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A Panel VARX Analysis of Debt and Natural Disasters in SIDS

Abstract

This paper investigates whether there is statistical evidence to support a negative impact from natural disasters on Small Island Developing States' (SIDS') debt to GDP (gross domestic product) ratios. We study the difference between SIDS and non-SIDS in an effort to gauge whether size matters. This approach differs somewhat from the traditional literature, which focuses primarily on differences in development and educational attainment and institutional development when assessing the impact of disasters. Using a panel vector autoregression (PVARX) specification, our results suggest that debt to GDP ratios increase in SIDS following storms and floods and that, in contrast to recent findings, the changes in debt ratios are statistically significant. We also conclude that floods lead to faster debt accumulation than storms and that debt increases less in non-SIDS, mainly because of their stronger macro-economic fundamentals. The latter is observed when examining the significance of natural disaster intensity and the covariance between debt to GDP ratios, fiscal policy, growth and aid. Aid relief is found to play a significant mitigating role.

JEL Classification: C33, F34, F64, H63, H84

Keywords: SIDS, debt, natural disasters, small states, PVARX

Contents

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1. Introduction

In line with the steady rise in average global temperatures, the occurrence of natural disasters has increased dramatically (Figure 1). This change in climatic patterns has been particularly evident in Caribbean and Pacific Small Island Developing States (SIDS), where storms and floods are more frequent and where disaster-related costs now account for a higher proportion of gross domestic product (GDP).

Between 1994 and 2014, 168 disasters were recorded in SIDS,[1] the damage from which totalled US$3.9 billion, or approximately 1.6 per cent of SIDS' GDP. In contrast, over the same period, the damage from natural disasters that impacted 62 non-SIDS was estimated at less than 1 per cent of their GDP, despite these countries experiencing a significantly larger number of disasters per country (see Appendix A). These stylised facts alone suggest a differential impact from disasters on SIDS versus non-SIDS.

Empirical studies on the topic confirm this hypothesis. Specifically, the majority of authors (e.g. Noy and Nualsri 2011; Raddatz 2009; Rasmussen 2004) agree that disasters affect developing countries disproportionately and that events of this nature often have a negative macro-economic impact, including that on fiscal performance.

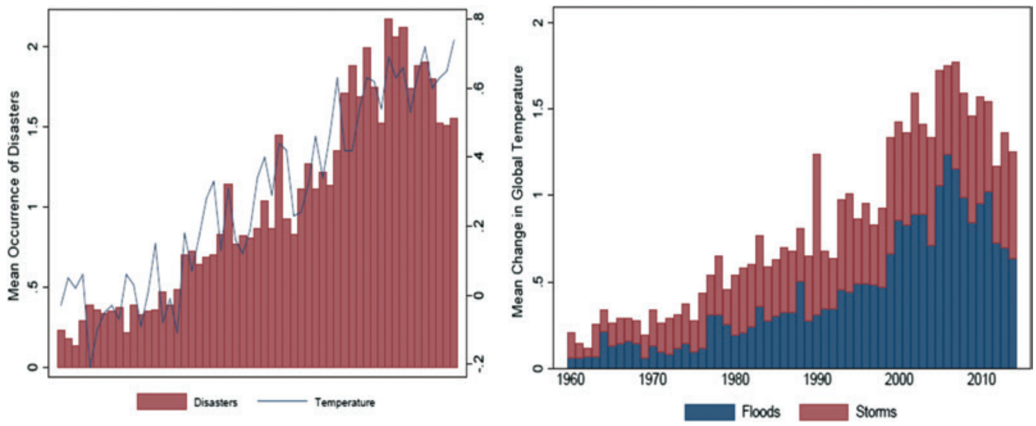
Our adjacent hypothesis is that there is likely to be a statistically significant and positive impact of natural disasters on debt; this is a huge development challenge for several SIDS. At present, more than half of SIDS have debt to GDP ratios well above the International Monetary Fund's (IMF's) 60 per cent threshold, and quite a number of SIDS have undergone debt restructurings, many of which occurred in the past decade.

To our knowledge, only Acevedo (2014) has attempted to investigate the relationship between natural disasters and debt empirically, and we note that he does not find a statistically significant result. In this regard, we digress from the traditional literature and test the significance of disaster impact by size of country, rather than by income or level of development. Our justification rests on the fact that small countries are inherently more susceptible to disaster shocks, particularly because of their comparatively tiny land masses and monocrop economies.

A disaster shock to a small land mass has a much greater probability of affecting the national population and GDP. Furthermore, most SIDS are dependent on one or two sectors, including tourism, commodity exports and mineral production, all of which are indefensible against shocks from natural disasters. The important prior information, however, is the fact that disasters in small countries often generate large and unexpected reconstruction costs, which in some cases have to be financed by debt, especially in the absence of sufficient aid or primary resources.

To investigate the impact of disasters, we use a panel vector autoregression (PVARX) analysis with generalised method of moments/instrumental variable (GMM/IV) estimators and dynamic response functions. In addition, we explore whether they are

Figure 1. Change in average global temperature and the frequency of natural disasters



indirect effects from disasters by way of analysing impulse response functions (IRFs). IRFs help us to trace the covariance and dynamic response of variables important to debt accumulation, namely the growth rate, primary balance and flows of net official development assistance (ODA).

We continue in the next section with a brief review of previous work done on this topic, and we then proceed to describing the PVARX model. In Section 4 we provide details on our data sources and describe important transformations. Results are discussed in Section 5 and then we conclude.

2. Review of Literature

Substantial research has been done on the macroeconomic implications of natural disasters. However, very few research papers have focused specifically on the direct impact of natural disasters on debt.

Studies suggest that the relative costs from natural disasters are much higher in developing economies than in advanced ones, and that SIDS are particularly vulnerable. Rasmussen (2004) found that the countries of the Eastern Caribbean stand out as among the most disaster prone in the world. There is support for this view from work conducted by Sosa and Cashin (2009), who highlight the susceptibility of the Eastern Caribbean to disaster shocks. Using country-specific vector autoregression (VAR) models, they found that external shocks explain more than half of macroeconomic fluctuations in the region and that domestic business cycles are especially vulnerable to changes in climatic conditions. They conclude, however, that negative effects from disasters in this region are short rather than long lasting.

On the contrary, Raddatz (2009) uncovered a long-term relationship between natural disasters and output when using panel time series techniques. According to his study, a climate-related disaster reduces real GDP per capita by at least 0.6 per cent, with droughts having the largest average impact of approximately 1 per cent of GDP per capita. Similar to Rasmussen (2004) and Sosa and Cashin (2009), he also found that small states are more vulnerable to natural disasters than other countries, particularly to windstorms. Furthermore, Raddatz also found that aid plays a mitigating role, and hence that a country's level of external debt is not necessarily statistically related to the impact on output from disasters.

Because of the multi-country nature of this work, the chosen approach has usually been panel data analysis and, in a lot of cases, panel data analysis is combined with VAR techniques. This is not surprising, given several data limitations and the fact that there are no specific theoretical models that provide an explanation of the macro-economic impact of disasters. One of the most comprehensive pieces of work using the PVARX approach is reported in a paper by Fomby et al. (2009), who argue that the impact of some natural disasters can in fact be beneficial, but only if they are of moderate intensity, and that severe disasters never have a positive impact.

Authors have also sought to shed light on what determines the extent of natural disaster damage. These papers tend to have the objective of helping countries find appropriate mitigating policy options. Toya and Skidmore (2007) found that income (including aid) is not the only important factor in reducing deaths and damage due to disasters. Other factors, such as higher educational attainment, greater openness, more complete financial systems and smaller governments, can also lead to fewer losses. Conversely, Noy (2009) argues that countries with an increased ability to mobilise resources for reconstruction are better able to withstand an initial disaster shock and prevent further spillovers to the macro-economy.

The studies that have looked at the fiscal implications of disasters have found significant negative impacts on fiscal variables. Benson and Clay's (2004) analysis suggests that natural disasters cause significant budgetary pressures, with both short-term and long-term implications for economic growth and development. In addition, they point out that the primary fiscal response to disasters is a reallocation of resources. Benson and Clay (2004) also found that disasters have little impact on trends in flows of aid, a result that is in direct contradiction to that reported by Raddatz (2009).

Melecky and Raddatz (2011) used a PVARX model and data from 1975 to 2008 for high- and middle-income countries to investigate fiscal impacts. Their results are not entirely different from previous findings that found negative fiscal impact. What is unique, though, is that they argue that natural disasters cause fiscal pressures through their effect on output, rather than directly, especially in lower- to middle-income countries. Finally, they found that countries with more developed financial or insurance markets suffer less from disasters in terms of output declines.

Research by Noy and Nualsri (2011) links the fiscal impact of natural disasters to governments' policy behaviour. They find that, in the aftermath of a disaster, developed countries adopt counter-cyclical policies, while developing countries adopt a more procyclical stance. Scott-Joseph (2010) provides support for this conclusion. She empirically explores the effects of expenditure on natural disasters on fiscal policy cyclicality, using a panel of Eastern Caribbean Currency Union (ECCU) states for the period 1980–2008. Her findings indicate that natural disasters create pressure for governments in the ECCU to run procyclical fiscal policies, and she identifies external public sector debt as the most important channel through which expenditure on natural disasters affects fiscal cyclicality.

In perhaps the only piece of empirical research explicitly focusing on the impact of natural disasters on debt, Acevedo (2014) used panel data and a VAR model with exogenous natural disaster shocks to examine the effects of natural disasters on per capita GDP and the debt to GDP ratio. He found that both storms and floods have a negative effect on growth and that, despite its statistical insignificance, debt increases with floods but not with storms. His evidence further suggests that there is weak support for the role of debt relief in easing the negative effects of storms on debt.

3. Empirical Approach

We utilise the PVARX specification described in equation (3.1). The PVARX is an extension of the basic panel VAR (PVAR) to allow for a linear relationship with a set of exogenous covariates (see Canova and Ciccarelli, 2013).

$$Y_t = A(l)_{i0} + A(l)_{i1}Y_{t-1} + F(l)_{ij}X_t + \mu_{it} \quad (3.1)$$

All variables in the vector Y_t are treated as endogenous, allowing us to uncover their joint dynamics. In addition, Y_t comprises a cross-section dimension such that $y_{it} = \left(y'_{1t}, y'_{2t}, \dots y'_{Nt}\right)$, where $i = 1, 2 \dots N$, indicates the number of cross-sections, each of which possesses $t = 1, 2 \dots T_i$ observations.

If we let G denote the number of endogenous variables (the debt to GDP ratio, real GDP growth, the primary balance and net ODA), then vector Y_t takes on a $G \times 1$ dimension in the panel VAR. The choice of variables comprising Y_t is motivated by our discussion of the literature.

Panel fixed effects are captured by the $G \times 1$ vector $A(l)i0$, where l is a polynomial in the lag operator, with $A(l)i = \sum_{i=0}^{N} A_i l^j$ for $j = 1, 2 \dots \rho$ lags. The term $A(l)_{i1}$ is a $G \times N$ matrix of lagged coefficients, while $F(l)_{ij}$ is a $G \times M$ matrix of coefficients for the exogenous variables (natural disasters, financial crisis shocks and oil shocks) in the $G \times 1$ vector X_t. Disturbances are labelled $\mu_{it} = (\mu_{1t}, \mu_{2t}, \dots \mu_{Nt})'$, where μ is $\sim iid(0, \Sigma)$ and has dimension $N \times 1$.

The model is estimated using the GMM/IV estimator. This estimator provides consistent estimates of the PVAR parameters even in panels with short time series, albeit normally with a large N. The methodology provides three alternatives for removing bias, caused by $A(l)_{i0}$ and its correlation with the disturbance term. We opt for the forward orthogonal deviation approach, illustrated by the following equation:

$$m_{it} = \left(m_{it} - \overline{m_{it}}\right)\sqrt{T_{it}/\left(T_{it}+1\right)} \quad (3.2)$$

where m_{it} is an untransformed variable, respecifying the model in this form eliminates the time-invariant characteristics. The mean $\overline{m_{it}}$ is derived from available future observations T_{it} rather than from past realisations of m_{it}. This specific estimator is preferred to the first differenced GMM/IV estimator, primarily because of the relatively small N in our sample (see Abrigo and Love 2016).

The GMM/IV estimator uses instrumentation to find the matrix of coefficient A that satisfies the sample moment conditions. It is given by:

$$A = \left(\overline{Y}^{*\prime} Z\hat{W}Z'\overline{Y}^{*}\right)\left(\overline{Y}^{*\prime} Z\hat{W}Z'Y^{*}\right) \quad (3.3)$$

where Y^* are the endogenous variables to the left of each equation and $Y^{*\prime}$ are those on the right.

The estimator assumes non-zero covariance $E[Y^*] \neq 0$ between the endogenous variables and the matrix of instruments Z. Furthermore, the estimator assumes that $E[\mu_{it}] = 0$, and that the disturbances and matrix of instruments Z are orthogonal. Using these assumptions for each equation, the GMM/IV estimator chooses a weighting matrix $\hat{W}$ to minimise the covariance between the instruments and disturbances. The weighting matrix is held to be non-singular, symmetric and positive semi-definite.

Before estimation, the lag order of the PVAR specification has to be chosen. More lags ensure that $E[\mu_{it}] = 0$, but at the same time, this implies that as j gets larger, $E[Y^*]$ tends to zero. We go about selecting the appropriate lag order using Andrews and Lu's (2001) consistent moment and model selection criteria (MMSC) for GMM models, which are based on Hansen's (1982) J statistic of overidentifying restrictions.

We consider three different versions of the MMSC, namely the Akaike information criteria (AIC), Bayesian information criteria (BIC) and the Hannan–Quinn information criteria (HQIC), together with the model coefficient of determination. The MMSCs with the lowest calculated value suggest optimality at the respective lag order, while the coefficient of determination captures the proportion of variation explained by the PVAR model at different lags.

Ultimately, we are interested in tracing the impact from natural disaster shocks on debt and its determinants. This requires model stability. The PVARX model is stable if all moduli of the companion matrix A lie within the unit circle. From this point, we can proceed with computing impulse response and dynamic multiplier functions.

Consider the compact form of the PVAR model in equation (3.1), abstracting for a moment from the exogenous terms. A stable model provides for invertibility and allows us to express Y_t as an infinite order vector moving average (VMA) of disturbance terms or innovations. Starting from the PVAR compact form, the impulse response function is derived as follows:

$$Y_t = A(l)Y_{t-1} + \mu_t \tag{3.4}$$

$$(I - A(l))Y_t = \mu_t \tag{3.5}$$

$$Y_t = A_0 + A(l) - 1\mu_t \tag{3.6}$$

$$Y_t = \psi(l)\mu_t \tag{3.7}$$

where $\psi(l) = \sum_{j=0}^{\infty} \varphi_j l^j = \sum_{j=1}^{\infty} A^j l^j$ is a polynomial of reduced-form responses to innovations. Note that $\varphi_0 = A_1^0 \equiv I$.

For the PVARX:

$$Y_t = \psi(l)\mu_t + D_t \tag{3.8}$$

where D_t is the dynamic multiplier. This multiplier allows us to trace the impact on Y_t for a one-unit change in the exogenous variables.

4. Data

The study includes 83 countries, of which 20 are SIDS. The United Nations definition of SIDS was used to select the countries. Our data cover the period 1994–2014, giving us a balanced panel with a total of 1,743 observations.

Data on natural disasters are taken from the International Disaster Database, EM-DAT (Guha-Sapir). These include data on floods, storms, wild fires, extreme temperatures, landslides and droughts. As the data show, storms and floods are much more prominent in both SIDS and non-SIDS than the other set of disasters (see see Tables A.1 and A.2). Hence, we focus on the impacts of storms and floods, and we let these variables equal 1 whenever a relevant natural disaster occurs.

In addition, we follow Acevedo (2014) and Fomby et al. (2009) and construct a disaster intensity variable. We code the intensity as 1 if any disaster of type k in country i, of any year t, affects 0.01 per cent of the population. The intensity variable is as follows:

$$intensity_{i,t}^k = \begin{cases} 1, if \left(fatalities_{i,t}^k + \left(0.3 * total\ affected_{i,t}^k \right) \right) \\ \quad / population_{i,t} \\ \qquad 0, otherwise \end{cases} \tag{4.1}$$

Data on nominal GDP come from the World Development Indicators (WDI) database (2016). Nominal GDP is measured in US dollars and at current prices. Data for general government gross debt and the primary balance come from the IMF's World Economic Outlook (2016). The primary balance is defined as general government net lending/borrowing plus net interest payments. Both are measured as a ratio to nominal GDP and in US dollars. A positive primary balance signifies a primary surplus. These data are supplemented by information from IMF Article IV reports and their statistical annexes. Data on net ODA come from the WDI database. Net ODA is also measured in US dollars.

Dummy variables are employed to control for impacts on debt and growth caused by the financial crisis and oil crises. The former is defined as 1 for the years 2008 and 2009, and as 0 otherwise. The dummy variable for oil shock has been defined as 1 for the years 1998, 2007 and 2008, and as 0 otherwise.

According to the summary statistics for the review period, the average primary surplus is higher in non-SIDS than in SIDS and so is the level of debt relative to GDP ratios. More importantly, on average, non-SIDS debt ratios are slightly lower than the IMF's 60 per cent threshold, while SIDS generally hold more elevated debt. In terms of net ODA, SIDS receive a larger proportion of the assistance and are not as high performing. SIDS mean growth rates lag behind those of non-SIDS by 0.6 of a percentage point.

Non-SIDS experience a larger number of disaster events per country and these disasters are on average more intense. Whereas storms and floods are almost equally common in SIDS, in non-SIDS storms are relatively more frequent than floods (see Table 4.1).

5. Results

The final model specification employed is a PVARX of order 1, with one to six lags in our endogenous instruments and the exogenous variables in levels. The AIC, BIC and HQIC have the

Table 1. Summary statistics

	N	Mean	SD	Min.	Max.
SIDS					
Primary balance (% of GDP)	420	0.2	5	−17.7	18
Gross debt (% of GDP)	420	71.5	47.1	12.6	377.1
Net ODA (% of GNI)	358	6.4	8.9	−2.6	78.7
Growth (%)	420	3.1	4.2	−28.1	19.2
Intensity of natural disasters (dummy)	420	0.2	0.4	0	1
Occurrence of floods (number of events)	420	0.1	0.3	0	2
Occurrence of storms (number of events)	420	0.2	0.5	0	3
Non-SIDS					
Primary balance (% of GDP)	1323	0.3	5.4	−29.9	36
Gross debt (% of GDP)	1323	58	37.9	0	355.1
Net ODA (% of GNI)	778	5.4	7.7	−0.6	94.9
Growth (%)	1311	3.7	4.2	−50.2	35.2
Intensity of natural disasters (dummy)	1323	0.4	0.5	0	1
Occurrence of floods (number of events)	1323	1	1.7	0	17
Occurrence of storms (number of events)	1323	0.7	1.5	0	14

Notes: GNI, gross national income; SD, standard deviation.

lowest values at lag order 1, and the coefficient of determination is highest at this lag order. This model is estimated using a 'GMM style' instrument setup with robust standard errors (see Abrigo and Love 2016).[2] Stability checks suggest that the PVARX is stable, since all moduli are within the unit circle (see Appendix B).

Being mindful of degrees of freedom limitations, we test the impact of storms and floods, as well as disaster intensity, via individual PVARX regressions. This involves swapping in and out each disaster variable. Here we are particularly interested in the dynamic response of our endogenous variables to one unit innovation in each of the disaster variables. We also assess the covariance between our endogenous variables through orthoganalised impulse response functions. In conjunction with Granger causality tests, we attempt to assess the extent to which there is an indirect impact of natural disasters on macroeconomic activity and debt.

Finally, we proceed to check the sensitivity of our results by reordering our variables in the PVARX. The results indicate that the results of the PVARX (1) are robust to changes in ordering. The specific results based on graphs of dynamic and impulse response functions are discussed in Figure 2 and Figure 3. Discussions on the variables' contemporaneous statistical significance are based on the results tables in Appendices C and D.

5.1 The Impact of Floods and Storms

The results suggest that floods generally have a larger impact than storms, in both SIDS and non-SIDS, and that the impact from floods is relatively more persistent. We find that SIDS' gross debt to GDP ratio rises with floods and that the effects of this natural disaster on debt can linger for up to five years. Storms, on the other hand, have less of an impact on SIDS' debt ratios.

This debt accumulation after floods observed in SIDS is probably linked to reconstruction costs, thereby explaining the subsequent, albeit short-lived, increase in GDP growth. On the contrary, we find that storms depress rather than boost economic activity but that its effect on the economy disappears almost immediately.

Floods attract a greater level of aid than storms, according to our estimates. As would be expected, however, aid relief is delayed, but picks up sharply just around a year after the flood. This delay in aid disbursement after floods is common, given the need to assess damage, complete necessary paper work and agree on disbursement amounts. It is more than likely that the persistence in aid is linked to the staggering of aid disbursements. In SIDS, aid relief following storms arrives within the year of the disaster.

With respect to the fiscal implications, our estimates indicate that SIDS run a primary surplus in the aftermath of floods and storms. However, this positive externality is more pronounced following a flood. Savings from donor interventions, the switch to debt financing and the use of these proceeds for expenditure additional to reconstruction, together with windfalls from expanded growth in the case of floods, could all explain this outcome.

In non-SIDS, debt to GDP ratios fall on average after both floods and storms; however, they experience a surge in growth similar to that observed in SIDS. Unlike SIDS, non-SIDS seem to finance any reconstruction via primary balances, causing them to run small primary deficits in subsequent years. Disbursements of official aid to assist non-SIDS are quick but not as high in volume.

5.2 The Intensity of Natural Disasters

Using the disaster intensity indicator, we find that after an intense climatic event, SIDS' gross debt to GDP ratio increases gradually year on year, with the effects of that shock fading by the end of five years. GDP growth following intense floods, for example, is noticeably higher, although it also loses steam after roughly two years. When we compare receipts of net aid for SIDS in the years after intense disasters, one major difference is that aid flows decrease during the first two years and then increase for the next three to four years thereafter. This lends weight to our explanation above, whereby one would expect even greater delays in assessment and aid agreement, if there is substantial disaster damage. SIDS seem to run a similar, albeit larger, primary surplus following intense disasters.

The growth dividend from reconstruction is much steeper and persists for longer than normal. In tandem, debt ratios in non-SIDS show a more pronounced decline, while inflows of net ODA are fairly constant. That is, there does not seem to be a differential response in aid to intense versus less intense floods or storms.

We notice that the mean primary balance response for non-SIDS is fairly benign, which brings into question our expenditure switching argument. However, such would be the case if reconstruction efforts were carried out by the private sector on behalf of the government, for example through a public–private partnership (PPP) arrangement.

5.3 Role of Growth, Primary Balance and Net ODA

In the above, we looked at the direct impact of storms, floods and intense disasters on macro-economic activity and debt. We are also interested in the indirect impact on the debt to GDP ratio, which can occur as a result of the covariance between intervening variables, including growth, the primary balance and net ODA.

Assessing the interactions between these variables in the face of natural disaster shocks can inform the channels through which debt to GDP ratios can be affected, beyond the direct influence of natural disasters on debt. To do this, we analyse the orthogonal impulse response functions and Granger causality tests. The impulse response functions are generated using a composite disaster variable for both SIDS and non-SIDS. This variable comprises all natural disasters affecting country *i* in any year *t*. The Granger causality test allows us to determine which variables are at least weakly exogenous in driving debt accumulation following floods or storms.

The IRFs for the weakly exogenous variables are provided in Figure 5 for SIDS and Figure 6 for non-SIDS. It would seem that aid does play a mitigating role in SIDS, at least in the context of natural disasters. Our results indicate that the debt to GDP ratio falls in response to rises in net ODA innovations, when SIDS are struck by a disaster. Aid increases following an exogenous expansion in the primary surplus, but this trend reverses fairly quickly. This implies a delay in government disaster spending of roughly one to two years. In addition, this implies that it takes donors and affected countries at least one year to finalise aid assistance.

Debt ratio levels also fall with increases in growth, suggesting that growth too plays a mitigating role. Put differently, the growth dividend gained through reconstruction efforts helps to ease the direct impact of natural disasters on debt. So, debt to GDP ratios would grow in SIDS if net ODA were small and late in arriving, following disasters, and if countries lack the resources to commence reconstruction.

In non-SIDS, the IRFs suggests more mainstream economic relationships and a larger tool kit for responding to accelerations in debt. This could explain the finding that, in non-SIDS, the impact on debt is softer than that in SIDS. Governments in non-SIDS respond positively and successfully to increases in the debt to GDP ratio. Furthermore, if this debt is used for reconstruction, the response of growth is large and long lasting, which contributes positively to the subsequent debt reduction effort. We find that donors provide support for non-SIDS even after their economy is growing. This all points to a low probability of indirect effects on non-SIDS debt to GDP ratios.

6. Conclusion

The study investigated the impact of natural disasters on debt in SIDS and non-SIDS. We demonstrate statistical evidence that debt to GDP ratios rise in SIDS following natural disasters and that the accumulation of debt is greater than in non-SIDS. The result is more in line with expectations than that derived by Acevedo (2014). It is worth explaining why this is the case.

Most of the literature has focused on the differential impact of natural disasters for developing and developed countries. None of the authors have considered whether size, rather than income, determines disaster impact. Acevedo's (2014) data set is limited to the set of ECCU countries, which many in the literature have found to suffer negative macro-economic effects following natural disaster events. In the context of debt, however, it is not surprising that the author failed to find a significant result, given that these countries have limited access to capi-

Figure 2. The impact of flood shocks

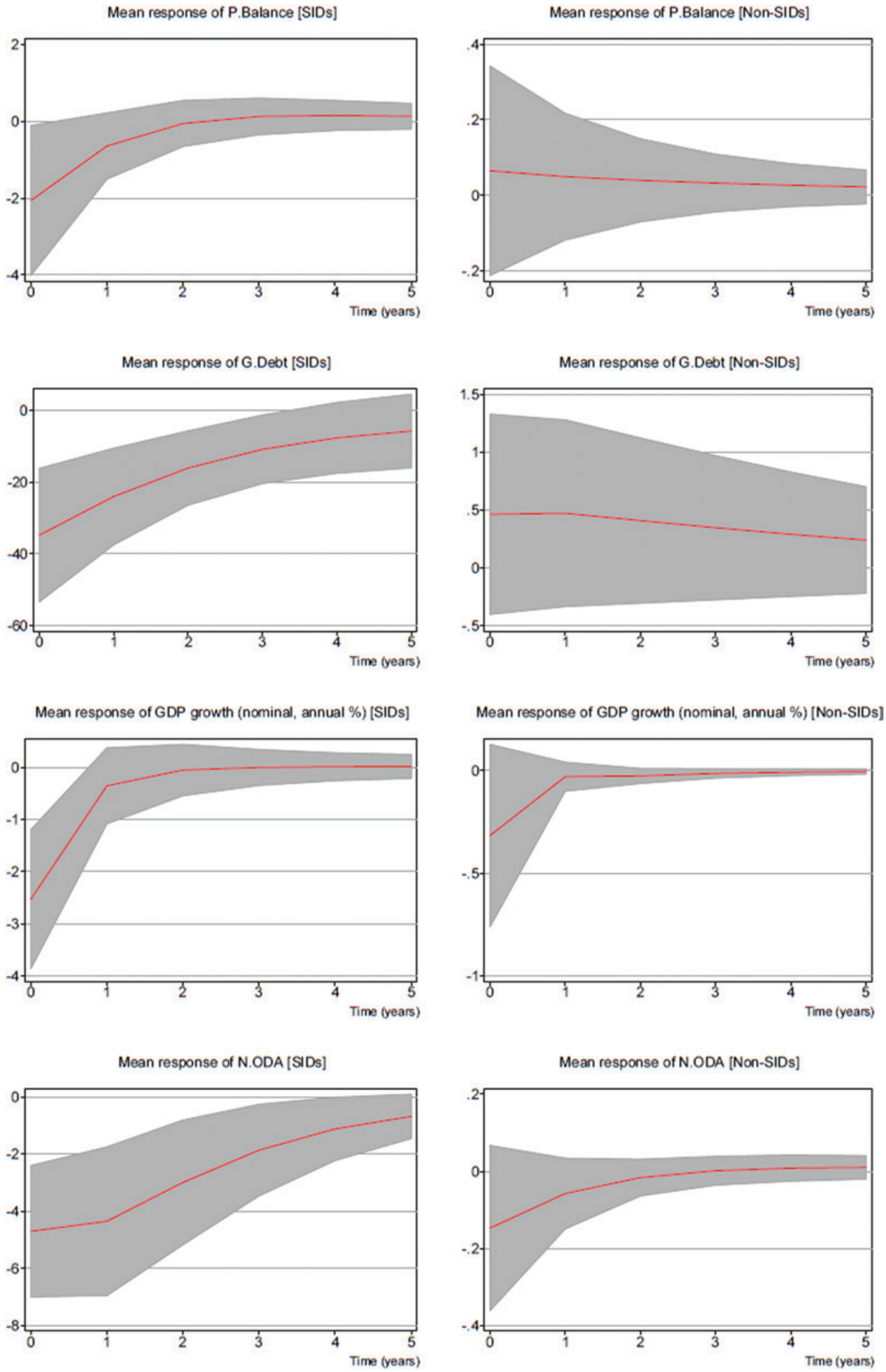


Figure 3. The impact of storm shocks

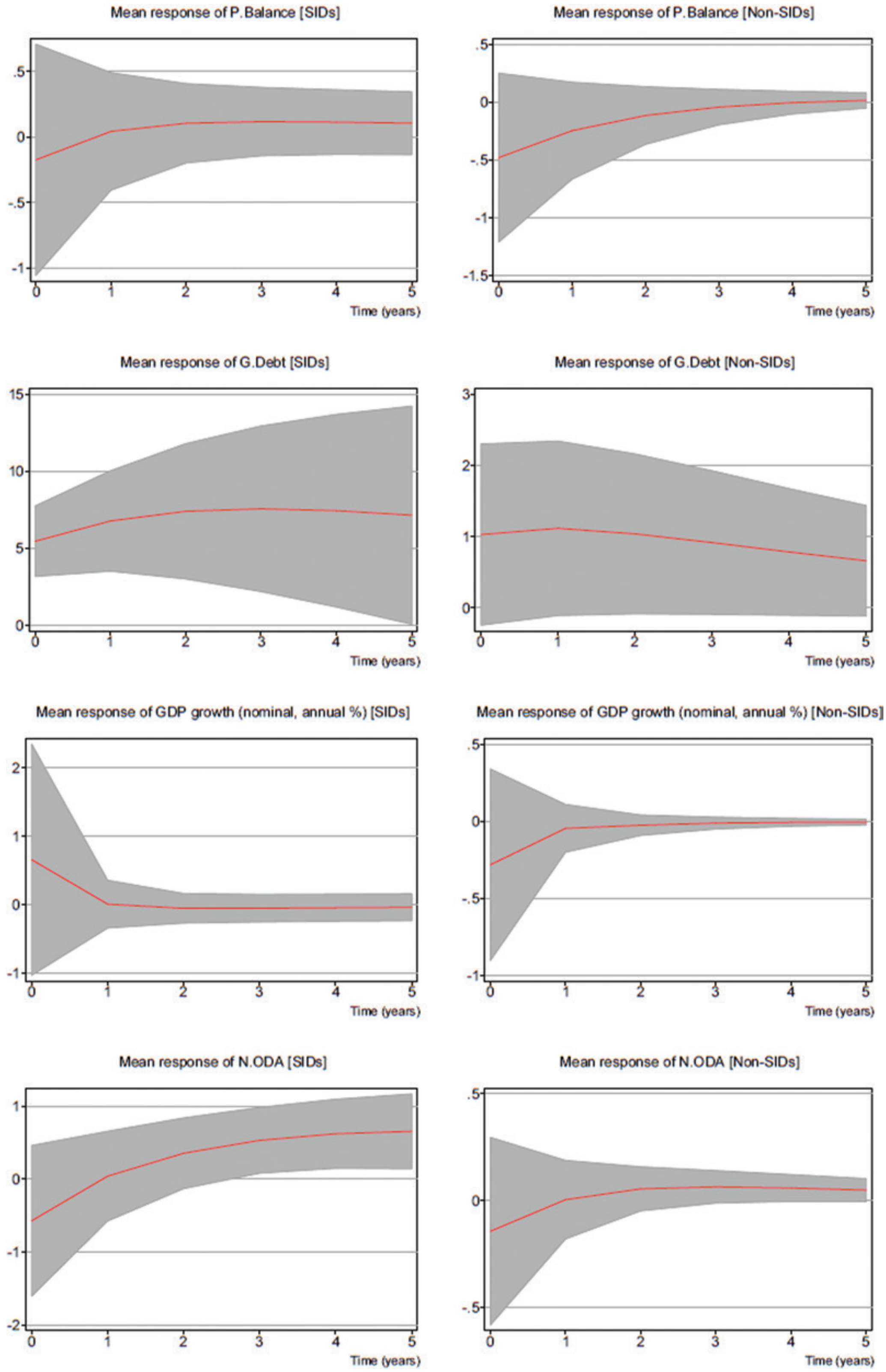


Figure 4. The impact of intense natural disasters

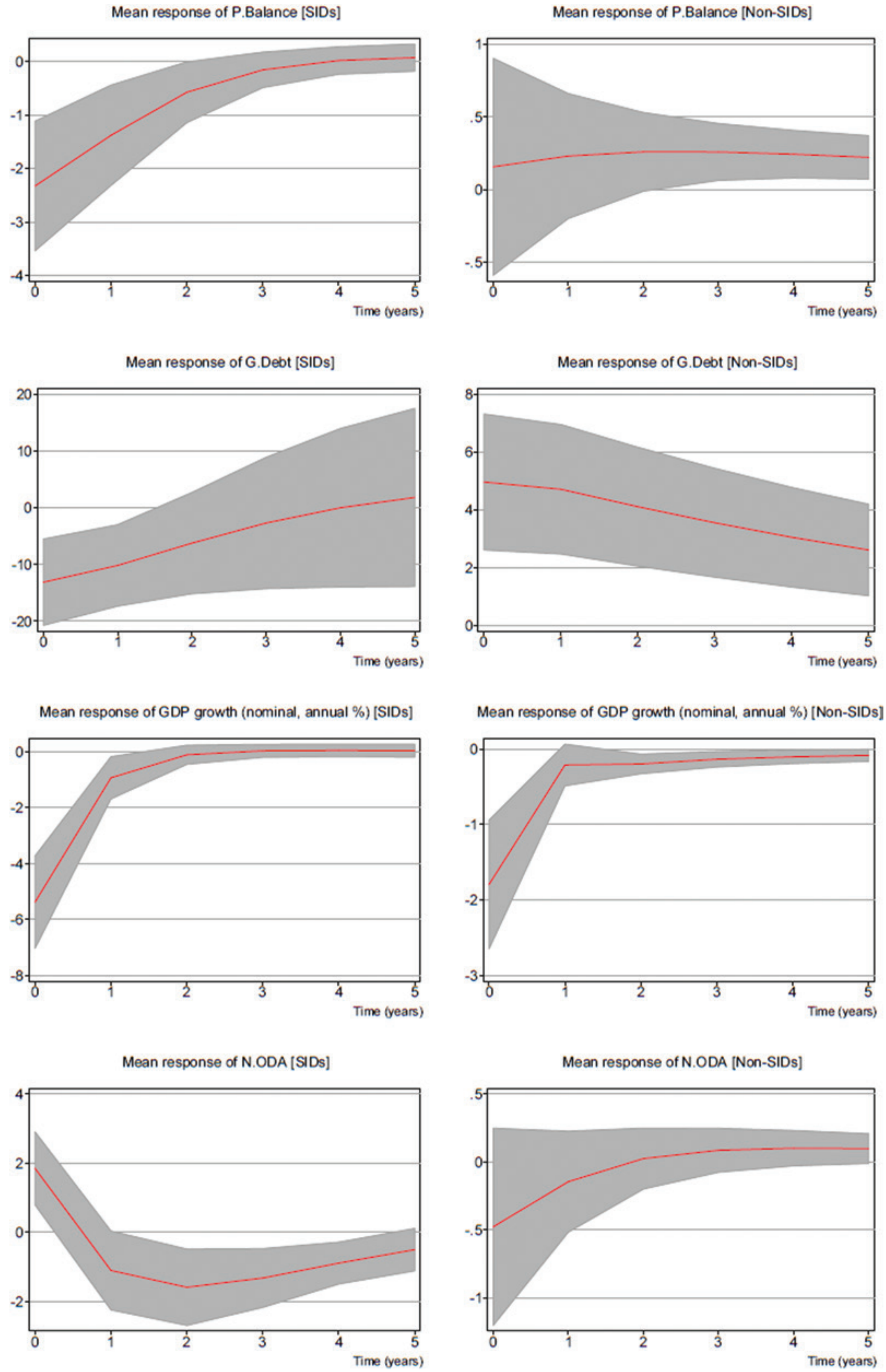
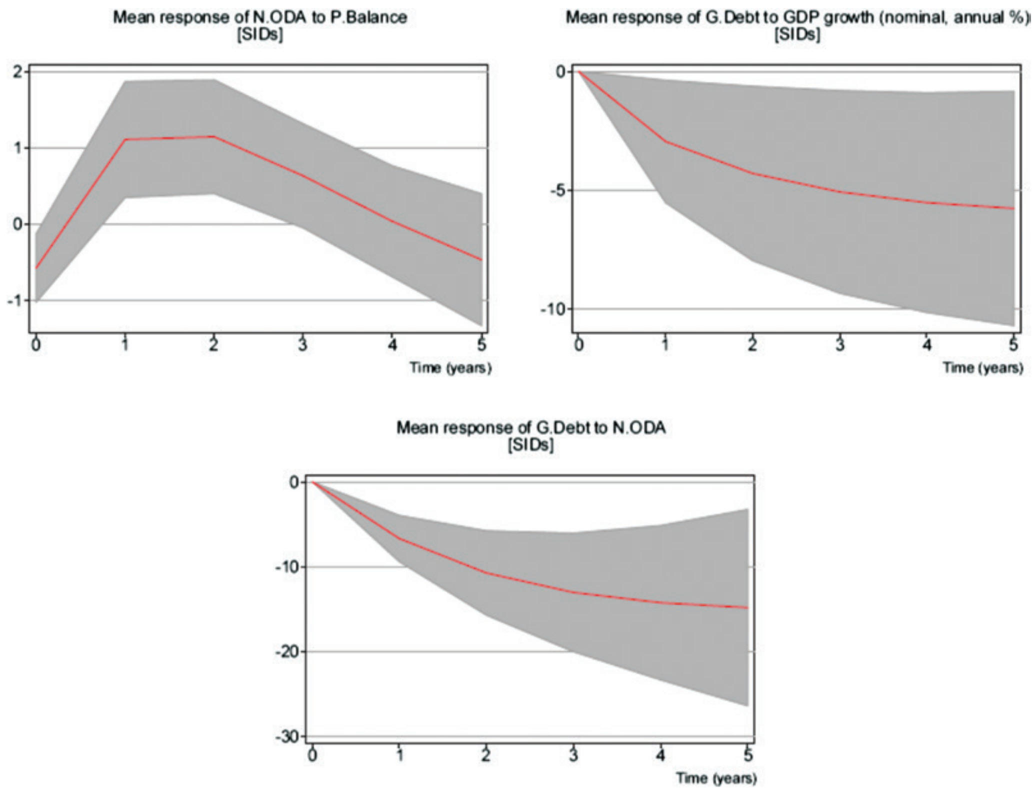


Figure 5. Natural disaster shocks and the covariance of macro-economic variables in SIDS



tal markets and that they are more dependent on aid for relief and other purposes. Our data set is wider than the ECCU and includes a set of countries that are more indebted and have access to capital markets. Jamaica is a good example.

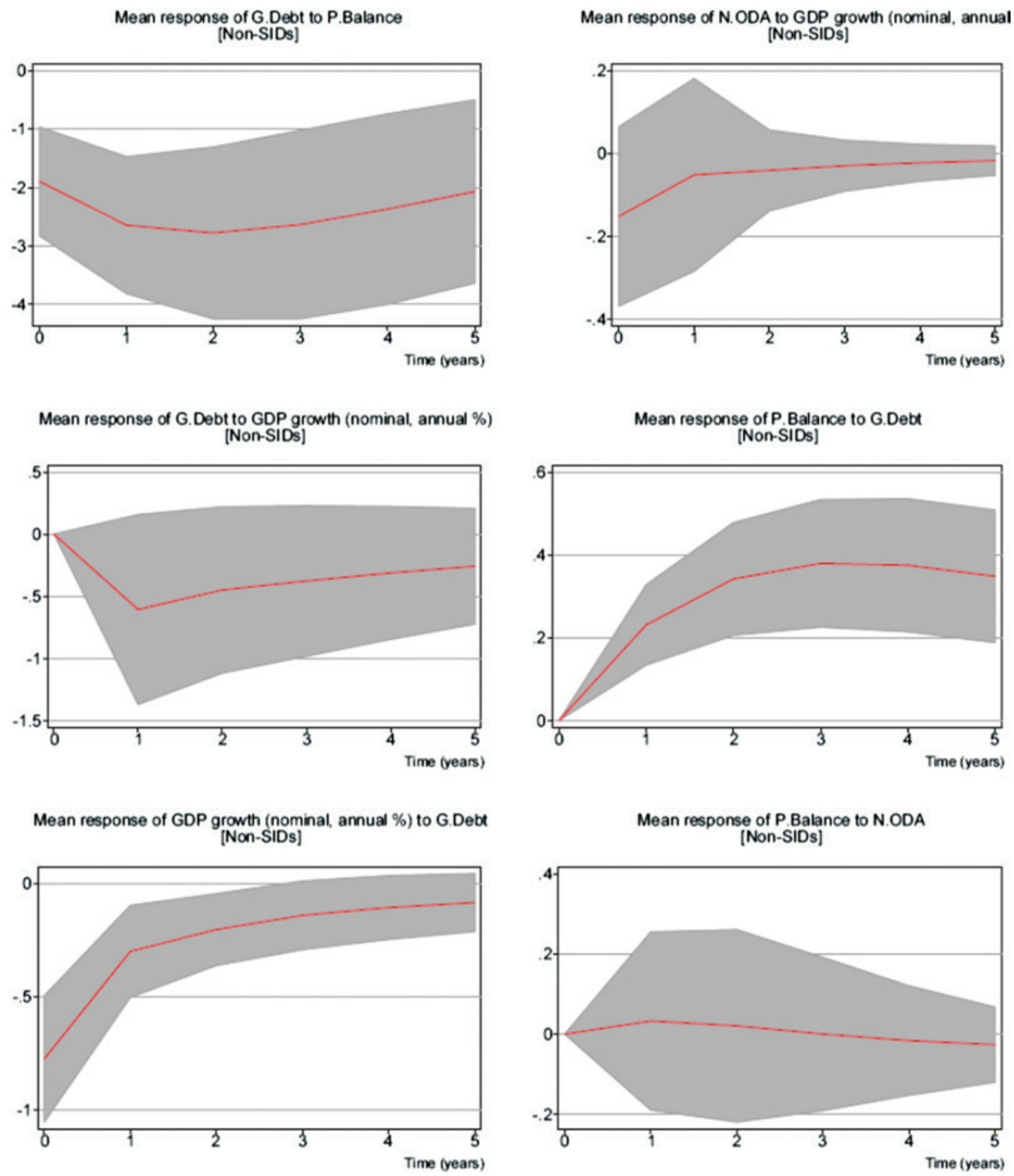
In addition to the above, we find that the impact on debt in SIDS differs when we disaggregate disasters by floods and storms. Floods cause more damage and thus invoke a larger increase in debt as measured against GDP.

In both cases there is evidence of a growth dividend, which we attribute to reconstruction efforts post disaster. However, we found that, in contrast to floods, storms actually depress economic activity.

Our evidence lends support to the claim that aid plays a mitigating role with respect to the impact of disasters on debt. The IRFs indicate that this occurs by way of donors' budget support, which helps to cushion SIDS' and non-SIDS' primary balances.

Intense disasters increase debt in SIDS but not in non-SIDS. We provide a few explanations to support this finding. SIDS have fiscal tools that are better equipped to respond to natural disaster shocks and which thus have the capability of limiting pass-through effects. Furthermore, there is a larger and much more protracted growth dividend in non-SIDS, driven in part it would seem by PPPs rather than by pure increases in government activity.

Figure 6. Natural disaster shocks and the covariance of macro-economic variables in non-SIDS



Endnotes

1 Based on our sample of 20 SIDS.
2 The GMM style instrument estimator replaces all missing values with 0, which allows for more efficient estimates. It is computed using the PVAR.ado Stata package.

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Appendices

Appendix A: Disaster Statistics

Table A.1 Occurrence of natural disasters in SIDS

SIDS	**Storms**	**Floods**	**Droughts**	**Landslides**	**Wildfires**	**External temperatures**
Antigua and Barbuda	6	0	0	0	0	0
The Bahamas	12	1	0	0	0	0
Barbados	4	0	1	0	0	0
Cape Verde	0	1	2	0	0	0
Comoros	2	2	0	0	0	0
Dominica	6	0	0	0	0	0
Fiji Islands	12	9	1	0	0	0
Grenada	3	0	1	0	0	0
Guinea-Bissau	0	4	2	0	1	0
Jamaica	16	2	2	0	0	0
Lesotho	6	2	3	0	0	0
Mauritius	5	1	1	0	0	0
Papua New Guinea	4	9	1	8	1	0
St Lucia	5	2	1	1	0	0
St Vincent and the Grenadines	5	2	0	0	0	0
Seychelles	2	2	0	0	0	0
Singapore	0	0	0	0	0	0
Suriname	0	2	0	0	0	0
Trinidad and Tobago	2	1	1	1	0	0
Vanuatu	8	2	0	0	0	0
Total	98	42	16	10	2	0

Table A.2. Occurrence of natural disasters in non-SIDS

Non-SIDS	Storms	Floods	Droughts	Landslides	Wildfires	External temperatures
Albania	0	0	0	0	0	0
Algeria	0	0	0	0	0	0
Australia	50	38	2	2	20	5
Austria	7	11	0	2	0	5
Bahrain	0	0	0	0	0	0
Bangladesh	79	46	1	3	0	17
Belgium	13	10	0	0	0	6
Bhutan	2	3	0	0	1	0
Botswana	1	7	1	0	0	0
Brazil	9	69	10	11	3	4
Brunei Darussalam	0	0	0	0	1	0
Bulgaria	4	18	1	0	4	9
Canada	24	26	0	0	12	2
Denmark	7	0	0	0	0	0
El Salvador	12	11	4	0	0	1
Ethiopia	0	39	9	2	1	0
Finland	0	1	0	0	0	0
France	32	32	1	2	5	11
Gabon	3	1	0	0	0	0
Germany	31	13	0	1	0	10
Ghana	0	14	0	0	0	0
Greece	4	20	0	0	8	3
Haiti	28	33	2	0	0	0
Honduras	13	20	9	0	1	0
Iceland	0	0	0	2	0	0
India	67	153	4	25	1	31
Italy	7	28	3	5	4	8
Japan	72	18	0	6	1	6
Jordan	2	1	2	0	0	1
Kenya	0	40	9	4	0	0
Kuwait	0	1	0	0	0	0
Madagascar	36	5	5	0	0	0
Malawi	2	27	4	0	0	0
Malaysia	6	29	2	4	4	0
Morocco	4	20	1	0	0	2
Namibia	0	13	5	0	0	0
New Zealand	8	10	2	0	0	1
Nigeria	4	40	0	2	0	1
Norway	3	3	0	0	0	0
Pakistan	14	54	1	14	0	11

(*Continued*)

Table A.2. Occurrence of natural disasters in non-SIDS (*Continued*)

Non-SIDS	Storms	Floods	Droughts	Landslides	Wildfires	External temperatures
Panama	1	27	1	0	1	0
Paraguay	7	10	6	0	1	3
Philippines	156	99	3	21	1	0
Portugal	7	8	2	0	5	4
Qatar	0	0	0	0	0	0
Rwanda	0	9	3	3	0	0
Saudi Arabia	0	13	0	0	0	0
Senegal	3	14	3	0	0	0
South Africa	20	24	2	1	8	2
Spain	12	15	1	1	10	6
Sri Lanka	5	37	3	3	0	0
Sudan	2	29	4	0	1	0
Swaziland	2	3	2	0	1	0
Sweden	4	0	0	0	1	1
Switzerland	14	5	0	4	0	6
Tanzania	4	24	5	1	1	0
Tunisia	0	5	0	0	0	0
Uganda	4	18	6	4	0	0
United Kingdom	21	28	0	0	0	7
Venezuela	2	24	1	1	0	0
Vietnam	61	59	4	5	1	0
Zambia	0	16	2	1	0	0
Zimbabwe	2	11	5	0	0	0
Total	871	1332	131	130	97	163

Table A.3. Damage from natural disasters in SIDS (% of GDP)

SIDS	Storms	Floods	Droughts	Landslides	Wildfires	External temperatures
Antigua and Barbuda	4.193	0.000	0.000	0.000	0.000	0.000
The Bahamas	1.640	0.025	0.000	0.000	0.000	0.000
Barbados	0.007	0.000	0.000	0.000	0.000	0.000
Cape Verde	0.000	0.000	0.000	0.000	0.000	0.000
Comoros	0.000	0.043	0.000	0.000	0.000	0.000
Dominica	4.371	0.000	0.000	0.000	0.000	0.000
Fiji	0.272	0.231	0.000	0.000	0.000	0.000
Grenada	7.135	0.000	0.000	0.000	0.000	0.000
Guinea-Bissau	0.000	0.000	0.000	0.000	0.000	0.000
Jamaica	0.661	0.010	0.003	0.000	0.000	0.000
Lesotho	0.000	0.000	0.000	0.000	0.000	0.000
Mauritius	0.231	0.000	0.194	0.000	0.000	0.000
Papua New Guinea	0.000	0.068	0.000	0.000	0.000	0.000
Seychelles	0.031	0.014	0.000	0.000	0.000	0.000
St Lucia	0.167	0.000	0.000	0.000	0.000	0.000
St Vincent and the Grenadines	0.334	0.714	0.000	0.000	0.000	0.000
Singapore	0.000	0.000	0.000	0.000	0.000	0.000
Suriname	0.000	0.000	0.000	0.000	0.000	0.000
Trinidad and Tobago	0.000	0.000	0.000	0.000	0.000	0.000
Vanuatu	0.000	0.000	0.000	0.000	0.000	0.000
Total	0.952	0.055	0.010	0.000	0.000	0.000

Table A.4. Damage from natural disasters in non-SIDS (% of GDP)

Non-SIDS	Storms	Floods	Droughts	Landslides	Wildfires	External temperatures
Albania	0.000	0.000	0.000	0.000	0.000	0.000
Algeria	0.000	0.000	0.000	0.000	0.000	0.000
Australia	0.081	0.066	0.024	0.000	0.016	0.000
Austria	0.017	0.082	0.000	0.001	0.000	0.005
Bahrain	0.000	0.000	0.000	0.000	0.000	0.000
Bangladesh	0.269	0.697	0.000	0.000	0.000	0.000
Belgium	0.010	0.003	0.000	0.000	0.000	0.000
Bhutan	0.000	0.000	0.000	0.000	0.040	0.000
Botswana	0.000	0.004	0.000	0.000	0.000	0.000
Brazil	0.003	0.014	0.025	0.001	0.000	0.004
Brunei Darussalam	0.000	0.000	0.000	0.000	0.002	0.000
Bulgaria	0.046	0.106	0.000	0.000	0.007	0.000

(*Continued*)

Table A.4. Damage from natural disasters in non-SIDS (% of GDP) (*Continued*)

Non-SIDS	Storms	Floods	Droughts	Landslides	Wildfires	External temperatures
Canada	0.021	0.027	0.000	0.000	0.008	0.000
Denmark	0.095	0.000	0.000	0.000	0.000	0.000
El Salvador	0.474	0.206	0.082	0.000	0.000	0.000
Ethiopia	0.000	0.008	0.010	0.000	0.000	0.000
Finland	0.000	0.000	0.000	0.000	0.000	0.000
France	0.055	0.014	0.000	0.000	0.000	0.011
Gabon	0.000	0.000	0.000	0.000	0.000	0.000
Germany	0.033	0.046	0.000	0.000	0.000	0.004
Ghana	0.000	0.022	0.000	0.000	0.000	0.000
Greece	0.007	0.037	0.000	0.000	0.048	0.000
Haiti	0.618	0.001	0.000	0.000	0.000	0.000
Honduras	3.564	0.120	0.014	0.000	0.000	0.000
Iceland	0.000	0.000	0.000	0.004	0.000	0.000
India	0.076	0.164	0.021	0.000	0.000	0.003
Italy	0.003	0.085	0.006	0.000	0.000	0.014
Japan	0.044	0.011	0.000	0.000	0.000	0.000
Jordan	0.000	0.001	0.000	0.000	0.000	0.000
Kenya	0.000	0.017	0.000	0.000	0.000	0.000
Kuwait	0.000	0.000	0.000	0.000	0.000	0.000
Madagascar	0.616	0.130	0.000	0.000	0.000	0.000
Malawi	0.000	0.022	0.000	0.000	0.000	0.000
Malaysia	0.003	0.029	0.000	0.000	0.014	0.000
Morocco	0.013	0.033	0.108	0.000	0.000	0.000
Namibia	0.000	0.010	0.025	0.000	0.000	0.000
New Zealand	0.001	0.021	0.029	0.000	0.000	0.018
Nigeria	0.000	0.024	0.000	0.000	0.000	0.000
Norway	0.002	0.009	0.000	0.000	0.000	0.000
Pakistan	0.054	0.473	0.019	0.000	0.000	0.000
Panama	0.000	0.009	0.022	0.000	0.000	0.000
Paraguay	0.004	0.004	0.000	0.000	0.010	0.000
Philippines	0.356	0.096	0.000	0.002	0.000	0.000
Portugal	0.006	0.027	0.034	0.000	0.090	0.000
Qatar	0.000	0.000	0.000	0.000	0.000	0.000
Rwanda	0.000	0.000	0.000	0.000	0.000	0.000
Saudi Arabia	0.000	0.012	0.000	0.000	0.000	0.000
Senegal	0.000	0.040	0.000	0.000	0.000	0.000
South Africa	0.008	0.017	0.000	0.000	0.007	0.000
Spain	0.009	0.008	0.024	0.000	0.011	0.011
Sri Lanka	0.004	0.054	0.002	0.000	0.000	0.000
Sudan	0.000	0.099	0.000	0.000	0.000	0.000

(*Continued*)

Table A.4. Damage from natural disasters in non-SIDS (% of GDP) (*Continued*)

Non-SIDS	Storms	Floods	Droughts	Landslides	Wildfires	External temperatures
Swaziland	0.000	0.000	0.000	0.000	0.000	0.000
Sweden	0.037	0.000	0.000	0.000	0.001	0.000
Switzerland	0.036	0.035	0.000	0.020	0.000	0.004
Tanzania	0.000	0.000	0.000	0.000	0.000	0.000
Tunisia	0.000	0.000	0.000	0.000	0.000	0.000
Uganda	0.000	0.001	0.001	0.000	0.000	0.000
United Kingdom	0.017	0.045	0.000	0.000	0.000	0.000
Venezuela	0.000	0.159	0.000	0.000	0.000	0.000
Vietnam	0.477	0.350	0.101	0.001	0.000	0.000
Zambia	0.000	0.028	0.000	0.000	0.000	0.000
Zimbabwe	0.001	0.227	0.000	0.000	0.000	0.000
Total	0.112	0.059	0.009	0.000	0.004	0.001

Appendix B: Model Specification and Stability

Table B.1. Consistent moment and model selection criteria

Lag	CD	*J*	*J p*-value	MBIC	MAIC	MQIC
1	1.0	75.4	0.6	−358.9	−84.6	−195.3
2	1.0	69.7	0.3	−277.8	−58.3	−146.8
3	1.0	57.1	0.2	−203.5	−38.9	−105.3
4	1.0	20.1	1.0	−153.7	−43.9	−88.2

Note: with IV1) lags, the CD, MBIC, MAIC and MQIC all indicate a PVAR of lag order 1.

Table B.2. Roots of the companion matrix

Eigenvalues		
Real	**Imaginary**	**Modulus**
0.89	0.00	0.89
0.48	−0.13	0.50
0.48	0.13	0.50
0.14	0.00	0.14

Notes: Eigenvalues lie inside the unit circle. PVAR satisfies the stability condition.

Appendix C: PVARX Results for SIDS

Table C.1. Impact of floods in SIDS

	Endogenous variables			
	Primary balance b/se	**Gross debt b/se**	**GDP growth b/se**	**Net ODA b/se**
L. primary balance	0.42***	−0.27	0.02	0.41***
	(0.07)	(0.28)	(0.06)	(0.11)
L. gross debt	−0.00	0.99***	−0.01	0.04*
	(0.01)	(0.06)	(0.01)	(0.02)
L. GDP growth	0.02	−0.79*	0.16**	0.11+
L. net ODA	−0.03	−1.66***	0.04	0.42***
	(0.04)	(0.29)	(0.04)	(0.06)
Floods	−2.06*	−34.82***	−2.53***	−4.71***
	(1.00)	(10.13)	(0.73)	(1.17)
Financial crisis	1.94*	−0.31	−1.01	−7.15***
	(0.94)	(4.61)	(0.70)	(1.67)
Oil price crisis	−1.69*	1.34	−0.89	2.33**
	(0.83)	(3.58)	(0.71)	(0.79)
No. of observations	318.00	-	-	-
No. of panels	18.00	-	-	-
Max. lag order	1.00	-	-	-
Criterion function	0.21	-	-	-
Hansen's *J* stat.	65.56	-	-	-
Hansen's *J* df	80.00	-	-	-

Notes: $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table C.2. Impact of storms in SIDS

	Endogenous variables			
	Primary balance b/se	Gross debt b/se	GDP growth b/se	Net ODA b/se
L. primary balance	0.39***	−0.66**	−0.03	0.24** balance
	(0.07)	(0.20)	(0.06)	(0.08)
L. gross debt	0.01	1.11***	−0.01	0.05**
	(0.01)	(0.04)	(0.01)	(0.02)
L. GDP growth	0.00	−0.51*	0.11+	0.11*
L. net ODA	−0.06	−1.67***	0.05	0.44***
	(0.05)	(0.22)	(0.05)	(0.06)
Storms	−0.17	5.45***	0.66	−0.57
	(0.44)	(1.19)	(0.89)	(0.49)
Financial crisis	1.93*	2.86	−1.38+	−6.24***
	(0.95)	(1.75)	(0.71)	(1.52)
Oil price crisis	−1.61+	−0.10	−0.69	2.19**
	(0.84)	(1.61)	(0.94)	(0.70)
No. of observations	318.00	-	-	-
No. of panels	18.00	-	-	-
Max. lag order	1.00	-	-	-
Criterion function	0.20	-	-	-
Hansen's *J* stat.	63.14	-	-	-
Hansen's *J* df	80.00	-	-	-

Notes: $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table C.3. The intensity of natural disasters

	Endogenous variables			
	Primary balance b/se	Gross debt b/se	GDP growth b/se	Net ODA b/se
L. primary balance	0.41***	−1.22***	−0.03	0.36***
	(0.07)	(0.28)	(0.07)	(0.07)
L. gross debt	(0.01)	(0.06)	(0.01)	(0.01)
L. GDP growth	(0.06)	(0.31)	(0.06)	(0.05)
L. net ODA	−0.07	−2.11***	−0.03	0.58***
	(0.04)	(0.29)	(0.06)	(0.05)
Disaster intensity	−2.33***	−13.12***	−5.38***	1.85***
	(0.62)	(3.71)	(0.90)	(0.49)
Financial crisis	2.24*	−3.49	−0.61	−5.14***
	(0.87)	(3.18)	(0.86)	(1.07)
Oil price crisis	−1.90*	7.29*	−0.76	1.22+
	(0.78)	(2.90)	(0.83)	(0.64)
No. of observations	318.00	-	-	-
No. of panels	18.00	-	-	-
Max. lag order	1.00	-	-	-
Criterion function	0.30	-	-	-
Hansen's *J* stat	95.00	-	-	-
Hansen's *J* df	96.00	-	-	-

Notes: $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Appendix D: PVARX Results for Non-SIDS

Table D.1. Impact of floods in non-SIDS

	Endogenous variables			
	Primary balance b/se	**Gross Debt b/se**	**GDP growth b/se**	**Net ODA b/se**
L. primary balance	0.61***	−0.30*	−0.00	−0.07*
	(0.06)	(0.13)	(0.05)	(0.03)
L. gross debt	0.02***	0.86***	−0.03***	0.03***
	(0.00)	(0.03)	(0.01)	(0.01)
L. GDP growth	−0.00	−0.20*	−0.07	−0.00
	(0.04)	(0.10)	(0.05)	(0.03)
L. net ODA	−0.00	−0.22	0.27***	0.46***
	(0.04)	(0.14)	(0.05)	(0.04)
Floods	0.07	0.46	−0.32	−0.15
	(0.15)	(0.48)	(0.22)	(0.10)
Financial crisis	0.03	−7.25***	−0.22	1.53***
	(0.41)	(1.80)	(0.62)	(0.43)
Oil Price crisis	−0.27	4.83***	−0.20	0.02
	(0.33)	(1.44)	(0.42)	(0.24)
No. of observations	691.00	-	-	-
No. of panels	40.00	-	-	-
Max. lag order	1.00	-	-	-
Criterion function	0.15	-	-	-
Hansen's *J* stat.	104.25	-	-	-
Hansen's *J* df	80.00	-	-	-

Notes: $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table D.2. Impact of storms in non-SIDS

	Endogenous variables			
	Primary balance b/se	**Gross debt b/se**	**GDP growth b/se**	**Net ODA b/se**
L. primary balance	0.57***	−0.30*	−0.00	−0.09*
	(0.06)	(0.14)	(0.05)	(0.03)
L. gross debt	0.02***	0.86***	−0.03***	0.03***
	(0.01)	(0.03)	(0.01)	(0.01)
L. GDP growth	−0.01	−0.21*	−0.07	0.01
	(0.04)	(0.09)	(0.05)	(0.03)
L. net ODA	−0.00	−0.24+	0.27***	0.44***
	(0.04)	(0.14)	(0.05)	(0.04)
Storms	−0.48	1.03	−0.28	−0.14
	(0.40)	(0.68)	(0.34)	(0.23)
Financial crisis	0.41	−5.92***	−0.59	1.35**
	(0.47)	(1.61)	(0.57)	(0.45)
Oil price crisis	−0.38	3.97**	0.05	−0.02
	(0.35)	(1.38)	(0.41)	(0.27)
No. of observations	691.00	-	-	-
No. of panels	40.00	-	-	-
Max. lag order	1.00	-	-	-
Criterion function	0.14	-	-	-
Hansen's *J* stat.	99.42	-	-	-
Hansen's *J* df	80.00	-	-	-

Notes: $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table D.3. The intensity of natural disasters in non-SIDS

	Endogenous variables			
	Primary balance b/se	**Gross debt b/se**	**GDP growth b/se**	**Net ODA b/se**
L. primary balance	0.63***	−0.20	−0.03	−0.09*
	(0.06)	(0.14)	(0.05)	(0.03)
L. gross debt	0.03***	0.87***	−0.03***	0.03***
	(0.00)	(0.03)	(0.01)	(0.01)
L. GDP growth	−0.01	−0.24*	−0.05	0.02
	(0.04)	(0.11)	(0.05)	(0.03)
L. net ODA	−0.04	−0.21	0.25***	0.46***
	(0.04)	(0.14)	(0.04)	(0.05)
Disaster intensity	0.20	4.71***	−1.72***	−0.45
	(0.42)	(1.32)	(0.45)	(0.37)
Financial crisis	0.37	−7.00***	−0.55	1.54**
	(0.47)	(1.82)	(0.58)	(0.48)
Oil price crisis	−0.34	4.47**	0.01	−0.09
	(0.35)	(1.60)	(0.44)	(0.27)
No. of observations	691.00	-	-	-
No. of panels	40.00	-	-	-
Max. lag order	1.00	-	-	-
Criterion function	0.14	-	-	-
Hansen's *J* stat.	95.08	-	-	-
Hansen's *J* df	80.00	-	-	-

Note: $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Appendix E: PVAR Granger Causality Wald Tests

Table E.1. Testing for weak exogeneity of endogenous variables

Equation\excluded	SIDS			Non-SIDS		
	χ^2	df	Prob.>χ^2	χ^2	df	Prob.>χ^2
Gross debt						
Net ODA	32.97	1	0.00	2.66	1	0.10
Primary balance	0.90	1	0.34	5.08	1	0.02
Growth	5.53	1	0.02	4.13	1	0.04
ALL	34.25	3	0.00	13.64	3	0.00
Net ODA						
Gross debt	4.10	1	0.04	27.29	1	0.00
Primary balance	13.37	1	0.00	4.44	1	0.04
Growth	2.92	1	0.09	0.01	1	0.93
ALL	21.16	3	0.00	29.20	3	0.00
Primary balance						
Gross debt	0.10	1	0.75	17.99	1	0.00
Net ODA	0.50	1	0.48	0.00	1	0.97
Growth	0.12	1	0.73	0.00	1	0.99
ALL	2.60	3	0.46	21.58	3	0.00
Growth						
Gross debt	0.30	1	0.58	19.56	1	0.00
Net ODA	0.66	1	0.42	34.47	1	0.00
Primary balance	0.09	1	0.77	0.01	1	0.93
ALL	0.80	3	0.85	40.35	3	0.00

Ho: excluded variable does not Granger-cause Equation variable.
Ha: excluded variable Granger-causes Equation variable.

Appendix F: Robustness Checks

Table F.1. Impact of floods in SIDS

	Endogenous variables			
	Gross debt b/se	**Net ODA b/se**	**Primary balance b/se**	**GDP growth b/se**
L. gross debt	0.94***	0.02	0.02	0.02
	(0.07)	(0.02)	(0.01)	(0.02)
L. net ODA	−1.73***	0.45***	−0.09+	−0.04
	(0.24)	(0.06)	(0.05)	(0.06)
L. primary balance	−0.33	0.34**	0.47***	0.08
	(0.31)	(0.11)	(0.08)	(0.07)
L. GDP growth	−0.66+	0.13+	−0.02	0.09
	(0.36)	(0.07)	(0.06)	(0.08)
Floods	−47.04***	−6.21***	0.00	0.77
	(14.19)	(1.49)	(0.72)	(0.95)
Financial shock	−1.82	−6.82***	−0.04	−3.06***
	(4.60)	(1.70)	(0.70)	(0.73)
Debt restructuring	−9.65	4.23*	4.92	3.93
	(6.52)	(2.02)	(3.50)	(3.73)
No. of observations	318.00	-	-	-
No. of panels	18.00	-	-	-
Max. lag order	1.00	-	-	-
Criterion function	0.21	-	-	-
Hansen's *J* stat.	65.56	-	-	-
Hansen's *J* df	80.00	-	-	-

Notes: +p<0.1; * p<0.05; ** p<0.01; *** p<0.001.