	Н	L
Ecuador	Latin America	Н	H
Egypt	Africa	Н	Н
Ethiopia	Africa	L	Н
Ghana	Africa	L	L
Guatemala	Latin America	Н	L
Haiti	Latin America	L	L
Honduras	Latin America	L	H
India	Asia	H	Н
Indonesia	Asia	Н	Н
Jordan	Asia	Н	L
Kenya	Africa	Н	H
Lebanon	Asia	Н	L
Madagascar	Africa	L	H
Mali	Africa	L	H
Morocco	Africa	H	L
Mozambique	Africa	п L	L H
Myanmar	Asia	L	L
Nepal	Asia	L	L H
Nicaragua	Latin America	L	Н
Niger	Africa	L	Н
Pakistan	Asia	H	Н
	Latin America	н L	н L
Paraguay Peru	Latin America	H	L H
	Africa	н L	Н
Rwanda Sonogal		L L	H
Senegal Svi Lanka	Africa Agia		
Sri Lanka	Asia	Н	H
Sudan Tu	Africa	H	H
Tanzania	Africa	$^{ m L}$	H
Thailand	Asia	Н	L
Tunisia	Africa	Н	L
Turkey	_	Н	L
Uganda	Africa	L	L
Vietnam	Asia	Н	Н
Zambia	Africa	\mathbf{L}	L
Zimbabwe	Africa	\mathbf{L}	\mathbf{L}

Table A.1: Country characteristics

Notes: high/low exports/aid = above/below median exports/aid. H = High and L = Low

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