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Relation of Debt Relief to Social and Military Expenditures: Empirical Evidence

Bachelor's Thesis

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Declaration of Authorship

I hereby declare that I created this thesis independently, using only the resources and literature shown in the *References* section. I also declare that I have not used this thesis to obtain any other degree.

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Prague, May 4, 2021

Jan Nykl

Abstract

This work focuses on the relationship between sovereign debt relief on one side and government expenditure on healthcare, education, and armed forces on the other side. Each effect is estimated separately using two dynamic panel data methods: Arellano-Bond Difference GMM and Arellano-Bover/Blundell-Bond System GMM. I use three subsets of a dataframe that contains 114 recipients of post-1991 debt relief. The health spending analysis was performed on 110 countries observed in the period of 1995 to 2017; the education expenditure equation was estimated using data on 104 countries from the period 1991 to 2018; and the military spending subset contains data on 103 countries also observed between 1991 and 2018.

I found a statistically significant negative effect of debt relief on military expenditure and a significant positive effect of debt relief on education spending. The latter was, however, sensitive to the choice of estimation method. The effect on health expenditure is unclear.

JEL Classification	E62, F34, F35, H51, H52, H56, H63
Keywords	sovereign debt relief, HIPC, public expenditure, panel data, GMM
Title	Relation of Debt Relief to Social and Military Expenditures: Empirical Evidence

Abstrakt

Tato práce se zaměřuje na vztah mezi oddlužením států na jedné straně a vládními výdaji na zdravotnictví, vzdělávání a ozbrojené síly na straně druhé. Každý dopad je odhadován zvlášť, a to pomocí dvou dynamických modelů pro panelová data: Arellanovy-Bondovy metody Difference GMM, a Arellanovy-Boverovy/Blundellovy-Bondovy metody System GMM.

Používám tři výběry z datasetu, který obsahuje 114 zemí obdrživších dluhovou úlevu po roce 1991. Analýza zdravotnických výdajů byla provedena na 110 zemích sledovaných v rozmezí let 1995 až 2017; rovnice pro vzdělávací výdaje byla odhadnuta pomocí dat o 104 zemích z let 1991 až 2018; a výběr pro vojenské výdaje obsahuje data o 103 zemích, taktéž z let 1991 až 2018.

Nalezl jsem statisticky signifikantní záporný efekt odpuštění dluhů na vojenské výdaje a signifikantní kladný efekt oddlužení na výdaje vzdělávací. Druhý z nich však byl citlivý na volbu odhadové metody. Efekt na zdravotnické výdaje je nejasný.

Klasifikace JEL	E62, F34, F35, H51, H52, H56, H63
Klíčová slova	oddlužení států, HIPC, veřejné výdaje, panelová data, GMM
Název práce	Jaký je vliv odpuštění dluhů na skladbu veřejných výdajů?

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Contents

List of Tables

List of Figures

Acronyms

DALY	Disability-adjusted life years
dep.	Dependency
D-GMM	Difference Generalised Method of Moments
exp.	Expenditure
FOD	Forward orthogonal deviations
GBD	Global Burden of Disease
GBS	General budget support
GDP	Gross domestic product
GMM	Generalised method of moments
GNI	Gross national income
gov.	Government
HIPC	Heavily Indebted Poor Countries
IMF	International Monetary Fund
inf.	Infectious
LIC	Low-income country
MDRI	Multilateral Debt Relief Initiative
NPV	Net present value
ODA	Official development assistance
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
UN	United Nations
UNCTAD	United Nations Conference on Trade and Development
USD	United States Dollar
S-GMM	System Generalised Method of Moments
SURE	Seemingly unrelated regression equations

1. Introduction

1.1 The context

It has been almost nine centuries since sovereign territorial units started borrowing money. From 1149 on, some Italian autonomous cities were even able to borrow long term. And already in 1254, there was a documented case of sovereign debt relief: the Pope, an international authority of that time, freed an autonomous commune of Beauvais from the obligation to pay interest on its loans. (Munro, 2003, pp. 514 - 520)

Yet, this was not a common action in European history. Most of the sovereign debt reductions were involuntary. Absolute monarchs could have chosen not to repay, and autonomous cities occasionally experienced a revolution which resulted in some debt being repudiated (Stasavage, 2016). But as the territories would normally need additional financing straight after the default, creditors could heal their wounds just by charging higher interest rates on the new loans (Drelichman & Voth, 2011).

In modern times, the repudiation of external debt is no longer that easy. And there is hardly any modern country that returned to debt markets shortly after declaring bankruptcy or unwillingness to repay. The arrears just do not disappear.

But still, there are even modern versions of sovereign debt relief. These began in 1980 when the UN Conference on Trade and Development adopted the first rules for sovereign debt restructuring (UNCTAD, 1986, pp. 139 - 140). There were sound reasons for creating such terms. At that time, many African countries were assuming heavy external debt loads to finance natural resource projects (Cameroon, DRC, Ivory Coast, Niger) or to pay for imports (Ghana, Kenya). As these countries exported a few commodities at maximum, the first drop in respective commodity markets was often enough to make their external debts unsustainable (Brooks et al., 1998). In some cases, the low commodity prices pushed the operating profitability of the resource projects below zero, further draining these countries' budgets. Concurrently, Afghanistan, Chad, or Nicaragua were plagued by wars, which significantly reduced their potential output.

Under the UNCTAD terms, official creditors granted US$6 billion in debt reduction to 45 of the world's poorest countries. The relief consisted primarily of rescheduling

and interest forgiveness (Easterly, 2002, p. 1678). However, after this period, the beneficiaries have acquired additional debt, mainly from bilateral loans. Moreover, their economic situation did not improve much.

Thus, in 1988 the Group of Seven agreed on new terms under which the external debt of poor countries was to be restructured. Called Toronto terms, they led to Paris Club creditors forgiving or rescheduling another US$6 billion of payments from the low-income countries. The operation was concluded in 1991. But even before this year, it was apparent that such a relief alone would not be enough to make the debts of poor countries sustainable (Daseking & Powell, 1999, p. 10).

In 1991, the Paris Club agreed on another framework called London terms. It foresaw an immediate NPV reduction of 50 % for the low-income sovereign debtors. Shortly afterwards, in 1994, the official creditors went even further. An agreement known as Naples terms called for 67% NPV reduction. Based on London and Naples terms, numerous LICs benefited from a cancellation or postponement of US$25 billion of payments.

Daseking & Powell (1999) estimate that the total NPV reduction granted by Paris Club under the Toronto, London, and Naples terms was at least US$19 billion.

This was all before the best-known debt relief journey began. It was 1996 when the IMF and the World Bank launched the initiative called Heavily Indebted Poor Countries. Under this framework, countries eligible for International Development Association loans can have their debts forgiven, provided their debt burden is unsustainable. There are two steps in the HIPC process: a decision point and a completion point. To reach a decision point, an eligible country must prepare a Poverty Reduction Strategy Paper in cooperation with elected representatives of its citizens and with a wide spectrum of civil society groups (IMF, 1999, part IV A.). After the decision point, all repayments falling due are temporarily cancelled. A permanent cancellation occurs at the completion point. The condition for the beneficiary is to have been successful in implementing the Poverty Reduction Strategy and to have realised key reforms agreed at the decision point (IMF, 2020a).

The cost of the HIPC programme should have been borne by the IMF and the World Bank (approx. 44 %), by the Paris Club creditors (approx. 30 %), and by the other bilateral creditors (26 %). In 2005, HIPC was complemented by the Multilateral Debt Relief Initiative (MDRI). This subsequently led to multilateral creditors writing off all their loans to countries beyond the HIPC completion point.

Moreover, the IMF cancelled the whole sum owed to it by Cambodia and Tajikistan, two low-income countries which were not heavily indebted (IMF, 2017).

IMF (2019) estimates that the total NPV reduction given under the HIPC and MDRI terms is equal to US$120 billion (2017 prices).

1.2 The contribution

The main goal of the HIPC and MDRI programmes is to reduce poverty. However, the link between debt relief and various poverty indicators is complex and depends on a series of factors. Let me name just a few:

(1) The countries must actually benefit from the relief – if a country does not service any of its debt, the relief does not free up its resources. It might still enable the country to borrow additional funds, but would not this debt again become unbearable?

(2) Decision-makers in the recipient countries must redirect the saved funds into expenditures or tax reductions which are able to reduce poverty.

(3) If they choose the expenditure path, the funds must reach their intended destination.

(4) Finally, the resources must translate into poverty reduction at the micro level.

Still, we can measure what effort the recipient governments have put into poverty alleviation. And we might guess that the health and education expenditure has greater potential to reduce poverty than the military spending – especially in the low-income countries without military research (see Dunne & Mohammed, 1995, or Galvin, 2003, for a discussion). Moreover, the IMF often mentions that freeing up resources to finance health and education is one of the HIPC initiative's key goals (e. g. IMF, 2020a).

Therefore, I will perform panel data regression analysis to investigate whether this goal has been fulfilled. That is, whether the countries benefiting from the debt relief have increased their public education and health expenditure after controlling for other possible determinants. Besides that, I will check whether these countries have not increased military spending more than what would be expected given the political situation in their region.

To gain a general insight into the effect of debt relief on the public expenditure mix, I will be looking at all developing countries which have received NPV reduction on

their public debt in the period 1991 to 2018. Data for the whole period will be used, wherever possible, as mentioned in the following chapters.

The rest of this thesis is organised as follows:
(1) Literature review
(2) Data
(3) Methodology
(4) Results
(5) Conclusion

2. Literature review

Debt relief seems to be a popular focus among economists. By simply typing "debt relief" into the Web of Science search, one can find 570 scientific papers. As of January 2021, one finds 94 studies on "debt relief growth" or 22 studies on "debt relief war". Yet, there are no more than ten papers containing a thorough econometric analysis of the social expenditure topics. There is not a single study on the (cor)relation between debt relief and military spending.

2.1 Debt relief and social expenditure

Probably the oldest empirical paper on the social expenditure ~ debt relief relationship is Chauvin & Kraay (2005). The authors focused on a panel of 62 countries and a period from 1989 to 2003. They split the timespan into three subperiods. After that, they estimated the amount of debt relief for each country in each five-year subperiod. This was done using two distinct methods, one based on data from the World Bank, the other using creditor-reported figures. On this dataset, the authors performed a pooled OLS regression. As their model is based on differenced data, the authors argue that all factors other than debt relief should disappear. Therefore, they do not control for any other variable. The result is inconclusive: no significant relation was found.

It was already in May 2006 when the first working version of Lora & Olivera (2007) was released. At that time just a technical report of the African Development Bank, the article argued that debt stock has a stronger effect on social expenditure than on other government expenses. The authors estimate the effect on health expenditure, education expenditure, and overall social spending separately. They use the Arellano-Bond approach and therefore circumvent the fixed-effects-related trouble by design. Despite this, they control for changes in the ratio of primary expenditures to GDP, as well as for revenues/GDP ratio and the magnitude of debt service.

Their source data were observed in the years 1985 to 2003. The authors do not average the data over multiannual periods, but they delete data points where the debt to GDP ratio is above 150 per cent. Therefore, they are working with an un-

balanced panel of 43 countries for the health and education equations and with a panel of 50 and 53 countries for two specifications of the total social expenditure equation. Although the authors are focusing on the developing world, their sample also includes South Korea, Czechia, Hungary, or Qatar, which could hardly be considered emerging markets for most of the period.

The results of Lora & Olivera (2007) are consistent with the assumption that debt relief is followed by an increase in education and health expenditure, although debt relief itself is not included in their model.

Concurrently, an IMF economist Alun Thomas performed a very similar study on a panel of 110 developing countries. Utilising data for the same period, he was only working with total social expenditure as a response variable. The researcher also uses the Arellano-Bond approach, but he controls for different variables than Eduardo Lora and Mauricio Oliveira do. He focuses on changes in budget balance, youth literacy rate, population density, and GDP per capita. He also adds the amount of development grants to his equation. As a result, Thomas (2006) shows a statistically significant negative relation between debt service and social expenditure. Therefore, debt relief might lead to increased social spending in debtor countries. Besides that, Thomas (2006) claims that social spending is unaffected by the grants.

Only a few months later, Fosu (2007) showed that higher external debt service is statistically related to a smaller part of the public budget being allocated to education, at least among African countries. The author uses World Bank data for 35 countries located south of Sahara, with a time frame of 20 years, beginning in 1975 and ending in 1994. To minimise noise, he works with five-year averages of the data points. Using a random effects model, the author controls for the levels of official development assistance (ODA) received, the gross national product per capita, as well as for the share of population in agriculture.

Augustin Kwasi Fosu also addresses the problem of arrears and the possible choice of African countries not to service their debts in certain years. To mitigate related issues, he regresses the actual debt service levels on net external debt. Then, the author saves the estimated parameter. For each data point, he then multiplies the net debt using this estimate.

It is directly this estimated level of debt service what leads to the conclusion that debt relief should be followed by an increase in education expenditure in the recipient country.

In October 2007, Dessy & Vencatachellum (2007) showed a positive statistical relationship between debt relief and social expenditure, but only if the recipient country's governance is of high quality. Besides relief and its interaction with institutional quality, the authors included three other regressors: (1) the institutional quality itself, (2) the Official Development Assistance received (ODA, measured in US$ millions), and (3) the interaction of ODA with debt relief. They do not control for any other time-variant country-specific characteristics.

In a panel of all African countries in 1994 – 2003, the authors did not merge health and education expenditure into a single variable but rather estimated the effects on the two sectors separately. As they suspected the errors in the two equations to be cross-correlated, the researchers chose to use the Seemingly Unrelated Regression Equations (SURE) model to maximise the estimation efficiency. The main result for the two sectors does not, however, differ significantly.

During spring 2010, the single most influential article showing the effect of debt relief on social expenditure appeared. The Lancet published Lu et al. (2010), a study focusing on displacement of domestic healthcare expenditure by healthcare aid (i.e. the fungibility of healthcare ODA). Debt relief to GDP was only one of the regressors, and based on the results, it does not affect healthcare expenditure from non-aid sources.

When it comes to the methodology, Lu et al. (2010) used the Arellano-Bover/Blundell-Bond approach. By imposing stricter conditions on the correlation between lagged dependent variable and the errors, they managed to attain lower variance than they would reach using the standard Arellano-Bond method. The source dataset, from a great part reliant on estimates of the authors, contains data for 111 countries in all four-year periods between 1995 and 2006.

Later in 2010, Mr Fosu revisited the topic of his paper from 2007. This time, he did not focus on education expenditure alone. Rather, Fosu (2010) looks at the effect of debt relief on health expenditure, education expenditure, and the summary social spending. On the dataset from his original study, he employs the SURE estimation. The results are consistent with those of his study from 2007: debt relief is expected to precede increases in all specified types of social spending.

A similar estimation was then done in Quattri & Fosu (2012), this time with a panel of 40 countries in Sub-Saharan Africa, with the data observed in the years 1995 to 2009, averaged into three-year periods. Besides investigating the effect of debt relief on health and education spending, the authors also examine its statistical

influence on public investment. Once again, the authors transform the debt service variable in a similar way to Fosu (2007). They claim, however, that the effect of the transformed variable converges to that of the actual debt service over the years.

Besides the two specifications of debt service, the authors control for ODA share in GDP[1], GNI per capita, government effectiveness (based on the World Bank database), and the level of ethnic fractionalisation of the country. The core equation is estimated in the form of random effects model. Even this time, the results show a significant negative relation between debt service and social spending, and therefore argue that sovereign debt relief should help redirect funds towards health and education.

The same conclusion could be reached based on Van de Sijpe (2013a). Although the main focus of the study is to reinvestigate the fungibility of sector-specific aid, the author includes debt service and debt burden as regressors. Besides that, he controls for urbanisation, the intensity of external trade, as well as for GDP per capita and its growth. In a dataset of 108 countries observed in the years 1990 to 2003, the debt service variable has a significant negative influence on both education and health aid. The author uses pooled OLS, fixed effects, and the first difference model, and the relation is robust to the model specification. However, when five countries with outlier observations are dropped, the effect on health spending moves into insignificance.

Van de Sijpe (2013b) then does a limited review of Lu et al. (2010), but without reestimating the debt relief coefficient. The study provoked an immediate reaction, a paper by Dieleman et al. (2013). The authors show that debt relief is positively related to a level of health spending coming from non-aid sources. Yet, the relief variable is close to being insignificant. To defend the original article by Lu et al. (2010), the authors also use the Arellano-Bover/Blundell-Bond approach. They even chose the same set of independent variables, only with GDP per capita in logarithm. However, the dataset is larger – it covers 134 countries and a time span of 16 years, starting in 1995 and ending in 2010.

All in all, the current scientific consensus is that sovereign debt relief should not harm the social sector. Seven of the ten papers reviewed and five of the eight authors cited hint at a positive correlation of debt relief with social expenditures.

However, only four of the studies cited use debt relief itself as an independent variable, and only one of them shows its positive effect on social spending – but on

[1] they use three different specifications of ODA

the margin of statistical significance. How is this reported discrepancy between the results possible? In fact, the debt burden might force a decrease in social spending, but a reduction of the burden might not actually lead to a return to pre-burden levels.

Nevertheless, there might be other aid modalities with an effect similar to debt relief.

2.2 General budget support and social expenditure

When the budget support is not restricted to a specific sector, it enlarges the sum that the recipient government can freely redistribute. Debt relief in the form of concessional rescheduling should do the same thing. But there are two caveats in this consideration:

(1) From the publicly available debt relief data, we can hardly distinguish what is concessional rescheduling and what is a reduction in the principal amount. The latter should enlarge space for new debt – and thus have a larger effect.

(2) Even if the cases of rescheduling could be separated, there is no data on whether the recipient countries would make the payments had the rescheduling not been made.

Still, these differences might cancel each other if a country services only a part of its debt and receives a mix of reschedulings and principal reductions.

To my knowledge, there is currently a single study assessing the impact of general budget support (GBS) on health expenditure: Antunes et al. (2013). The authors apply the Arellano-Bond procedure on a panel of 82 countries covering the period 2002 to 2007. After controlling for the level of ODA for health, size of the economy, and the level of expenditures coming from other sources than GBS, the researchers found no statistical relationship between the budget support and the non-aid health spending.

2.3 Fungibility of sector-specific aid

Antunes et al. (2013) find, however, that international aid to the health sector displaces domestically-sourced health expenditure. The above-mentioned papers of Lu et al. (2010) and Dieleman et al. (2013) reached the same conclusion. With somewhat lower estimates, the fungibility is also supported by Ke et al. (2011).

Although Van de Sijpe (2013a, 2013b) claims that the fungibility is limited to none, he does not claim there is additionality.

These findings show a somewhat dimmer picture of the possible effect of debt relief on social spending. ODA for the social sector usually mandates the recipient not to decrease the domestically-sourced social spending (Van de Sijpe, 2013a, p. 325). The debt relief does not. Therefore, the debt relief providers are in a worse position than social-sector aid donors when persuading the recipients to increase their social spending.

3. Data

To be able to perform a panel data regression, I aimed to include data for all debt relief recipients from the longest possible timespan. Yet, data availability is limited.

Therefore, the datasets used for estimating the three different equations differ both in length and in countries used. For the effect of debt relief on health expenditure, I use a collection of 110 developing countries in the period of 23 years – from 1995 to 2017. For the effect on military expenditure, I utilise a panel of 103 debt relief recipients in the interval from 1991 to 2018. The same timespan is then used also for the education expenditure equation, but this time with 104 countries.

In all cases, I averaged the data over four-year intervals. The key benefits are two:

(1) the aggregation reduces noise in the individual time series

(2) the ratio of missing observations to the overall panel size decreases, taking us closer to a balanced panel

Even though this reduces the number of time periods that can be used for statistical inference, it is still possible to find a suitable estimation procedure.

3.1 Choice of variables

But what data was I even working with? The literature hints at the necessity to include debt relief itself as a regressor of interest. But what else?

3.1.1 Health expenditure

Government health expenditure is expected to be determined as follows:

$$\frac{health\ exp.}{GDP} \sim \frac{debt\ relief}{GDP} + \frac{health\ aid}{GDP} + inf.\ disease\ prevalence + \\ + old\text{-}age\ dep.\ ratio + \frac{GDP}{capita} + freedom + \frac{general\ gov.\ exp.}{GDP}$$

The dependent variable should only include health expenditure coming from non-aid sources, so that we can see some patterns in decisions of the debtor governments.

This then necessitates the inclusion of the health aid variable as the aid fungibility is likely.

When it comes to the prevalence of infectious diseases, this should be a crucial determinant of government health expenditure. Although the severity of the diseases varies by region and time, mild infections appear everywhere. Thus, the true hardship caused by infections should be captured by the indicator.

But why am I excluding non-communicable diseases? The reason is simple: they are often age-related. And the effect of population ageing is better reflected by the metric of its own. Thus, I include the old-age dependency ratio, in a fashion similar to Barros (1998) or Pammolli et al. (2012).

The GDP per capita is used because the richer countries tend to spend a higher portion of their GDP on health than the poorer ones (Newhouse, 1977; Culyer, 1989; Gerdtham & Jönsson, 1991; Gerdtham et al., 1992). Although numerous economists disagree (see e. g. Barros, 1998, or Okunade, 2005), the variable should still be controlled for.

I also include freedom as a regressor: based on various research findings, democratic governments tend to have higher social expenditures than autocracies (Avelino et al., 2005; Ansell, 2008; Habibi, 1994)

After all, I also control for the size of government. If more resources are redistributed in general, the government is likely to allocate more also towards the health sector.

3.1.2 Education expenditure

Similarly, for the education expenditure, I am choosing the following variables:

$$\frac{education\ exp.}{GDP} \sim \frac{debt\ relief}{GDP} + youth\ dep.\ ratio + \frac{war\ deaths}{capita} \cdot E + \\ + \frac{GDP}{capita} + freedom + \frac{general\ gov.\ exp.}{GDP}$$

The youth dependency ratio should be influencing education spending significantly, whatever the rest of the model is. Trivially, countries with a larger ratio of minors to the working-age population shall spend a larger part of their GDP on education (see e. g. Busemeyer, 2007, p. 596).

The inclusion of war deaths into this equation might seem counterintuitive. How are they even connected to education? The hypothesis is that countries at war have to

lower the education spending to finance the war effort. On the other hand, education spending could hardly affect the number of war deaths.

Still, there is a problem if a debtor country *chooses* to wage war after it receives debt relief. In such a case, we might have trouble with this model – we could see a positive effect of debt relief on education even though most resources were reallocated towards the military.

To alleviate this issue, I will assess how *guilty* the given government is for the conflict recorded in the given year. Thus, for each occasion when $\frac{war\ deaths}{capita} > 0$, I will compute $E_{it} = (1 - gov.\ guilt\ share_{it})$. Although this is a subjective judgment, it is necessary to get any meaningful results.

Finally, the triplet of GDP per capita, the freedom variable, and the general government expenditure. Logics for its inclusion is the same as in the health spending equation.

3.1.3 Military expenditure

In the end, the foreseen specification of the military spending model is

$$\frac{military\ exp.}{GDP} \sim \frac{debt\ relief}{GDP} + \frac{war\ deaths}{capita} \cdot E + \frac{neighbour\ war\ deaths}{capita} \cdot G + \\ + homicide\ rate + \ pop.\ density + freedom + \frac{general\ gov.\ exp.}{GDP}$$

Once again, the war deaths variable will be transformed using my subjective judgment. In the same way, I will transform the war deaths in the neighbouring countries, as a government can also choose to wage war abroad.

The importance of war deaths at home is probably apparent. Of course, it might happen that an internal war is waged by non-governmental factions and the government military expenditure is left intact (Fordham & Walker, 2005, p. 150). Still, it is a crucial variable to be controlled for (Goldsmith, 2003; Fordham & Walker, 2005).

The deaths in neighbouring countries caused by conflicts do not typically appear in studies explaining military expenditures. But how better to capture the regional security situation? Controlling for actively waged wars would violate the core idea of the analysis. And including military spending of country's enemies (Rosh, 1988; Dunne & Perlo-Freeman, 2003) would introduce a more complex relationship: besides judging who the enemy is, we would also need to filter the effect of domestic

military spending on that of the enemies. And such a task would be much more complex than tracking igniters of local conflicts.

The intentional homicide rate is included as some countries can possibly use military forces for policing tasks, especially during volatile times.

Population density also plays a role: if it grows, the country gains potential soldiers, logistics might become simpler and the armed forces should be able to achieve a higher manpower to capital ratio, rendering defence cheaper.

Furthermore, I include the freedom variable once again. Most of the relevant papers show that democratic governments spend less on the military (Rosh, 1988; Hewitt, 1992; Goldsmith, 2003; Brauner, 2015). Even a more sceptical study of Dunne & Perlo-Freeman (2003) shows one model in which the relation of democracy and military spending is negative and statistically significant.

Another repeatedly appearing variable is the government size. In this case, the relation might be weaker as military spending fulfils rather strategic government goals. Still, relatively larger redistribution machineries have more resources to put into the military. Therefore, even in this case, this ratio is not to be overlooked.

3.2 Sources

The health expenditure and health development aid data are taken from the Institute for Health Metrics and Evaluation (2020a). The desired $\frac{health\ expenditure}{GDP}$ ratio is included as *ghes_per_gdp_mean*. The $\frac{health\ aid}{GDP}$ ratio is reported under *dah_per_gdp_mean*.

The $\frac{military\ expenditure}{GDP}$ ratio is taken from Stockholm International Peace Research Institute (2020), probably the most influential public source of security data.

The last of the dependent variables, $\frac{education\ expenditure}{GDP}$ ratio comes from World Bank (2020a).

When it comes to sovereign debt relief, the data availability is limited. There does not seem to be a single source showing summary debt relief provided. The Creditor Reporting System of OECD, the International Debt Statistics Database of the World Bank, and the Aid Disbursements database of OECD all display only debt relief given by official donors. Moreover, the amounts of sovereign debt relief disbursed differ among these databases. And there is only a single resource containing data for years before 2002. It is accessible via OECD (2020). To get as close to the actual

value as possible, I take a sum of Grants: Debt Forgiveness and Other Debt Grants, Total. The flows are recorded in the years when they were truly disbursed, not only promised.

As the debt relief data are recorded in millions of current USD, we also need relevant GDP data to obtain the regressor of interest. These were found at IMF (2020b).

The same database was also queried for GDP per capita in constant 2017 international dollars (IMF, 2020c). Such an indicator is not influenced by inflation, and it should not contain noise caused by exchange rate variation. Therefore, it should be preferable for estimating the impact of wealth on the public expenditure mix.

The final query on the World Economic Outlook was done to obtain the $\frac{public\,expenditure}{GDP}$ ratio (IMF, 2020d).

Further, I envisaged including a freedom or democracy variable in all three equations. Now, an obvious question probably comes to mind: where to find such an indicator? If freedom is a subjective feeling, can it even be quantified? In fact, it would be difficult to quantify it on a cardinal basis. It is, however, possible to claim that civil liberties in the U. S. Deep South these days are much broader than they were in the 1950s. In the same way, we can argue that today's India is more democratic than contemporary Russia, which is in turn freer than North Korea. And there are more rankings that try to capture these differences. For example, Dessy & Vencatachellum (2007) used Polity 2 panel. Then, there is The Economist's Democracy Index. After all, there is Freedom in the World Report.

Sadly, The Economist publishes its ranking only since 2002, and at least some data in the Polity series are highly suspicious. For example, Montenegro, a country which since the 1980s has hardly experienced a different leader than Milo Djukanović, was attributed the same score as Croatia, a stable electoral democracy. The same wrong equality is shown between Ukraine and Russia, Moldova and Romania, or Qatar and North Korea.

Therefore, I chose to take the data from Freedom House (2021). Their datasets contain two main indicators: civil liberties and political rights. In both, lower values are better. As the correlation between these two indicators is approx. 0.93, I sum them together to avoid multicollinearity issues. It is this aggregate *unfreedom* indicator what I include in the regressions.

Three additional control variables were then taken from the World Bank databases. Population density comes from the number of inhabitants at World Bank (2020b)

divided by surface area from World Bank (2020c). The youth dependency ratio originates from World Bank (2020d) and the old-age dependency ratio is taken from World Bank (2020e). As the dependency ratios lack all values from the Commonwealth of Dominica, I looked into the country's census data (Commonwealth of Dominica, 2011) to obtain at least partial knowledge of its situation. Less reliable recent data on Dominica were later obtained from Countrymeters (2021), with the missing values linearly interpolated.

Finally, I employed the Global Burden of Disease Study (IHME, 2020b) to obtain data on three remaining variables. First, the overall prevalence of infectious diseases was taken as a sum of data points under causes A.1 to A.5, with *Context: Cause*, *Measure: Prevalence*, and *Metric: Rate*.

Second, the intentional homicide rate comes from data under the cause C.3.2, with *Context: Cause*, *Measure: Deaths*, and *Metric: Rate*. According to the dataset description, this indicator should not include state-originated violence, which further mitigates reverse causality issues.

Third, the data on war-related deaths were taken from the cause C.3.3, again with *Context: Cause*, *Measure: Deaths*, and *Metric: Rate*. Although the indicator does not include executions and police brutality, it contains the massacre in Abu Salim prison in Tripoli, Libya. Further, it shows suspicious data on Mali between 1996 and 2003. As I cannot consistently reestimate the data, I changed all Malian values in the period to zero – which might be even close to the true values (Uppsala University, 2020b).

Further, the GBD dataset seems to be significantly understating the death tolls of some major conflicts. For example, the number of Bosnian Wars victims is understated by approx. 75 % (see Ingrao & Emmert, 2013, p. 140), the number of fatalities in the Donbas War by approx. 40 % (OHCHR, 2020, p. 8), and the toll of the Second Congo War by approx. 94 % (page 4 of Coghlan et al., 2006).

However, it should be noted that the Uppsala Conflict Data Program, a highly influential source, offers even lower estimates in these situations. Therefore, I chose to stay with the GBD data despite some flaws.

3.3 The war data adjustments

But even if the war data were flawless, the correction for the government guilt needs to be done. Therefore, I reviewed 6160 data points and assessed the level of voluntary

involvement of each government in each war at home and inside its neighbouring countries. Especially in domestic conflicts, judging who was the initiator or who escalated the war the most is close to impossible. Thus, E is lower than one (i. e. the government guilt share higher than 0) only in cases when the government is known to have taken up arms first, or when the government used a strategy of deliberate one-sided violence. In other words, if a rebel force starts an insurgency in a country because of flawed elections or discrimination of a minority, E will be equal to 1, even though the rebels' motives might be legitimate. On the other hand, if such an insurgency begins because government forces systematically murder members of a specific political or ethnic group, E shall be lower than 1.

I acknowledge that such work requires a high level of transparency. Because of that, I am commenting on almost all important decisions in my dataset, which I have published online.

Although numerous data points were corrected significantly, the resulting panels are very strongly correlated with the unadjusted ones: when it comes to the domestic wars, there is a correlation of 0.6, and when we look at the neighbourhood wars, the correlation is 0.99. This suggests that results without my adjustments would not differ strongly.

3.4 Statistical properties

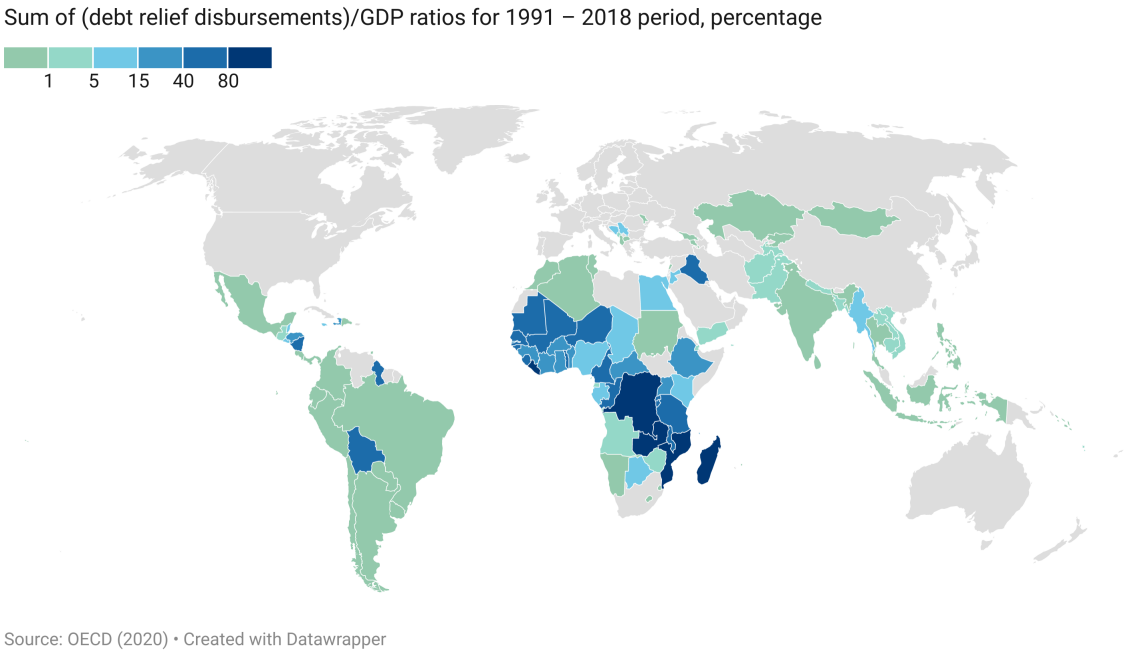
Now, let us explore a few basic facts about the data collected. First, the debt relief. In nominal terms, the single largest yearly NPV reduction was granted to Iraq in 2005. The transactions lowered Iraqi sovereign debt outstanding by almost US$14 billion, measured in that year's prices. Second comes Nigeria: in 2006, this Gulf of Guinea country benefited from summary debt grants of US$11 billion. Yet, Nigeria is surely not a small market, and when standardised by GDP, the 2006 debt reduction barely made it into 100 largest of its kind.

When we are looking at the $\frac{debt\,relief}{GDP}$ ratio, the largest beneficiary was Sao Tome and Principe in 2007. In per-GDP basis, its debt was slashed by 91 percentage points. Some other major recipients include Malawi and Liberia, which had their $\frac{debt}{GDP}$ ratios cut by approx. 60 % in years 2006 and 2010, respectively.

After aggregation into four-year blocks, Liberia in the 2007 – 2010 period is still prominent. It was granted debt relief tantamount to 31 % of all goods and services produced on its territory within the time span.

As visible in the following map, it has been one of the largest debt relief recipients in general, when recorded in per-GDP terms.

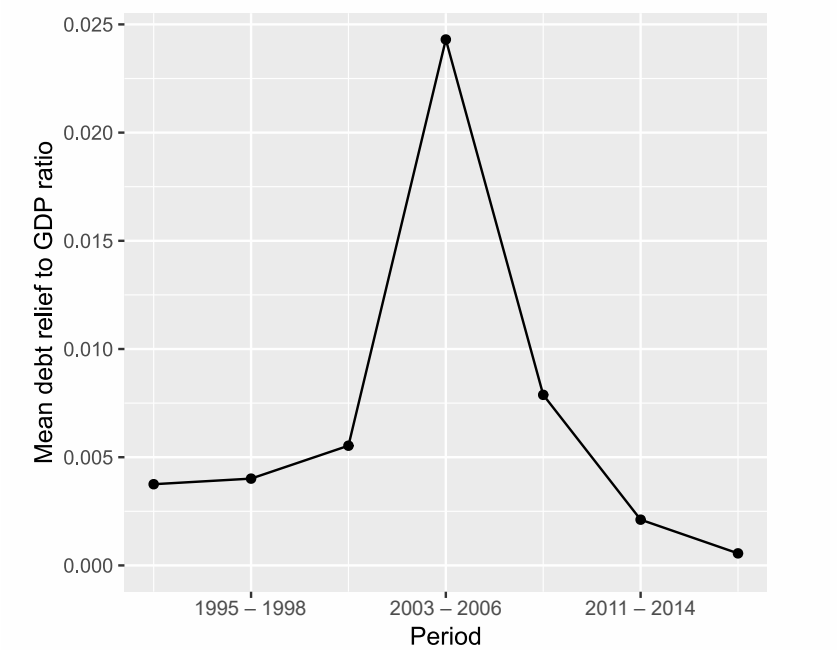
Figure 3.1: Debt relief received to GDP



The significance of Africa-oriented debt relief is self-evident. Besides previously mentioned Iraq, we also can clearly distinguish the Latin American HIPC, i. e. Bolivia, Guyana, Haiti, Honduras, and Nicaragua. Most other countries in the dataset benefited from much smaller relief when standardised by GDP.

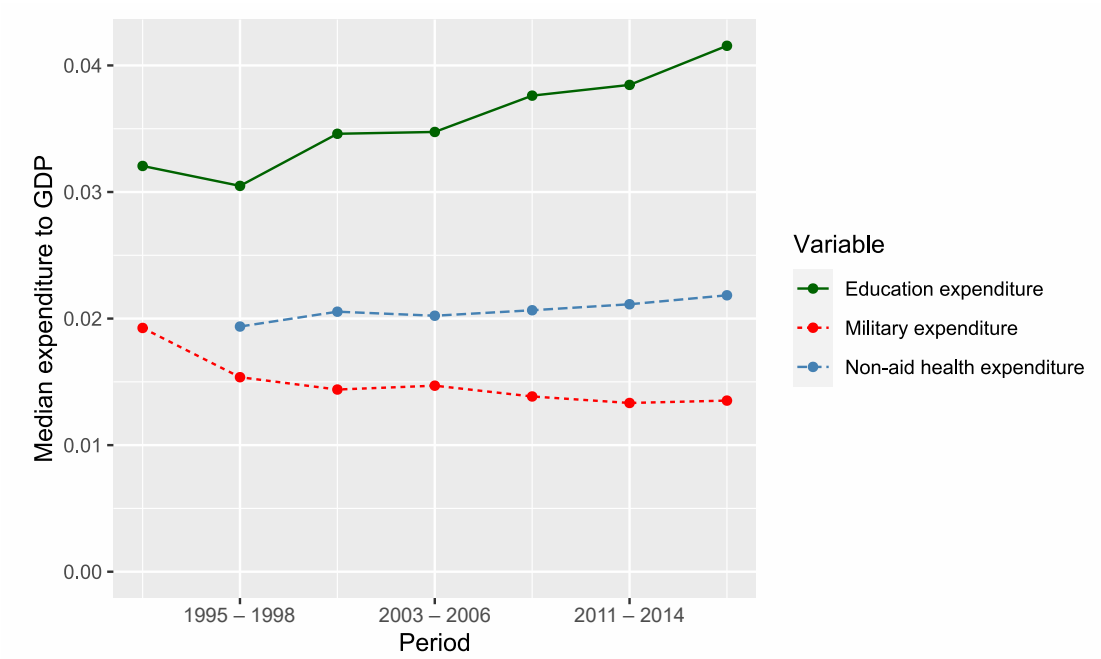
Looking at the time dimension, the $\frac{debt\ relief}{GDP}$ variable is non-trending. This holds independent of whether we look at individual countries, whether we divide summary relief to all countries by sum of their gross domestic products, or whether we just average the ratios over all countries in any given period.

Figure 3.2: Debt relief to GDP



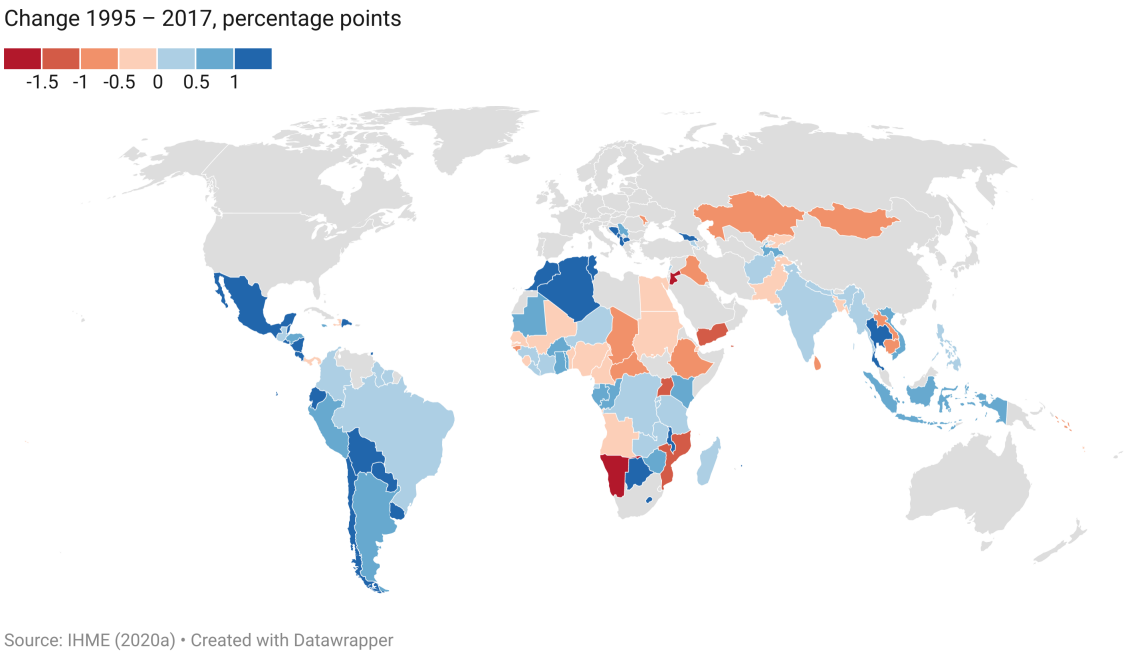
On the other hand, the three sector-specific expenditure ratios are highly trending. As illustrated in the following chart, the median $\frac{education\ expenditure}{GDP}$ ratio of the sample countries rose by almost one percentage point in the investigated period. During the same time span, median $\frac{military\ expenditure}{GDP}$ went down by approx. 0.6 pp. The $\frac{health\ expenditure}{GDP}$ ratio is the most stable of the triplet, at least when we look at the domestically-sourced spending.

Figure 3.3: Public expenditure ratios



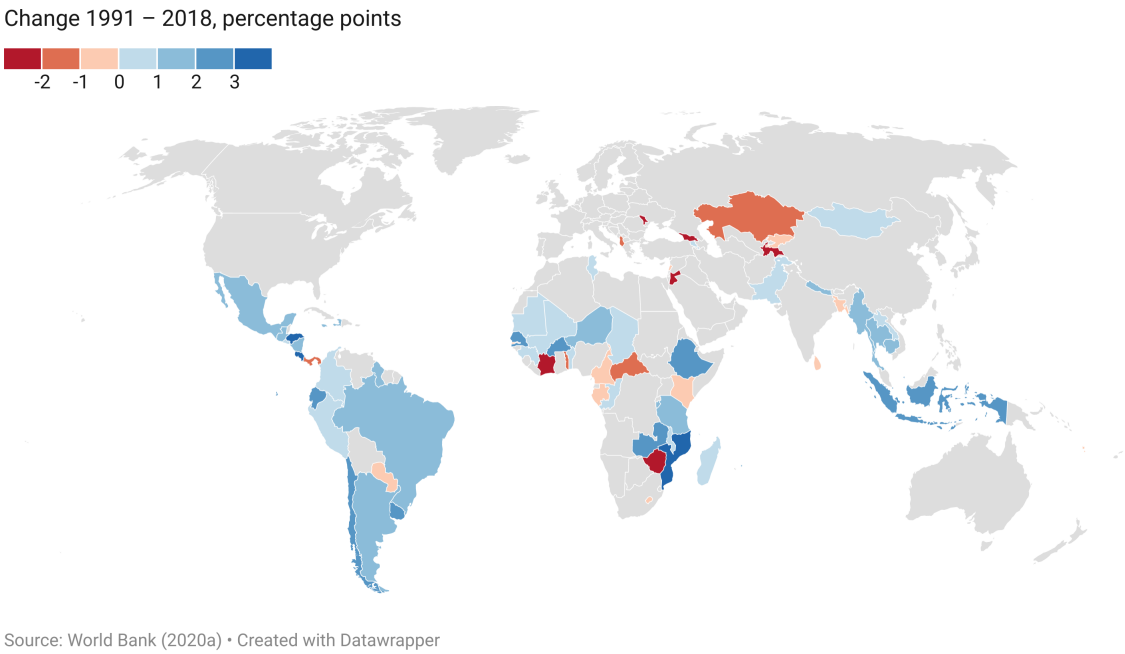
Still, it is has risen in most parts of the developing world. Latin America seems to be the champion: from 17 American countries included in the dataset, only Haiti and Panama decreased the fraction of GDP allocated towards public health. Yet, the trends among major debt relief recipients are diverse: while increases in the ratio in Bolivia, DR Congo, Liberia, and Zambia are apparent, so are the significant downward trends in Ethiopia, Iraq, or Mozambique.

Figure 3.4: Health expenditure as a percentage of GDP



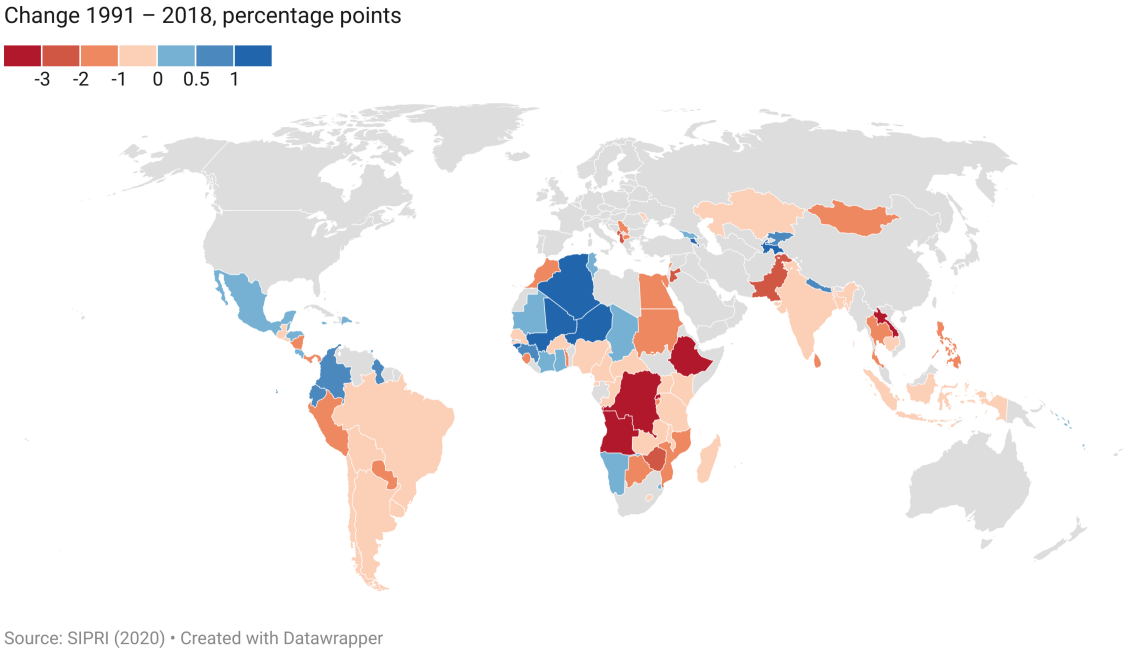
The $\frac{education\ expenditure}{GDP}$ fraction also saw increases mainly in Latin America. On the other end of the spectre lies the post-Soviet area: some increase in the ratio is visible only in Armenia. When Africa is being looked at, major debt relief recipients like Mozambique or Ethiopia did allocate greater shares of their wealth to public education spending. However, gaps in the data, as well as Cameroonian and Togolese experience, bar us from any premature conclusions.

Figure 3.5: Education expenditure as a percentage of GDP



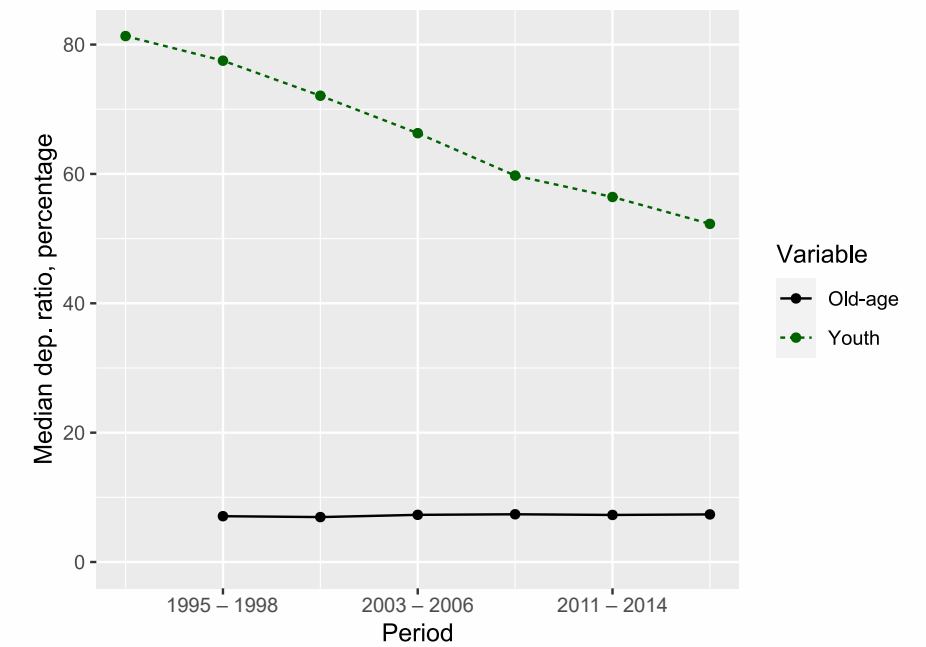
The decreases in the $\frac{military\ expenditure}{GDP}$ ratios around the developing world are then connected mainly to declines in violence levels. Countries that demilitarised the most during the period include Ethiopia, which waged two bloody wars over Eritrea and surrounding territories in the 1990s but was largely peaceful in the 2010s. The Great Lakes region, which experienced genocide and two large-scale wars, including the so-called First African World War, does not even need mentioning. Other countries in dark orange colour formerly either intervened in conflicts abroad (Angola, Pakistan, Sudan, Zimbabwe) or lived through civil wars of their own (the Balkans countries, Mozambique, Peru, but Angola and Sudan as well).

Figure 3.6: Military expenditure as a percentage of GDP



Besides the three to-be-regressands, we can see some trends also in the dependency ratios. These are, however, unsurprising. The youth dependency ratios are strongly declining as the low-income countries gradually reach the demographic transition. And although even the developing world is ageing, the old-age dependency ratios might not be rising fast simply because of an increasing denominator. The large generations of young people just grow into the working-age population.

Figure 3.7: Dependency ratios



The other trending series include infectious disease prevalence (generally declining), population density (generally rising), GDP per capita (mostly rising), and war deaths per capita (declining almost everywhere, please see Uppsala Conflict Data Program for a general overview).

The ratios of $\frac{government\,budget}{GDP}$ and $\frac{health\,aid}{GDP}$ do not show clear trends. Neither does the (un)freedom variable.

Further, it would be hard to find a normally distributed variable in the dataset. Almost all of them – in all periods – show specific distributions with heavy right tails. With the exception of GDP per capita, logarithmisation does not change the situation significantly. Yet, the exclusion of outliers is out of the question. The countries receiving massive debt relief are mostly outliers. The times of large-scale military conflicts are fortunately also uncommon. So are situations of short-time, large-scale changes in the public expenditure mix. But it is these moments what is most interesting about the whole estimation.

Finally, a minor remark to the trends in the sectoral expenditure-to-GDP ratios. Although trending variables are naturally dependent on their past realisations, in this case even the differences seem to be dependent on past differences. This is underlined by an OLS regression in the first difference form. In both the $\frac{health\,expenditure}{GDP}$ and the $\frac{education\,expenditure}{GDP}$ ratio regressions, two lags appear as statistically significant. Although the estimators are plagued by endogeneity bias, they are consistent. Thus, the possibility that current changes in expenditure mix are influenced by changes that happened ten years ago needs to be considered.

4. Methodology

The economic intuition is not to be ignored: if the public expenditure structure follows long-term strategies of the government, current changes in the spending ratios must be influenced by past changes. Therefore, there is a need to include at least one lag of the dependent variable into all equations.

As the lag is not exogenous, and neither are many of the other regressors, the fixed effects estimators would be biased in this context (Nickell, 1981).

This leads me to the choice of the dynamic panel data method proposed by Arellano & Bond (1991), and its improved version coming from Arellano & Bover (1995) and Blundell & Bond (1998). I will refer to these methods as Arellano-Bond Difference GMM (D-GMM) and Arellano-Bover/Blundell-Bond System GMM (S-GMM), respectively. Both methods are suitable for models with country-specific fixed effects, autocorrelation, and heteroskedasticity in individual panels. Moreover, the original study (Arellano & Bond, 1991) employed the technique on a dataset of 140 entities observed across 7 to 9 periods, together making 1031 observations, which closely resembles the dataframe I am working with: 103 to 110 entities in 6 to 7 periods, summarily 660 to 728 observations.

A closer look at the methods follows.

4.1 Difference GMM

Let us designate the number of periods as T, the number of regressors different from the lagged dependent variable as k, the number of countries as n and the total number of observations $N = nT$.

Then for each $t \in \{3, 4, ..., T\}$ the model can be specified as

$$\Delta y_t = \alpha_1 \cdot \Delta y_{t-1} + \Delta X_t \alpha_2 + \Delta u_t$$

where $\Delta y_t, \Delta y_{t-1}, \Delta u_t \in M(n \times 1)$, $\Delta X_t \in M(n \times k)$, and $\alpha_2 \in M(k \times 1)$. In human language, the Δy_t is a vector of changes in the dependent variable observed across all countries in time t. Besides being influenced by the past changes of itself, it also depends on contemporaneous (and possibly even past) changes in a set of other

regressors, all of which might be endogenous. And it also responds to changes in unobserved effects, Δu_t.

The specification can be rewritten in terms of the complete matrix of differenced regressors, i. e.

$$\Delta y = \Delta R\beta + \Delta u$$

where $\Delta y, \Delta u \in M(n(T-2)\times 1)$, $\Delta R \in M(n(T-2)\times(k+1))$, and $\beta \in M((k+1)\times 1)$.

Further, we construct an instrument matrix Z of the form

$$Z = \begin{pmatrix} Z_1 \\ Z_2 \\ \vdots \\ Z_n \end{pmatrix}$$

where for each $i \in \{1, 2, ..., n\}$ holds

$$Z_i = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & \dots & 0 \\ y_{i1} & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & \dots & 0 \\ 0 & y_{i2} & y_{i1} & 0 & 0 & 0 & \dots & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & y_{i3} & y_{i2} & y_{i1} & \dots & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & y_{i(T-2)} & y_{i(T-3)} & \dots & y_{i1} \end{pmatrix}.$$

This means that we are using no instrument for ΔR_{i2}, but use one instrument y_{i1} for ΔR_{i3}, two instruments for ΔR_{i4}, etc., up to $(T-2)$ instruments for $\Delta R_{i(T-1)}$.

As for any instrument matrix, we must, of course, impose an orthogonality condition, i. e.

$$\mathbb{E}\left(Z^T \Delta u\right) = 0$$

which is, in fact, equivalent to

$$\mathbb{E}\left[Z^T \left(\Delta y - \Delta R\beta\right)\right] = 0.$$

In a typical two-step GMM procedure, we first need to minimise the criterion function

$$Q(\beta) = N\left[\frac{1}{N}\left(\Delta y - \Delta R\beta\right)^T Z\right]\left(Z^T\Omega^* Z\right)^{-1}\left[\frac{1}{N}Z^T\left(\Delta y - \Delta R\beta\right)\right]$$

with the middle factor in the first-step weighting matrix being equal to

$$\Omega^* = \begin{pmatrix} 2 & -1 & 0 & \dots & 0 \\ -1 & 2 & -1 & \dots & 0 \\ 0 & -1 & 2 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 2 \end{pmatrix}.$$

We will thus obtain the first step estimator of the form

$$\hat{\beta}_{1S} = \left[\Delta R^T Z(Z^T\Omega^* Z)^{-1} Z^T \Delta R\right]^{-1} \Delta R^T Z(Z^T\Omega^* Z)^{-1} Z^T \Delta y.$$

Now, we use residuals $\Delta\hat{u}$ to create skedasticity matrices

$$\hat{\Omega}_i = \begin{pmatrix} \Delta\hat{u}_{i3}^2 & \Delta\hat{u}_{i3}^2\Delta\hat{u}_{i4}^2 & \dots & \Delta\hat{u}_{i3}^2\Delta\hat{u}_{iT}^2 \\ \Delta\hat{u}_{i4}^2\Delta\hat{u}_{i3}^2 & \Delta\hat{u}_{i4}^2 & \dots & \Delta\hat{u}_{i4}^2\Delta\hat{u}_{iT}^2 \\ \vdots & \vdots & \ddots & \vdots \\ \Delta\hat{u}_{iT}^2\Delta\hat{u}_{i3}^2 & \Delta\hat{u}_{iT}^2\Delta\hat{u}_{i4}^2 & \dots & \Delta\hat{u}_{iT}^2 \end{pmatrix}$$

which in turn serve us to create a block skedasticity matrix such that

$$\hat{\Omega} = \begin{pmatrix} \hat{\Omega}_1 & 0 & \dots & 0 \\ 0 & \hat{\Omega}_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \hat{\Omega}_n \end{pmatrix}.$$

Finally, we only plug the skedasticity matrix in the original estimator formula instead of Ω^*. Thus, the resulting estimate vector takes on a value of

$$\hat{\beta}_{D-GMM} = \left[\Delta R^T Z(Z^T\hat{\Omega} Z)^{-1} Z^T \Delta R\right]^{-1} \Delta R^T Z(Z^T\hat{\Omega} Z)^{-1} Z^T \Delta y.$$

4.2 System GMM

As the System GMM procedure is an upgrade of the Difference GMM, the means of estimation is similar. There are only two crucial distinctions. The most obvious one concerns the form of the estimated model. Instead of one differenced matrix equation, System GMM estimates a *system* of two matrix equations. Of course, the unique solution is then computed by combining the two equations in a single block matrix model. However, its representation is non-trivial, as the two equations transform the variables in a different way. One of them uses the forward orthogonal deviations (FOD) transformation, while the other uses the standard level form. Thus, the easiest way to display the system is in terms of individual rows of the dataset, i. e.

$$\widetilde{y_{it}} = \gamma_1 \cdot \widetilde{y_{i(t-1)}} + \gamma_2 \cdot \widetilde{x_{1it}} + \gamma_3 \cdot \widetilde{x_{2it}} + ... + \gamma_{k+1} \cdot \widetilde{x_{kit}} + \widetilde{u_{it}}$$

$$\&$$

$$y_{it} = \gamma_1 \cdot y_{i(t-1)} + \gamma_2 \cdot x_{1it} + \gamma_3 \cdot x_{2it} + ... + \gamma_{k+1} \cdot x_{kit} + u_{it}$$

But what do the terms in the first equation actually mean?

Let us denote P_{0it^+} the number of observations of y for country i from later periods than t. Similarly, let us for each $j \in \{1, ..., k\}$ denote P_{jit^+} the observation count of x_j for country i from all periods after t. Naturally, $P_{0i(t-1)^+}$ will then symbolise the number of times y was observed in country i later than at $(t-1)$. Then

$$\widetilde{y_{it}} = \sqrt{\frac{P_{0it^+}}{P_{0it^+} + 1}} \cdot \left(y_{it} - \frac{\sum_{s>t} y_{is}}{P_{0it^+}} \right)$$

$$\widetilde{y_{i(t-1)}} = \sqrt{\frac{P_{0i(t-1)^+}}{P_{0i(t-1)^+} + 1}} \cdot \left(y_{it} - \frac{\sum_{v>t} y_{iv}}{P_{0i(t-1)^+}} \right)$$

and for any $j \in \{1, ..., k\}$

$$\widetilde{x_{jit}} = \sqrt{\frac{P_{jit^+}}{P_{jit^+} + 1}} \cdot \left(x_{jit} - \frac{\sum_{w>t} x_{jiw}}{P_{jit^+}} \right).$$

An analogous thing would hold for the unobserved effects, if they were actually observed.

Such a model lets us then use $t \in \{2, 3, ..., T\}$, which means we now have n more observations than in the previous case – if there are no gaps in the dataset. And

even if there are some, we will have fewer problems with them than in the previous approach. As Difference GMM requires consistent subtractions, the existence of gaps triggers a further observations loss. When using forward orthogonal deviations, we only subtract some averages. And the number of data points over which the mean was taken does not matter much. The second equation in the *system* then does not even contain any differences.

The other crucial distinction is the instrument matrix. Although the overall format is the same as in the previous case, i. e.

$$Z = \begin{pmatrix} Z_1 \\ Z_2 \\ \vdots \\ Z_n \end{pmatrix},$$

the individual blocks now look different:

$$Z_i = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & \dots & 0 & 0 & 0 & 0 & \dots & 0 \\ y_{i1} & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & \dots & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & y_{i2} & y_{i1} & 0 & 0 & 0 & \dots & 0 & 0 & \dots & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & y_{i3} & y_{i2} & y_{i1} & \dots & 0 & 0 & \dots & 0 & 0 & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & y_{i(T-2)} & y_{i(T-3)} & \dots & y_{i1} & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & \dots & 0 & \widetilde{y_{i1}} & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & \dots & 0 & 0 & \widetilde{y_{i2}} & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & \dots & 0 & 0 & 0 & \widetilde{y_{i3}} & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & & \vdots & \vdots & & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & \dots & 0 & 0 & 0 & 0 & \dots & \widetilde{y_{i(T-1)}} \end{pmatrix}$$

The construction assures that the observations transformed via FOD are instrumented by y in level form, while those left in levels are instrumented by y under FOD.

Of course, with such an expanded instrument matrix, we also have a much stricter orthogonality condition. Luckily, its validity can be tested, as will be mentioned further.

After all, there is one subtle distinction: the middle factor Ω^* in the first-step weighting matrix is an identity matrix in the case of S-GMM. The second-step matrix $\hat{\Omega}$ is still the skedasticity matrix obtained from the first-step estimate.

4.3 Standard errors

Traditional GMM theory would suggest that the estimated variance of $\widehat{\beta_{D-GMM}}$ should be equal to

$$\widehat{\mathbb{V}\mathrm{ar}}(\widehat{\beta_{D-GMM}}) = \left[\Delta R^T Z (Z^T \hat{\Omega} Z)^{-1} Z^T \Delta R\right]^{-1}.$$

An analogous thing would hold for the System GMM estimator – only ΔR would need to be replaced by a matrix of all observations of X and lagged y, both transformed and left in levels.

Yet, Windmeijer (2005) showed that such estimates of variance could be severely downward biased. Thus, he proposed their non-trivial correction. Although the corrected standard errors are also biased, they seem to be superior to the original ones. Moreover, their usage assures superiority of the two-step estimators over the one-step ones (Roodman, 2009, p. 97).

Therefore, I base the inference on Windmeijer-corrected standard errors.

4.4 Testing

First, the overall significance of the regressions is tested using the Wald test. If all estimates are put in a single vector $\hat{\beta}$, the test statistic is computed as

$$W = \hat{\beta}^T \left[\widehat{\mathbb{V}\mathrm{ar}}(\hat{\beta})\right]^{-1} \hat{\beta}$$

Under the null hypothesis of joint insignificance of the regressors, W has χ^2_{k+1} distribution. The goal is to reject the null at least at the 10% significance level.

Second, both estimation procedures generate a large number of overidentifying restrictions. Their validity can (and should) be tested. This is done using the Sargan/Hansen J-test, an extension of the Wald test. Let us imagine that the orthogonality condition holds. Then for Difference GMM, it should also hold that the vector

$$\frac{1}{N} Z^T \Delta \hat{u}$$

is not statistically different from $\vec{0}$. Thus, the test statistic is equal to

$$J = \left(\frac{1}{N} Z^T \Delta \hat{u}\right)^T \left(Z^T \hat{\Omega} Z\right)^{-1} \left(\frac{1}{N} Z^T \Delta \hat{u}\right).$$

Under the null hypothesis of the validity of the overidentifying restrictions, J has χ^2_{j-k-1} distribution, with j being the number of instruments used for each country.

The test can be performed in the same way for the System GMM. If we denote ϵ the vector of all residuals from the estimation and Z the S-GMM instrument matrix, it should hold that

$$\frac{1}{N} Z^T \hat{\epsilon}$$

is statistically indistinguishable from $\vec{0}$. Therefore, the test statistic will be

$$J = \left(\frac{1}{N} Z^T \hat{\epsilon}\right)^T \left(Z^T \hat{\Omega} Z\right)^{-1} \left(\frac{1}{N} Z^T \hat{\epsilon}\right),$$

again with the χ^2_{j-k-1} distribution.

It needs to be remarked that the Sargan-Hansen test is a key part of the estimation procedure. If the null hypothesis of restrictions' validity is rejected, the results are worthless. Yet, if the null hypothesis seems extremely likely based on the Sargan/Hansen p-value, we should not be too contented either. It might mean we introduced too many instruments, which is a problem similar to traditional overfitting of the OLS regressions. As the instrument count grows quadratically in T, panels with a lower $\frac{n}{T}$ ratio suffer more from this issue (see Roodman, 2009, p. 98 for a more detailed discussion). To clearly show that my regressions are not overinstrumented, I report the instrument count for each of them.

Finally, I am testing for second-order autocorrelation in the differenced error term using the Arellano-Bond test. This is necessary as autocorrelation can be a source of instrument endogeneity. Let me illustrate the situation for $t \in \{4, ..., T\}$. It clearly holds that $\rho\left(y_{t-2}, u_{t-2}\right) \neq 0$. Thus, if $\rho(\Delta u_t, \Delta u_{t-2}) = \rho(u_t - u_{t-1}, u_{t-2} - u_{t-3}) \neq 0$, it implies a correlation between y_{t-2} and u_t via the u_{t-1}, u_{t-2} twin. Although a first-order autocorrelation test might seem to be more suitable, this is not the case, as Δu_t and Δu_{t-1} share the term of u_{t-1} – which makes the result of the first-order autocorrelation test almost worthless.

Although the System GMM matrices contain variables transformed by forward orthogonal deviations, the autocorrelation testing is also performed using the differenced residuals. The FOD-transformed residuals would naturally be autocorrelated, as the older contain the newer ones by definition.

In all cases, it is suggested that when one finds second-order autocorrelation, one should include a second lag of the dependent variable (Roodman, 2009, p. 119). This would imply that after such an inclusion, third-order autocorrelation is to be tested. Although I found strong persistency in the health spending variable, I could not proceed with further testing due to the limited length of the dataset. As the second-order autocorrelation went down significantly with the inclusion of the second lag, I have to rely on the implausibility of the third-order autocorrelation in such a scenario.

4.5 Technical implementation

Whatever hurdles had to be jumped to perform the regressions, it all seemed almost suspiciously easy thanks to the plm package in R language (Croissant et al., 2021). I used mainly the pgmm and plm methods.

5. Results

The Difference GMM and System GMM estimates are shown next to each other as they are directly comparable. Significance levels for both types of estimates are based on z-tests, which is relevant given the numbers of observations used.

Please note that every time the effect of war deaths is displayed, it concerns the adjusted values exclusively.

5.1 Baseline model

5.1.1 Health expenditure

Estimating the health expenditure equation using Difference GMM, I reached results that are straightforward and in line with most of the previous findings. Somewhat unsurprisingly, the procedure does not display any significant effect of debt relief on government health spending. The insignificance persists even when distinct variables are excluded.

The *no effect* hypothesis is also plausible given the coefficient in front of the $\frac{health\ aid}{GDP}$ variable. This points at statistically significant fungibility of health-oriented development assistance. However, both the significance and the magnitude of the estimate are much lower than in Dieleman et al. (2013) or Lu et al. (2010). The reason is probably my inability to include only aid funnelled to the sector via governments. The publicly available estimates seem to include also the assistance provided via non-governmental organisations, which was not fungible in the estimates of my predecessors. After all, the estimates naturally confirm that ageing populations make governments spend more on healthcare, and that the share of government health spending in the economy grows with increasing government size.

Table 5.1: Health spending model – baseline

	Health exp. to GDP D-GMM
Lagged dependent	0.281*
	(0.161)
2x lagged dependent	−0.400***
	(0.135)
Debt relief to GDP	−0.005
	(0.006)
Health aid to GDP	−0.070*
	(0.038)
Inf. disease prevalence	0.000
	(0.00000)
Old-age dep. ratio	0.002***
	(0.0005)
log(GDP per capita)	0.001
	(0.002)
Unfreedom	−0.0002
	(0.0002)
General exp. to GDP	0.029***
	(0.005)
Observations used	330
Instruments used	13
Hansen test p-value	0.785
AR(2) test p-value	0.246
Wald test p-value	<0.001
Note:	*p<0.1; **p<0.05; ***p<0.01

When using the System GMM approach to estimate the same equation, I was facing appreciable endogeneity, documented by both the autocorrelation testing and the Sargan-Hansen test. Excluding the most recent lags from the instrument matrix did not mitigate this issue. Neither did collapsing the instruments into a lower diagonal matrix or inclusion of further lags as regressors. Still, even this endogeneity-driven regression did not show any effect of debt relief on health spending.

5.1.2 Education expenditure

In this case, both the Difference GMM and System GMM approaches were usable. Sadly, the results of the two procedures were quite dissimilar. This includes even the regressor of interest: the Arellano-Bond procedure shows a positive effect of debt relief on educational expenditure.

Table 5.2: Education spending model – baseline

	Education exp. to GDP			
	D-GMM	S-GMM	D-GMM	S-GMM
Lagged dependent	0.011	0.549***	0.015	0.577***
	(0.128)	(0.137)	(0.125)	(0.122)
Debt relief to GDP	0.069*	0.015	0.069*	0.022
	(0.038)	(0.031)	(0.038)	(0.030)
Youth dep. ratio	−0.0001	0.0001	−0.0001	0.0001
	(0.0002)	(0.00004)	(0.0002)	(0.00004)
War death rate, domestic	−0.0001	−0.00004		
	(0.0001)	(0.00002)		
log(GDP per capita)	−0.002	0.0004	−0.002	0.0003
	(0.004)	(0.001)	(0.004)	(0.0005)
Unfreedom	−0.00000	−0.0005**	−0.00003	−0.0005**
	(0.001)	(0.0002)	(0.0005)	(0.0002)
General exp. to GDP	0.036**	0.057***	0.038*	0.057***
	(0.018)	(0.021)	(0.020)	(0.019)
Observations used	280	669	280	669
Instruments used	18	29	17	27
Hansen test p-value	0.87	0.239	0.873	0.309
AR(2) test p-value	0.161	0.908	0.199	0.969
Wald test p-value	0.096	<0.001	0.063	<0.001
Note:				*p<0.1; **p<0.05; ***p<0.01

Although the debt relief effect is not robust to the choice of estimation method, it seems to be robust to exclusion of variables. Surprisingly, it stays positive even if the general government expenditure is excluded. The third and fourth column in Table 5.2 then show results of the estimation without the $\frac{war\ deaths}{capita}$ ratio, the variable with the highest risk of endogeneity. Even these look promising.

Yet, it is probably not the Holy Grail I was looking for. In this case, the Arellano-Bond procedure depends on an extremely low number of observations. Even the

averaged panel is unbalanced, especially due to hundreds of missing values in the $\frac{education\ expenditure}{GDP}$ ratio.

Another issue is that the debt relief effect falls into insignificance as soon as the second lag of the dependent variable is included as a regressor. Yet, in such a case, the estimation relies on no more than 198 observations, a small fraction of the original dataset with 728 country-years.

In the setting of this equation, the System GMM might be preferable, as it does not rely on differences between neighbouring data points. And however unconvincing the previous results are, the picture becomes much clearer when the $\log\left(\frac{GDP}{capita}\right)$ regressor is excluded.

Table 5.3: Education spending model – wealth excluded

	Education exp. to GDP S-GMM
Lagged dependent	0.563^{***} (0.131)
Debt relief to GDP	0.013 (0.029)
Youth dep. ratio	0.0001^{**} (0.00003)
War death rate, domestic	-0.00005^{***} (0.00002)
Unfreedom	-0.0003 (0.0002)
General exp. to GDP	0.063^{***} (0.020)
Observations used	669
Instruments used	27
Hansen test p-value	0.319
AR(2) test p-value	0.914
Wald test p-value	<0.001
Note:	*p<0.1; **p<0.05; ***p<0.01

Now, the education expenditures seem to be driven by the factors that are supposed to drive them. Directions of the effects are as expected: if a country is plagued by civil war, it certainly has other priorities than schooling. If any country experiences growth of young population relative to the working-age population, it has to finance education more heavily. And quite naturally, the fluctuation of education

expenditure is tied to the fluctuation of resources redistributed in general. Even the unfreedom variable is now very close to being significant. Whether that hints at undemocratic governments willing to have uneducated citizenry is up to the reader's judgment.

5.1.3 Military expenditure

Even in the case of military spending, we can use both the Difference GMM and System GMM, and even in this case, estimates produced by the two methods are significantly different.

Table 5.4: Military spending model – baseline

	Military exp. to GDP	
	D-GMM	S-GMM
Lagged dependent	0.119	0.550***
	(0.136)	(0.071)
Debt relief to GDP	0.005	−0.013
	(0.009)	(0.008)
War death rate, domestic	0.0002**	0.0001***
	(0.0001)	(0.00003)
War death rate, neighbours	−0.00002	0.0001***
	(0.0001)	(0.00004)
Homicide rate	0.00001	−0.00001
	(0.00003)	(0.00002)
Population density	−0.00003	−0.00000
	(0.00003)	(0.00000)
Unfreedom	0.0003	0.0005***
	(0.0003)	(0.0001)
General exp. to GDP	0.017*	0.013***
	(0.009)	(0.004)
Observations used	441	989
Instruments used	22	34
Hansen test p-value	0.121	0.304
AR(2) test p-value	0.323	0.883
Wald test p-value	0.053	<0.001
Note:	*p<0.1; **p<0.05; ***p<0.01	

Although neither model can be discarded purely based on diagnostics, results of the Arellano-Bover/Blundell-Bond procedure are undeniably simpler to interpret.

Although both models show a significant positive effect of domestic wars on the $\frac{military\ expenditure}{GDP}$ ratio and a comovement of military spending with the overall budget size, only the System GMM points at nondemocratic regimes spending more on armed forces and at external war (with external causes) leading to increases in the military budgets.

Of course, the effects of armed conflicts might not be as straightforward as they seem to be. In case of domestic power struggles, the military expenditure might even decline, but the decline of the GDP is probably faster. But especially in the developing world, conflicts in neighbouring countries can easily lead to decreases in domestic military spending: the worse the situation of my neighbours, the fewer resources they have to endanger me, to support insurgent groups on my territory, or to plunder my resources. Thus, the results of the Arellano-Bond procedure might also be logical.

5.2 Sensitivity: budget-standardised financial flows

As the previous results were inconclusive, it might be helpful to divide the dependent variables and the regressors recorded as fractions of GDP by the $\frac{government\ expenditure}{GDP}$ ratio. In other words, I am planning to replace the GDP in denominators by the government budget.

5.2.1 Health expenditure

Therefore, the health model will be specified in the following way:

$$\frac{health\ expenditure}{gov.\ budget} \sim \frac{debt\ relief}{gov.\ budget} + \frac{health\ aid}{gov.\ budget} + inf.\ disease\ prevalence +$$
$$+ old\text{-}age\ dependency\ ratio + log\left(\frac{GDP}{capita}\right) + freedom$$

Of course, I am now excluding the $\frac{government\ expenditure}{GDP}$ regressor itself: in a setting where all relevant variables are standardised by budget size, the standalone variable should be redundant.

Unfortunately, the resulting estimates are not in any way clearer than the previous ones. Once again, the System GMM estimates are plagued by endogeneity and thus cannot be reported. And the Difference GMM does not do more than support the

obvious: with an increasing number of elderly people in the population, the public health expenditures are rising (Table A.8).

Sadly, we have not become any wiser. Not even this time.

5.2.2 Education expenditure

In an analogous way to the health spending model, I estimated the following education-related equation:

$$\frac{education\ expenditure}{gov.\ budget} \sim \frac{debt\ relief}{gov.\ budget} + youth\ dep.\ ratio + \\ + \frac{war\ deaths}{capita} \cdot E + log\left(\frac{GDP}{capita}\right) + freedom$$

where E is the $(1 - guilt\ share)$ transformation used in the baseline model.

Table 5.5: Education spending model – budget basis

	Education to gov. budget	
	D-GMM	S-GMM
Lagged dependent	0.115	0.455***
	(0.146)	(0.130)
Debt relief to budget	0.034	0.008
	(0.040)	(0.035)
Youth dep. ratio	−0.001	0.001***
	(0.001)	(0.0002)
War death rate, domestic	−0.00001	−0.0002*
	(0.0003)	(0.0001)
log(GDP per capita)	−0.042*	0.008***
	(0.023)	(0.002)
Unfreedom	0.004	−0.001
	(0.002)	(0.001)
Observations used	258	623
Instruments used	14	24
Hansen test p-value	0.793	0.365
AR(2) test p-value	0.782	0.531
Wald test p-value	0.011	<0.001
Note:	*p<0.1; **p<0.05; ***p<0.01	

Even these results were, however, somewhat unclear. Once again, the System GMM showed straightforward, easy-to-interpret relations. Moreover, the results remained the same with specific variables excluded, as well as with a changed number of lags used as regressors. Yet, the estimates did not show any clear effect of debt relief.

What is worse, the System GMM results could not be in any way confirmed by the Difference GMM method. The most probable reason is the significant loss of observations due to the need for consistent differencing: the Arellano-Bond procedure used only 258 observations, about a third of the dataset.

5.2.3 Military expenditure

The third model investigated on a per-general-expenditure basis will be quite naturally specified as

$$\frac{military\ exp.}{government\ budget} \sim \frac{debt\ relief}{government\ budget} + \frac{war\ deaths}{capita} \cdot E + \frac{neigh.\ war\ deaths}{capita} \cdot G + homicide\ r. + \ pop.\ density + freedom$$

where E and G are the once again the individual $(1 - guilt\ share)$ transformations.

Now, it was possible to use both the dynamic methods without apparent endogeneity problems or significant losses of observations – and their results were similar to each other. Still, there were differences in statistical significance of specific regressors.

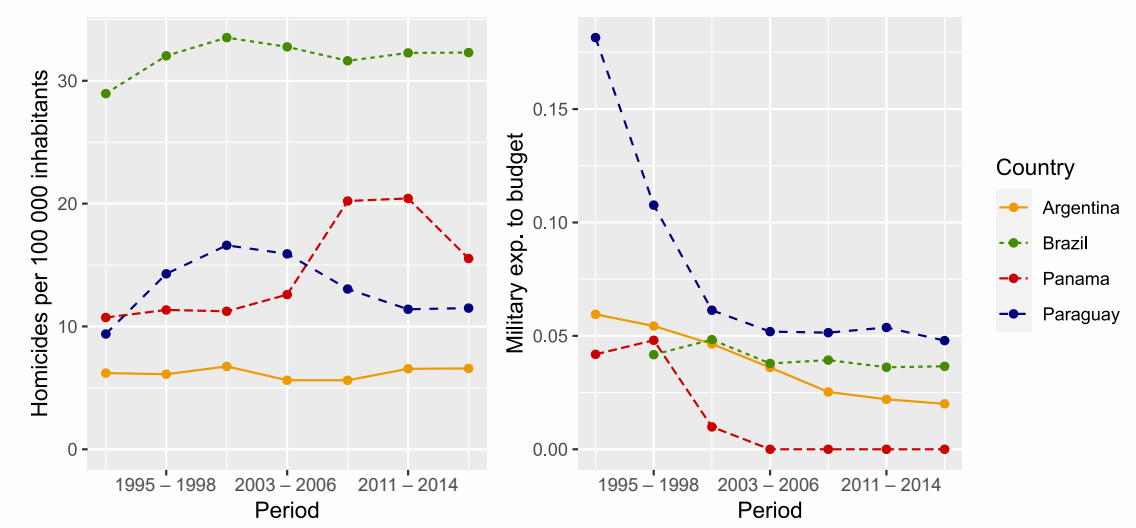
As visible, the effect of debt relief is still questionable. Although results of the Arellano-Bond procedure hint at a negative effect of debt relief on the share of military spending in the budget mix, the coefficient is insignificant when we use the Arellano-Bover/Blundell-Bond procedure.

Table 5.6: Military spending model – budget basis

	Military exp. to budget	
	D-GMM	S-GMM
Lagged dependent	0.639***	0.636***
	(0.119)	(0.095)
Debt relief to budget	−0.015*	−0.014
	(0.009)	(0.011)
War death rate, domestic	0.001**	0.0005***
	(0.0004)	(0.0002)
War death rate, neighbours	0.0001	0.0004**
	(0.0003)	(0.0002)
Homicide rate	−0.0002	−0.00001
	(0.0001)	(0.0001)
Population density	−0.00002	−0.00001
	(0.0001)	(0.00001)
Unfreedom	0.002	0.003***
	(0.002)	(0.001)
Observations used	406	918
Instruments used	15	26
Hansen test p-value	0.299	0.236
AR(2) test p-value	0.981	0.939
Wald test p-value	<0.001	<0.001
Note:	*p<0.1; **p<0.05; ***p<0.01	

At minimum, both methods underscore the obvious fact: domestic conflicts fuel domestic military spending, even if they are caused by external factors. And they tend to support previous findings that nondemocratic regimes invest more in the military. Somewhat surprisingly, they show a negative relation of homicide rate and military part of the budget on the margin of 10% significance. This runs contrary to the hypothesis of significant army involvement in policing when crime rates are high. A possible explanation could be that some military spending is replaced by police budget as crime spins out of control. An alternative hypothesis is a spurious relation – for example, there are multiple countries in Latin America where military spending has been going down steadily, with crime levels remaining approximately the same.

Figure 5.1: Crime and military budgets, Latin America



5.3 Sensitivity: Is Africa different?

All the previous estimations have one important problem: they were done on data from almost the whole developing world. But most of the countries in the dataset received debt relief in such low amounts that it could not be material for their decision making. There are only five countries outside Africa where the ratio $\frac{summary\ debt\ relief}{summary\ GDP}$ was greater than 5 % in any multiannual period I observed.

So why did I waste so much effort on collecting the data, doing the regressions and writing two chapters about it? The reason is straightforward: the statistical methods rely on large-sample inference. Having at most 48 African countries observed across 6 to 7 periods, with many observations missing, is just not enough for a proper estimation – especially not for the Difference GMM. Yet, my temptation to revisit the regressions using African countries only was simply too strong to be ignored.

The estimates of the health equation once again underline the importance of an ageing population for public health spending. And the comovement of health expenditure and total government spending also obviously holds everywhere.

Clearly, the effect of debt relief on public health expenditure cannot be statistically shown, not even in Africa. And *not enough debt relief* shall not be a problem. Virtually the same conclusion can be reached using the budget-standardised equation.

Table 5.7: Health spending model – African subset

	Health exp. to GDP	
	D-GMM	S-GMM
Lagged dependent	0.591	0.976***
	(0.407)	(0.111)
2x lagged dependent	−1.378***	−0.567***
	(0.386)	(0.108)
Debt relief to GDP	−0.013	0.005
	(0.017)	(0.005)
Health aid to GDP	−0.103	0.039
	(0.075)	(0.029)
Inf. disease prevalence	0	0
	(0)	(0)
Old-age dep. ratio	0.004	0.002***
	(0.004)	(0.001)
log(GDP per capita)	0	0
	(0)	(0)
General exp. to GDP	0.069**	0.02**
	(0.028)	(0.01)
Observations used	144	384
Instruments used	12	22
Hansen test p-value	0.103	0.226
AR(2) test p-value	0.75	0.242
Wald test p-value	<0.001	<0.001
Note:	*p<0.1; **p<0.05; ***p<0.01	

A completely different picture arises with the military spending equations. Although the effect of debt relief does not appear when we use $\frac{military\ expenditure}{GDP}$ as the dependent variable, the other results are intuitive and easy to interpret. Besides the correlation of military spending with domestic conflicts and the $\frac{government\ budget}{GDP}$ ratio, we can finally see that – at least in Africa – population density matters. A *Doubting Thomas* could possibly argue that it is purely a time effect, but the variable stays significant even after introducing time dummies.

In such a case, the debt relief effect reappears. It remains significant even after exclusion of two variables, which was done to avoid overfitting problems.

Table 5.8: Military spending model – African subset

	Military exp. to GDP	
	S-GMM	S-GMM & trend
Lagged dependent	0.404***	0.513***
	(0.096)	(0.075)
Debt relief to GDP	−0.010	−0.019*
	(0.010)	(0.011)
War death rate, domestic	0.0002***	0.0002***
	(0.00003)	(0.00002)
War death rate, neighbours	0.0001	0.0001
	(0.0001)	(0.0001)
Homicide rate	0.0001	
	(0.0002)	
Population density	−0.00001**	−0.00002***
	(0.00001)	(0.00001)
Unfreedom	0.0004**	
	(0.0002)	
General exp. to GDP	0.030***	0.023***
	(0.010)	(0.008)
Observations used	434	434
Instruments used	24	20
Hansen test p-value	0.5	0.377
AR(2) test p-value	0.954	0.852
Wald test p-value	<0.001	<0.001
Note:	*p<0.1; **p<0.05; ***p<0.01	

This effect is then supported even by the second specification, where $\frac{military\ expenditure}{government\ budget}$ is used as regressand (Table A.9). The only important change is the exit of population density from the significance territory.

Therefore, it seems that sovereign debt relief has not been supporting local arms races. Although the evidence of a positive debt relief – social spending relation is weak, at least the side effects and unintended consequences seem to be limited at maximum (see Collier & Hoeffler, 2007, for a similar discussion about ODA).

Now, why am I not showing any estimates of the education spending equation? The reason is that the number of observations is simply *too* low. A high number of missing observations in the $\frac{education\ expenditure}{GDP}$ ratio makes even the System GMM estimation unviable.

5.4 Sensitivity: OLS estimates

As mentioned previously, models based on ordinary least squares estimation are not suitable for this analysis. Their estimates are biased and inconsistent due to endogeneity of regressors and persistence in the dependent variables. Still, they might serve us as a reference and possibly also a robustness check.

And although all OLS estimates are probably wrong in this context, some of them are more wrong than the others. As the equations include country-specific time-invariant unobserved effects, pooled OLS or between estimates would be meaningless. As these effects are probably correlated with some of the regressors[1], there is also no point in using the FGLS-based random effects estimator. If we could claim the within estimator is close to being consistent, we could also reject the random effects based on the Hausman test – which in all cases showed p-values far below 10^{-3}.

5.4.1 Health expenditure

When revisiting health spending equation, both OLS models show results that are similar to the Difference GMM. At least the most obvious effects have withstood the complete change of approach. The fungibility of health aid has not. This once again underlines how important it is to distinguish health-sector assistance to the government from that given to the other actors.

Further, the OLS points at a deleterious effect of authoritarian and totalitarian regimes on health spending. Although it does not appear as significant in the D-GMM results, one should not overlook it. We have seen previously how education spending suffers under a dictatorship. And although the reasons why education and health spending should be treated differently are sound[2], the temptation of the authoritarians to cut *yet another social spending* might be strong.

Besides that, the estimates hint at a correlation between the prevalence of infectious diseases and health spending. Such a connection seems reasonable but can easily be endogeneity-driven: the long-term relationship between the two variables is two-sided.

[1] For example, the quality of democracy could correlate with the tradition of a regardful society, which then influences social expenditure. Similarly, the GDP per capita correlates with the incidence of natural resources, which might in turn correlate with the education expenditure as mining-oriented economies might need less human capital.

[2] Besides aiming for uneducated citizenry, the dictatorships might also rely on public support from the elderly. Moreover, healthcare is closer to a necessity than education. Cutting it might be to a detriment of the regime itself.

Table 5.9: Health spending model – OLS estimates

	Health exp. to GDP			
	Yearly data – all		Periods – Africa	
	FD	FE	FD	FE
Debt relief to GDP	0.0002	−0.002	0.001	−0.002
	(0.001)	(0.002)	(0.004)	(0.008)
Health aid to GDP	0.004	−0.019	−0.019	−0.013
	(0.007)	(0.015)	(0.038)	(0.040)
Inf. disease prevalence	$0.6 \cdot 10^{-7}$ *	$0.5 \cdot 10^{-7}$ ***	$1.4 \cdot 10^{-7}$ **	$0.6 \cdot 10^{-7}$
	$(0.3 \cdot 10^{-7})$	$(0.15 \cdot 10^{-7})$	$(0.6 \cdot 10^{-7})$	$(0.4 \cdot 10^{-7})$
Old-age dep. ratio	0.001***	0.002***	0.0001	0.001*
	(0.0002)	(0.0001)	(0.001)	(0.001)
log(GDP per capita)	−0.002**	0.002***	−0.0001	0.001
	(0.001)	(0.001)	(0.002)	(0.002)
Unfreedom	−0.0001	−0.0003***	−0.0004*	−0.001***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
General exp. to GDP	0.027***	0.030***	0.032***	0.036***
	(0.001)	(0.002)	(0.005)	(0.007)
Constant	0.0002***		0.001*	
	(0.0001)		(0.0004)	
Observations	2,244	2,354	226	274
R^2	0.309	0.212	0.182	0.218
Adjusted R^2	0.307	0.171	0.156	0.025
F-test p-value	<0.001	<0.001	<0.001	<0.001
Note:				*p<0.1; **p<0.05; ***p<0.01

When the financial flows are standardised by the summary budget, many correlations disappear (Table A.10). What is worse, estimates of the two models do not largely support each other. The only effect which is the same in both is that of the old-age dependency ratio, which is, however, trivial.

5.4.2 Education expenditure

In contrast to the health expenditure equation, OLS estimates of the education spending relations are not promising (Table A.11). It is pleasant that the first difference transformation supports the positive effect of debt relief on public education spending, but the ambiguity of almost all the other effects should raise eyebrows. So should the negative adjusted R^2 of the fixed effects transformation. And the

correlation of education spending with total spending, which survives any changes in variables and estimation techniques, is rather trivial and uninteresting.

Even a worse picture arises when the financial flows are standardised by the government budget. With negative adjusted R^2 and an F-test p-value of 0.3, the estimation results do not even deserve to be reported.

5.4.3 Military expenditure

After all, not even the military expenditure equation seems to be estimated well by OLS. The first difference estimator does not confirm the trivial relation between war deaths recorded on domestic soil and military budget. The estimates hinting at enmity of African despots and their armies are nonsensical. The low significance of government size, at least in Africa, is also implausible in the context of previous estimates. Still, we are able to confirm the negative effect of population density on military spending. However spurious the relation might be, the estimate for the African subsample should be valid.

Table 5.10: Military spending model – OLS estimates

	Military exp. to GDP			
	Yearly data – all		Periods - Africa	
	FD	FE	FD	FE
Debt relief to GDP	−0.002	−0.005	−0.004	−0.006
	(0.003)	(0.005)	(0.011)	(0.014)
War death rate, domestic	0.00002	0.0001***	0.0002***	0.0002***
	(0.00002)	(0.00002)	(0.0001)	(0.00004)
War death rate, neighbours	−0.00000	−0.00001	−0.00003	−0.00002
	(0.00001)	(0.00001)	(0.00005)	(0.00004)
Homicide rate	0.00002	−0.00001	0.0004	−0.0002
	(0.00005)	(0.00004)	(0.0004)	(0.0002)
Population density	−0.00000	−0.0001***	−0.00004	−0.0001***
	(0.00004)	(0.00001)	(0.0001)	(0.00003)
Unfreedom	0.00004	0.0001	−0.00001	−0.0001
	(0.0002)	(0.0001)	(0.0005)	(0.0004)
General exp. to GDP	0.006***	0.007***	0.004*	0.003
	(0.001)	(0.001)	(0.002)	(0.002)
Constant	−0.0003*		−0.001	
	(0.0001)		(0.001)	
Observations	2,215	2,318	232	278
R^2	0.008	0.103	0.073	0.146
Adjusted R^2	0.005	0.059	0.076	0.039
F-test p-value	0.017	<0.001	<0.001	<0.001
Note:				*p<0.1; **p<0.05; ***p<0.01

Nevertheless, the standardisation of the financial flows by general spending instead of GDP changes the picture for the better (Table A.12). The straightforward and GMM-confirmed positive effects of wars and dictatorships on military spending are now further underlined. And we see some confirmation of the previously found negative impact of debt relief on military expenditure. It was probably not a pure coincidence.

5.5 Limitations and further research opportunities

My inability to reach *robust enough* results is undoubtedly the single most important limitation of the analysis. Yet, it might not be an issue of model design, variable selection or econometric method chosen. I am afraid that establishing a solid relationship between debt relief and government expenditure mix using data analysis is close to impossible. The true mistake is the genre chosen. If a few competent journalists delved into this topic, they would likely gather much more information by interviewing a number of high-ranking officials across the developing world. As a bonus, they would gain insight into country-specific factors and would be spared of the generalisations an econometrician is forced to make.

But if we remain in the framework of data science, the data availability itself is a crucial limitation. The most troublesome point concerns debt relief: my data capture largely the periods when debt relief was disbursed, not when it was promised. As the promises were often conditional, some changes in the spending structures might have realised already before the disbursement itself. I tried to solve this issue by working with multiannual averages and experimented also with forward lags of the debt relief variable, but some effects might still have gone unnoticed.

A tempting idea would then be to select the large debt relief events manually, transform them into qualitative variables and then use difference-in-differences or the synthetic control method. In such a case, the challenge would be not only to find a suitable threshold for a *large* event, but also the necessity to use Asian or Latin American countries as a control group for the African ones.

Some more interesting improvements could be made to the military expenditure model. To capture the domestic security situation, I included the intentional homicide rate and deaths caused by wars on the given territory. But during the analysis, I recognised that this might be an oversimplification. If a country experiences regular prison uprisings with numerous fatalities, it influences military spending in a different way than a drug war. Similarly, deadly communal conflicts over grazelands will have a different effect than terrorism or an anti-government insurgency. The situation is even worse with the war deaths in neighbouring countries. Although they should capture how (in)secure the given region is, they might be misleading when the neighbouring countries are large. For example, the war deaths of Mongolia's neighbours include the Chechen Wars, even though the Caucasus is more than 3000 kilometres away from Mongolia. Thus, researchers revisiting this topic might be more comfortable if they exclude some deaths or if they separate the deaths into

more variables. The deaths abroad can possibly also be weighted using an inverse of the distance from the border to the location where they occurred.

Even if such a careful re-examination does not find any relation between debt relief and military expenditure, it might still enrich human knowledge. Especially given how rare studies explaining military spending are.

After all, one limitation lies also in the standardisation of financial flows. If debt relief leads to increases in both GDP and government budget of the recipients, it can indeed contribute to significant increases in social spending. Yet, if the spending does not increase relative to wealth, can the social sector expand? Can it attract more labour and capital? One can successfully doubt that. Besides that, notedly, the evidence of the debt relief – GDP growth relation is also rather weak (e. g. Chauvin & Kraay, 2005, Johansson, 2010, or Djimeu, 2018).

6. Conclusion

In this thesis, I examined the relationship of sovereign debt relief and recipients' expenditure on three key sectors: healthcare, education, and military. The choice was not random: an increase in health and education spending was one of the key goals of the HIPC debt relief initiative, and increases in military spending might have been an unintended consequence.

With the aim to perform three panel data regressions, I built a dataset containing 114 developing countries and numerous variables related to economics, society, and politics. The source values came from influential, authoritative databases and were often manually rechecked by other sources. In the case of conflict-related fatalities, they were even adjusted for the level of voluntary involvement of individual countries in the given conflicts.

Facing limited availability of some indicators, I created three subsets of the dataframe, one for each regression equation. To reduce noise and the number of gaps, I averaged all data into four-year intervals. Consequently, the health expenditure subset contains 110 countries observed in six multiannual periods from 1995 to 2017; the education expenditure subset encompasses 104 countries in seven periods from 1991 to 2018; and the military expenditure subset includes 103 countries also in seven intervals from 1991 to 2018.

As the regressands are in all cases dependent on their own past realisations, and at least some regressors are not strictly exogenous, I utilised two dynamic panel data approaches: the Arellano-Bond Difference GMM and the Arellano-Bover/Blundell-Bond System GMM.

The results are ambiguous. I found no statistically significant effect of sovereign debt relief on public health expenditure, regardless of the approach chosen or variables included. I reached a significant positive effect of debt relief on government education spending and a significant negative effect on military spending. Although both of them were robust to inclusion and exclusion of specific variables and to some changes in estimation approaches, a majority of the models showed them as insignificant. As the latter effect always remained negative and often only slightly behind the

significance threshold, there is a considerable probability that debt relief does not fuel arms races[1].

Researchers willing to reach more robust results might prefer to focus exclusively on determinants of military expenditure in the developing world. Influential, trustworthy studies on this topic are rather rare – and research largely overlooks case-specific dynamics.

[1]Please find the overview of the effects found in Table A.13

7. References

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A. Appendix

Health expenditure dataset: countries

Afghanistan
Albania
Algeria
Angola
Antigua and Barbuda
Argentina
Armenia
Bangladesh
Barbados
Belize
Benin
Bolivia
Bosnia and Herzegovina
Botswana
Brazil
Burkina Faso
Burundi
Cabo Verde
Cambodia
Cameroon
Central African Republic
Chad
Chile
Colombia
Comoros
Dem. Rep. of the Congo
Rep. of the Congo
Costa Rica
Cote d'Ivoire
Djibouti
Dominica
Dominican Republic
Ecuador
Egypt
El Salvador
Equatorial Guinea
Ethiopia
Gabon
The Gambia
Georgia
Ghana
Grenada
Guatemala
Guinea
Guinea-Bissau
Guyana
Haiti
Honduras
India
Indonesia
Iraq
Jamaica
Jordan
Kazakhstan
Kenya
Kyrgyzstan
Laos
Lebanon
Lesotho
Liberia
Madagascar
Malawi
Mali
Mauritania
Mauritius
Mexico
Moldova
Mongolia
Montenegro
Morocco
Mozambique
Myanmar
Namibia
Nepal
Nicaragua
Niger
Nigeria
North Macedonia
Pakistan
Panama
Paraguay
Peru
Philippines
Rwanda
Samoa
Sao Tome and Principe
Senegal
Serbia
Seychelles
Sierra Leone
Solomon Islands
Sri Lanka
St. Lucia
St. Vincent
Sudan
Suriname
Tajikistan
Tanzania
Thailand
Togo
Tonga
Trinidad and Tobago
Tunisia
Uganda
Uruguay
Vanuatu
Vietnam
Yemen
Zambia
Zimbabwe

Education expenditure dataset: countries

Afghanistan
Albania
Algeria
Angola
Antigua and Barbuda
Argentina
Armenia
Bangladesh
Barbados
Belize
Benin
Botswana
Brazil
Burkina Faso
Burundi
Cabo Verde
Cambodia
Cameroon
Central African Republic
Chad
Chile
Colombia
Comoros
Dem. Rep. of the Congo
Rep. of the Congo
Costa Rica
Cote d'Ivoire
Djibouti
Dominica
Dominican Republic
Ecuador
Egypt
El Salvador
Equatorial Guinea
Ethiopia
Gabon
The Gambia
Georgia
Ghana
Grenada
Guatemala
Guinea
Guinea-Bissau
Guyana
Haiti
Honduras
India
Indonesia
Jamaica
Jordan
Kazakhstan
Kenya
Kyrgyzstan
Laos
Lebanon
Lesotho
Liberia
Madagascar
Malawi
Mali
Mauritania
Mauritius
Mexico
Moldova
Mongolia
Morocco
Mozambique
Myanmar
Namibia
Nepal
Nicaragua
Niger
North Macedonia
Pakistan
Panama
Paraguay
Peru
Philippines
Rwanda
Samoa
Sao Tome and Principe
Senegal
Serbia
Seychelles
Sierra Leone
Solomon Islands
Sri Lanka
St. Lucia
St. Vincent
Sudan
Tajikistan
Tanzania
Thailand
Togo
Tonga
Trinidad and Tobago
Tunisia
Uganda
Uruguay
Vanuatu
Vietnam
Yemen
Zambia
Zimbabwe

Military expenditure dataset: countries

Afghanistan
Albania
Algeria
Angola
Argentina
Armenia
Bangladesh
Belize
Benin
Bolivia
Bosnia and Herzegovina
Botswana
Brazil
Burkina Faso
Burundi
Cabo Verde
Cambodia
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Dem. Rep. of the Congo
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Djibouti
Dominica
Dominican Republic
Ecuador
Egypt
El Salvador
Equatorial Guinea
Ethiopia
Gabon
The Gambia
Georgia
Ghana
Grenada
Guatemala
Guinea
Guinea-Bissau
Guyana
Honduras
India
Indonesia
Iraq
Jamaica
Jordan
Kazakhstan
Kenya
Kyrgyzstan
Laos
Lebanon
Lesotho
Liberia
Madagascar
Malawi
Mali
Mauritania
Mauritius
Mexico
Moldova
Mongolia
Montenegro
Morocco
Mozambique
Myanmar
Namibia
Nepal
Nicaragua
Niger
Nigeria
North Macedonia
Pakistan
Panama
Paraguay
Peru
Philippines
Rwanda
Samoa
Senegal
Serbia
Seychelles
Sierra Leone
Solomon Islands
Sri Lanka
St. Lucia
St. Vincent
Sudan
Tajikistan
Tanzania
Thailand
Togo
Trinidad and Tobago
Tunisia
Uganda
Uruguay
Vanuatu
Vietnam
Yemen
Zambia
Zimbabwe

Table A.1: List of variables

Variable	Explanation	Source
Health exp. to GDP	Government health expenditure coming from other sources than health-destined development aid, divided by GDP	IHME (2020a)
Education exp. to GDP	Government expenditure on education, divided by GDP	World Bank (2020a)
Military exp. to GDP	Government expenditure on military, divided by GDP	SIPRI (2020)
Debt relief to GDP	Sovereign debt relief provided by official creditors to the given country, divided by GDP	OECD (2020) IMF (2020b)
Health aid to GDP	Official development assistance for health sector from which the given country benefited, divided by GDP	IHME (2020a)
Inf. disease prevalence	Summary prevalence of infectious diseases, cases per 100,000 inhabitants	IHME (2020b)
Old-age dep. ratio	Number of people over 65 years of age per 100 people aged 15 to 65	World Bank (2020e)
log(GDP per capita)	GDP per capita in 2017 international dollars, natural log-transformed	IMF (2020c)
Unfreedom	Sum of the Civil liberties and Political rights variables from the Freedom in the World reports	Freedom House (2021)
General exp. to GDP	Sum of all government expenditures divided by GDP	IMF (2020d)
Youth dep. ratio	Number of people under 15 years of age per 100 people aged 15 to 65	World Bank (2020d)

Table A.2: List of variables, continued

Variable	Explanation	Source
War death rate, domestic	Number of people killed at war and army-perpetrated massacres per 100,000 inhabitants. Excludes crime and most police violence. Excludes deaths caused by unnecessary, unprovoked actions led by the government itself.	IHME(2020b)
War death rate, neighbours	Number of people killed at war and army-perpetrated massacres in neighbouring countries of the given entity, per 100,000 inhabitants of the neighbouring entities. Excludes crime and most police violence. Excludes deaths caused by an unnecessary military action led by the government of the given country.	IHME(2020b)
Homicide rate	Number of people intentionally killed by criminals per 100,000 inhabitants of the given country	IHME (2020b)
Population density	Number of inhabitants per one square kilometre of the country's area	World Bank (2020b) World Bank (2020c)

Table A.3: List of variables, continued

Variable	Explanation	Source
Health exp. to budget	*Health exp. to GDP* variable, divided by *General exp. to GDP* variable	IHME (2020a) IMF (2020d)
Education exp. to budget	*Education exp. to GDP* variable, divided by *General exp. to GDP* variable	World Bank (2020a) IMF (2020d)
Military exp. to budget	*Military exp. to GDP* variable, divided by *General exp. to GDP* variable	SIPRI (2020) IMF (2020d)
Debt relief to budget	*Debt relief to GDP* variable, divided by *General exp. to GDP* variable	OECD (2020) IMF (2020d)
Health aid to budget	*Health exp. to GDP* variable, divided by *General exp. to GDP* variable	IHME (2020a) IMF (2020d)

Table A.4: Health dataset: correlation matrix

	Unfreedom	Health exp. to GDP	Health aid to GDP	Debt relief to GDP	Inf. disease prevalence	GDP per capita	Old-age dep. ratio	General exp. to GDP
Unfreedom	1							
Health exp. to GDP	-0.481	1						
Health aid to GDP	0.084	-0.163	1					
Debt relief to GDP	0.023	-0.138	0.260	1				
Inf. disease prevalence	0.245	-0.517	0.356	0.294	1			
GDP per capita	-0.366	0.471	-0.438	-0.223	-0.523	1		
Old-age dep. ratio	-0.416	0.539	-0.347	-0.183	-0.622	0.572	1	
General exp. to GDP	-0.238	0.573	-0.040	-0.055	-0.485	0.320	0.361	1

Table A.5: Education dataset: correlation matrix

	Unfreedom	Population density	Education exp. to GDP	War death rate, domestic	Debt relief to GDP	GDP per capita	Youth dep. ratio	General exp. to GDP
Unfreedom	1							
Population density	-0.190	1						
Education exp. to GDP	-0.206	-0.082	1					
War death rate, domestic	0.240	-0.009	-0.026	1				
Debt relief to GDP	0.012	-0.073	-0.075	-0.009	1			
GDP per capita	-0.367	0.110	0.124	-0.147	-0.212	1		
Youth dep. ratio	0.400	-0.290	-0.123	0.205	0.248	-0.687	1	
General exp. to GDP	-0.073	-0.055	0.558	-0.025	-0.056	0.122	-0.138	1

Table A.6: Military dataset: correlation matrix

	Unfreedom	Population density	Military exp. to GDP	War death rate, domestic	Debt relief to GDP	Homicide r.	War death rate, neighbours	GDP per capita	General exp. to GDP
Unfreedom	1								
Population density	-0.146	1							
Military exp. to GDP	0.428	-0.080	1						
War death r., d.	0.254	0.002	0.232	1					
Debt relief to GDP	0.024	-0.082	-0.050	0.026	1				
Homicide rate	-0.235	-0.018	-0.094	-0.044	-0.073	1			
War death rate, neighbours	0.170	0.064	0.237	0.162	-0.001	-0.087	1		
GDP per capita	-0.353	0.082	-0.101	-0.131	-0.211	0.137	-0.042	1	
General exp. to GDP	-0.053	-0.067	0.108	0.043	-0.058	0.028	-0.001	0.136	1

Table A.7: Expenditure ratios: correlation matrix

	Military exp. to GDP	Education exp. to GDP	Health exp. to GDP
Military exp. to GDP	1		
Education exp. to GDP	-0.027	1	
Health exp. to GDP	0.003	0.451	1

Table A.8: Health spending model – budget basis

	Health exp. to gov. budget
	D-GMM
Lagged dependent	−0.049
	(0.342)
2x lagged dependent	0.245
	(0.246)
Debt relief to budget	0.005
	(0.006)
Health aid to budget	0.033
	(0.062)
Inf. disease prevalence	−0.00000
	(0.00000)
Old-age dep. ratio	0.004*
	(0.002)
log(GDP per capita)	0.003
	(0.009)
Unfreedom	−0.001
	(0.002)
Observations used	302
Instruments used	11
Hansen test p-value	0.497
AR(2) test p-value	0.314
Wald test p-value	0.0077
Note:	*p<0.1; **p<0.05; ***p<0.01

Back to text (1)

Table A.9: Military spending model – budget basis, African subset

	Military exp. to gov. budget	
	D-GMM (Africa)	S-GMM (Africa)
Lagged dependent	0.688***	0.586***
	(0.253)	(0.133)
Debt relief to budget	−0.016	−0.016*
	(0.014)	(0.009)
War death rate, domestic	0.001*	0.001***
	(0.001)	(0.0002)
War death rate, neighbours	0.001	0.001*
	(0.001)	(0.001)
Homicide rate	−0.001	0.001
	(0.001)	(0.0003)
Population density	0.0001	−0.0001
	(0.0001)	(0.00004)
Unfreedom	0.001	0.003**
	(0.003)	(0.001)
Observations used	177	403
Instruments used	15	22
Hansen test p-value	0.358	0.502
AR(2) test p-value	0.713	0.704
Wald test p-value	<0.001	<0.001
Note:	*p<0.1; **p<0.05; ***p<0.01	

Back to text (2)

Table A.10: Health spending model – OLS, budget basis

	Health exp. to gov. budget	
	FD	FE
Debt relief to budget	0.003	0.0004
	(0.004)	(0.008)
Health aid to budget	0.107***	0.029
	(0.038)	(0.045)
Inf. disease prevalence	$2.4 \cdot 10^{-7}$	$5.6 \cdot 10^{-7}$ ***
	$(2.2 \cdot 10^{-7})$	$(1.4 \cdot 10^{-7})$
Old-age dep. ratio	0.004***	0.005***
	(0.001)	(0.001)
log(GDP per capita)	−0.004	0.005
	(0.007)	(0.006)
Unfreedom	0.001	−0.001
	(0.001)	(0.001)
Constant	−0.001	
	(0.001)	
Observations	522	632
R^2	0.040	0.077
Adjusted R^2	0.029	−0.129
F-test p-value	0.002	<0.001
Note:	*p<0.1; **p<0.05; ***p<0.01	

Back to text (3)

Table A.11: Education spending model – OLS estimates

	Education exp. to GDP	
	FD	FE
Debt relief to GDP	0.034*	0.016
	(0.018)	(0.021)
Youth dep. ratio	0.00002	0.0001
	(0.0002)	(0.0001)
War death rate, domestic	0.00000	−0.0001
	(0.0001)	(0.00005)
log(GDP per capita)	−0.003	0.004
	(0.006)	(0.003)
Unfreedom	0.001	0.0002
	(0.001)	(0.0005)
General exp. to GDP	0.080***	0.098***
	(0.016)	(0.014)
Constant	0.001	
	(0.001)	
Observations	399	503
R^2	0.072	0.140
Adjusted R^2	0.057	−0.098
F-test p-value	<0.001	<0.001
Note:	*p<0.1; **p<0.05; ***p<0.01	

Back to text (4)

Table A.12: Military spending model – OLS, budget basis

	Military exp. to gov. budget	
	FD	FE
Debt relief to budget	-0.015^{**}	-0.015
	(0.007)	(0.011)
War death rate, domestic	0.001^{***}	0.001^{***}
	(0.0002)	(0.0002)
War death rate, neighbours	0.0001	0.0004^{***}
	(0.0001)	(0.0001)
Homicide rate	-0.0001	0.0002
	(0.0003)	(0.0004)
Population density	-0.0001	-0.0004^{***}
	(0.0001)	(0.0001)
Unfreedom	0.002	0.002
	(0.001)	(0.001)
Constant	-0.005^{***}	
	(0.002)	
Observations	520	623
R^2	0.089	0.171
Adjusted R^2	0.078	-0.004
F-test p-value	<0.001	<0.001
Note:	*p<0.1; **p<0.05; ***p<0.01	

Back to text (5)

Table A.13: Summary of the debt relief effects found

Method	Equation	Health exp.	Education exp.	Military exp.
GMM	GDP-standardised	0/N	+/0	0/0
GMM	Budget-standardised	0/N	0/0	-/0
GMM	African subset, GDP-std.	0/0	N/N	0/-
GMM	African subset, budget-std.	0/0	N/N	0/-
OLS	GDP-standardised	0/0	+/0	0/0
OLS	Budget-standardised	0/0	0/0	-/0
OLS	African subset, GDP-std.	0/0	N/N	0/0

Note: The first result comes from D-GMM for GMM rows & from FD for OLS rows
The second result comes from S-GMM for GMM rows & from FE for OLS rows

Back to text (6)