Foreign Aid and Structural Change

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Abstract

This paper explores the effects of DAC and Chinese aid on the sectoral structure of Sub-Saharan African economies. It extends the GGDC/UNU-WIDER Economic Transformation Database with sub-national sectoral employment data such that analysis can be performed at the national and sub-national levels. 2SLS regressions are estimated using a novel IV strategy for identifying the effects of aid which exploits exogenous variation in the frequency and severity of natural disasters in donor countries. The findings suggest that Chinese aid is more conducive for industrialization in recipient countries than DAC aid. On average, a ten percent increase in DAC aid causes an estimated 0.14 percentage point *decrease* in the manufacturing employment share after four years, whereas Chinese aid may cause an *increase*. Policy implications for DAC aid and industrialization-led development strategies are discussed.

Keywords— aid effectiveness, foreign aid, deindustrialization, structural change, DAC aid, Chinese aid, regional aid, Dutch Disease, urbanization, Economic Transformation Database, manufacturing share, agricultural share.

1 Introduction

Foreign aid from Development Assistance Committee [DAC] donors remains a major feature of the economic landscape of Sub-Saharan Africa. Whilst there is an extensive literature on the effects of such aid on many aspects of the macroeconomy, there is little direct research into the impact aid has on the *economic structure* of recipient countries. This is surprising given the influence structural change can have on the nature and magnitude of economic growth (Herrendorf et al. 2014; McMillan et al. 2014). Furthermore, the 21st-century has seen the rapid emergence of a major new international donor. China, which has never been a member of the DAC, on some occasions now gives more aid to specific countries than the entire DAC combined. There is evidence that aid from China differs vastly from DAC aid in terms of nature and intention (Bello 2019; Dunford 2020; Xu & Zhang 2020); development priorities and interventions (Berthelemy 2011; Brazys et al. 2017; Bluhm et al. 2018); and conditionality and expropriability (Dreher et al. 2018; Anaxagorou et al. 2020). This naturally begs the question of whether Chinese and DAC aid also differ in terms of *impact*, especially impact on structural transformation.

This paper positions itself at the intersection of the structural change and aid effectiveness literatures in order to the explore the effects of both DAC and Chinese aid on the economic structure of recipient countries, particularly as relates to industrialization. It is hypothesized that conventional aid inflows may suppress the manufacturing sector, but this is less likely so in the case of Chinese aid. The theoretical foundations for these hypotheses stem from the "Dutch-disease" mechanism, whereby aid as a large inflow of foreign capital drives an appreciation of the real exchange rate to the disadvantage of tradeable manufactures (Rajan & Subramanian 2011; Diao & McMillan 2018). However, this would only result in reduced relative manufacturing overall if the aid does not concomitantly increase manufacturing productivity (Gollin et al. 2015), and there is more reason to expect this in the case of DAC aid than Chinese aid (Berthelemy 2011; Page 2012). In particular, the explicit rural and agricultural focus of DAC aid in recent years (OECD 2012; United Nations 2016) contrasts starkly with the Chinese aid focus on urban and economic infrastructure (Bluhm et al. 2018; Xu & Zhang 2020), the latter of which can increase manufacturing productivity via externalities and agglomeration effects.

In order to explore the effects of aid on the structure of the economies of SSA at the national level, this paper utilizes the newly released Economic Transformation Database [ETD] from UNU-WIDER and the Groningen Growth and Development

Centre [GGDC] (de Vries et al. 2021) which provides sectoral employment and VA data for a large set of SSA countries. However, there is sometimes a healthy scepticism of aid effects estimated at purely the national level due to the broadness of these aggregates (Addison et al. 2017) and the tendency of findings to differ at lower levels of aggregation (Mosley 1986; Arndt et al. 2010). For this reason, this paper extends the GGDC/UNU-WIDER database to present a new Subnational Economic Transformation Database [SETD] which compiles regional sectoral employment shares across 122 regions of 8 different countries of Sub-Saharan Africa and allows for structural change analysis to be performed at the subnational level. Reliable data for Chinese aid comes from the pioneering new geolocated data-set of the universe of Chinese aid projects, compiled by Bluhm et al. (2018) and Dreher et al. (2021). The nature of this data-set allows for the isolation of only those Chinese aid flows which are directly comparable to conventional DAC aid in terms of financing structure and composition, so Chinese investment in the guise of aid is excluded.

At the national level, identification is established via 2SLS regressions with panel fixed effects, which are estimated using a novel IV strategy with newly constructed instrument sets inspired by Nunn & Qian (2014) and Dreher & Langlotz (2017), combining two sources of variation. First, this paper exploits plausibly exogenous time variation in the total volumes of both DAC and Chinese aid driven by the frequency and severity of natural disasters occurring in donor countries. Second, cross-sectional variation is introduced on the basis of varying likelihood of being a Chinese aid recipient, or varying weights of the composition of total DAC aid across the individual donor countries of the DAC. The interaction of these two sources of variation yields separate sets of instruments for Chinese and DAC aid which exhibit full panel variation. The disaster based instruments for Chinese aid were first presented in Hamilton et al. (2021); this paper expands upon the same principle by constructing a set of *weighted average index* instruments for the full DAC. It is shown that both instrument sets for DAC and Chinese aid are sufficiently strong, and it is argued that both satisfy the exclusion restriction. The control set includes alternative theoretical drivers of structural change (van Neuss 2019; Mensah 2020), which allows for comparison of the significance and magnitude of the aid effects. At the subnational level, results come from OLS panel fixed effects regressions.

The results show that DAC and Chinese aid differ greatly in terms of their impacts on recipient country economic structure, and that Chinese aid is in fact *more conducive* for recipient country industrialization and the relative size of the manufacturing sector in Sub-Saharan Africa. DAC aid is estimated to have reduced the relative manufacturing share of the economies of Sub-Saharan Africa, especially in terms of employment; these effects are statistically significant and economically meaningful. Conversely, there is no such deindustrializing effect of Chinese aid, and the preferred 2SLS specifications suggest that Chinese aid positively impacted the manufacturing share. In terms of the effect sizes, a ten percent increase in the flow of DAC aid causes an approximately 0.142 percentage point decrease in the relative size of the manufacturing share of employment after four years, *ceteris paribus*. By contrast, a ten percent increase in the flow of Chinese aid causes an approximately 0.052 percentage point increase in this manufacturing share. The effects on manufacturing value added share are similar for both aid types although not as regularly significant across all specifications. An econometric horse-race confirms the expectation that the pro-industrialization effects of Chinese aid were insufficient to fully mitigate the deindustrializing effects of DAC aid. At the subnational level, the results are the same in terms of direction and statistical significance, although they are of smaller magnitude and diffuse more quickly. This is likely because aid to regions is often 'one-shot', and less frequent or sustained than at the national level.

The paper primarily contributes to both the structural change and aid effectiveness literatures, as well as to the policy conversations around aid priorities and industrialization-led development. The structural change literature has raised serious concerns regarding the state of industrialization in Sub-Saharan Africa for quite some time (de Vries et al. 2013; McMillan et al. 2014; Rodrik 2016). As industrialization is seen as integral both to the early development of Europe and the USA (Maddison 2001), and to modern development success stories such as China and the economies of South-East Asia (Young 1995; Rodrik 2013), questions are being asked as to how rapid growth can take off in SSA in the absence of industrialization, and what may be driving the underwhelming industrial performance thus far. By demonstrating the contrasting roles aid from the DAC and from China have played in contributing to African industrialization, this paper both uncovers under-explored drivers of structural change (van Neuss 2019; Mensah 2020) and highlights the potential imbalance between DAC aid allocation priorities and industrialization led economic growth.

In constructing the SETD, this paper presents a new data source to the structural transformation literature which expands the scope of research questions that can be explored at the subnational level. As far as the author is aware, it is the first database of regional sectoral employment data in Sub-Saharan Africa which utilizes national statistical institute [NSI] primary sources and microdata, and represents the largest and most reliable such dataset now available. Baccini et al. (2021) explores structural change in SSA at the subnational level, but their employment data comes only from IPUMS census samples which frequently have no more than two benchmark years per country and make no use of labour force or household survey data. Furthermore, in many cases the SETD is able to supersede the relatively small census sub-samples provided by IPUMS with numbers based on the full census, either from original microdata or NSI census reports

In terms of the aid effectiveness literature, this paper contributes to the large canon of work investigating the impacts of aid on various aspects of the macroeconomy (Boone, 1996; Burnside & Dollar, 2000; Gong & Zou 2003; Rajan & Subramanian 2008; Doucouliagos and Paldam, 2009; Clemens et al., 2014; Dreher et al., 2015; Jones & Tarp 2016; Minasyan et al., 2017), and most notably to the nascent literature investigating the role of Chinese aid, and how Chinese aid impacts may differ from those of conventional aid (Isaksson & Kostsadam 2018; Dreher et al., 2019, Dreher et al., 2021; Hamilton et al. 2021). The cumulative results of the aforementioned papers on aid effectiveness, especially those exploring the effects of aid on growth, paint a highly mixed picture. Many studies find effects of aid on growth which are null, negative, or positive only when conditioned on specific institutional features which are not present in the poorest countries. As it has been established that structural transformation and deindustrialization can negatively impact growth even in the presence of within sector productivity gains (Herrendorf et al. 2014; McMillan et al. 2014), by exploring the impact of aid on structural change and industrialization this paper not only highlights to the literature an important side-effect of aid, but provides a potential mechanism by which aid can sometimes have underwhelming aggregate growth effects; a mechanism which was proposed explicitly by Rodrik (2008). This paper also makes a significant technical contribution in the form of new instrument sets for causally identifying aid effects.

The remainder of this paper will proceed as follows. Section 2 outlines the extant literature linking foreign aid and structural change, explores theoretical mechanisms, and develops three hypotheses. Section 3 compiles data, sources, and descriptive statistics. Section 4 outlines the empirical strategies and introduces the new instruments. Section 5 presents and discusses all results. Section 6 concludes.

2 Background Literature, Theory, and Hypotheses

There has been little direct research into the effects of foreign aid on structural change and industrialization. Ahlerup (2019) uses micro-level data and a DiD identification strategy to explore the effects of foreign aid on the economic structure of Uganda and finds that aid caused a reallocation of working hours to agriculture. Ahlerup speculates that this result may be due to crowding out of local suppliers of non-agricultural goods by aid projects providing mosquito nets, water pumps, school supplies, etc. Page (2012) presents a series of descriptives based on the African Sector Database, a precursor of the ETD, which chart both the process of deindustrialization in Africa and the priorities of DAC aid disbursement, arguing that the DAC aid was not conducive to industry. Specifically, it is argued that DAC aid had a low focus on infrastructure and human capital generation due to other development priorities. Perhaps the most comparable research is Selaya & Thiele (2010) which uses GMM to investigate the impacts of aid on the combined Agriculture and Manufacturing Sectors ("tradeables"), and the Services sector ("non-tradeables"), and finds a positive impact on both; however, by considering the manufacturing impact only in aggregation with agriculture, their results remain silent on the impact of aid on industrialization.

The primary theoretical mechanism[1] for the effect of aid on structural change and industrialization is that aid can lead to a form of 'dutch disease'. The dutch disease hypothesis proposes that large exogenous inflows of capital into the economy can result in a decline in the relative size and performance of non-capital receiving sectors (Buiter & Purvis 1983). Originally developed as a potential explanation for why natural resource discoveries sometimes fail to yield significant GDP growth, the name refers to the discovery of natural gas in the Dutch province of Groningen. The process works through the real exchange rate mechanism: the large capital inflows cause an appreciation in the recipient country exchange rate relative to other countries, therefore the recipient country imports more and exports less. As a result, the effect is especially harmful for recipient country sectors which produce internationally tradeable goods.

The potential for foreign aid to drive a form of dutch disease has been addressed

[1] Other potential mechanisms could be considered via the effects of aid on the *drivers of structural change* established in van Neuss (2019); for example through effects on international comparative advantage or on input-output linkages and the technological structure of the economy.

in the literature. A classic paper is Rajan & Subramanian (2011), which explores the effects of aid on the relative growth rates of more and less exportable manufacturing industries, and concludes that aid caused the exportable industries to grow relatively slower, thereby damaging recipient country competitiveness. The paper presents suggestive evidence that this process unfurled via the exchange rate mechanism. A theoretical underpinning for this finding can be found in Michaely (1981). More recently, Diao & McMillan (2018) update the Lewis (1954) model to include a third 'in-between-traditional-and-modern' sector, which they call non-tradeables. According to their model, when public investment is financed by foreign inflows, which would include but is not limited to foreign aid, the 'modern' sector becomes less competitive, again because of appreciation of the real exchange rate. Diao & McMillan empirically test this model for the case study of Rwanda, utilizing micro-level data, and find evidence of this effect. They also note that Rodrik (2008) proposed the appreciation of the real exchange rate as an explicit mechanism for the disappointing effects of aid on growth.

Gollin et al. (2015) create a model of structural change by which the nature of sectoral shifts, and resulting 'types' of urbanization, depends on the nature of exogenous capital inflows. Their model and empirics considers the role of capital inflows from natural resource extraction, but as with models of the dutch disease, it is easy to conceptualize aid as the capital inflow instead. Gollin et al. differentiate between 'production' and 'consumption' cities, arguing that as countries develop, cities tend to expand, but the nature of this expansion depends very much on changes in the underlying structure of the economy. If the economy reallocates productive resources in an efficient, growth-enhancing manner; the manufacturing sector increases in relative size and cities become centres of industrial production, benefitting from agglomeration, scale effects, and industrial externalities (Tolley & Thomas 1987). However, if an exogenous capital inflow concentrates wealth or yields rent extraction, the result may instead be a concentration of consumption power and increase in demand for consumption goods and services. In this case, manufacturing goods are instead imported due to the appreciation of the real exchange rate, and cities facilitate consumption by providing primarily non-tradeable goods and services.

The structural change implications of aid inflows are therefore clearly informed by the sectors and regions to which that aid is targeted. Whilst cities may be differentiated between consumption and production centres, agriculture takes place primarily in rural areas. Therefore, the expected effect of aid on the ratio of the agriculture to manufacturing sectors may be greatly informed by the effect of aid on urban-rural migration. Hamilton et al. (2021) explored the causal effect of aid on urbanization rates and found that DAC aid had a negative effect on urbanization rates in Sub-Saharan Africa, whereas Chinese aid had no such effect, and actually seems to have positively influenced urbanization. This research question was motivated by an explicit shift in DAC aid disbursement policy in recent years towards supporting rural projects (OECD 2012), with no such spatial targeting stated for Chinese aid. If indeed DAC aid facilitated urban-to-rural migration, it could therefore be expected that this would in turn lead to declines in the relative size of the manufacturing sector and increases in the relative size of the agriculture sector, especially in terms of employment.[2] Conversely, if Chinese aid lead to rural-to-urban migration, this might be expected to have a positive effect on manufacturing, although this expectation is weaker as the connection between urbanization and manufacturing may be less strong than the connection between deurbanization and agriculture.

Implicit in the hypothesis that aid drives a form of Dutch disease is the notion that aid does not flow especially to the manufacturing sector, or at least does not boost manufacturing productivity. Strong descriptive evidence for this can be found in the aforementioned paper of Page (2012). Additionally, Page & Shimeles (2015) find no effect of aid on overall employment levels in recipient countries, suggesting that aid is not boosting sectors which have a large capacity to generate employment, such as manufacturing. Boone (1996) found that aid led to increased government consumption and an expanded public sector, which suggests aid was not flowing largely to manufacturing.

The discussion thus far indicates that DAC and Chinese aid may impact structural change differently. Similarly, whilst Page (2012) suggests that DAC aid was not channeled towards infrastructure and other uses supportive of manufacturing, and OECD (2012) states instead that it was channeled more to rural areas and agriculture, there is evidence that Chinese aid is significantly targeted at infrastucture (Berthelemy 2011, Bello 2019). Additionally, both Dreher et al. (2018) and Anaxagorou et al. (2020) demonstrate that recipient country governments exert much more influence over the disbursement of Chinese as opposed to DAC aid, and that Chinese aid is more prone to political capture. This is likely part of the reason why Chinese aid is spent more commonly on infrastructure, as such spending is politically popular, and why it is targeted more commonly at urban areas where there are larger voter concentrations (Pugh 1996). It may alternatively lead to a deindustrialization effect if Chinese aid is prone to rent extraction as opposed to

[2]To the extent that the Lewis (1954) assumption of a zero marginal product of agricultural labour in developing countries still holds, increases in agricultural employment need not lead to increases in total agricultural value added.

productive use.

Whilst macro-level studies into the effects of aid on growth yield highly mixed results, micro-level and project specific studies into aid interventions are often much more optimistic. This is known as the 'micro-macro' paradox in the aid effectiveness literature[3] (Mosley 1986). One potential explanation for this paradox is that aid is fungible with government spending, but micro-level studies capture only the partial equilibrium effects. Arndt et al. (2010) also introduce an intermediate stage of 'meso-level' effects to capture effects between the individual and national level. Results based on country-level analysis alone may be insufficiently detailed as to facilitate quality policy prescription, especially in the presence of imperfect measurement and heterogeneous aid effects. It is for this reason that this paper opts to construct sub-national level data so as to establish the extent to which results also hold at the meso-level. By utilizing administrative regions, the units of observation should be large enough to capture general equilibrium effects, yet small enough as to demonstrate whether national level results are indeed consistent with the impacts on smaller communities.

On the basis of this overview of literature and theory, this paper draws three hypotheses which will be subjected to empirical testing. The *first hypothesis* is that DAC Aid has caused deindustrialization in SSA, particularly in terms of employment. This is because DAC aid was not targeted at uses conducive to manufacturing productivity, and instead reduced the competitiveness of recipient country exporting sectors and caused urban-to-rural migration. Therefore, DAC aid acted more as a consumption resource. The *second hypothesis* is that the expected effect of Chinese aid on industrialization is more ambiguous, and may balance out to a null effect. This is because Chinese aid focused more on infrastructure, and has caused rural-to-urban migration, but also may be more prone to political capture.

Finally, the *third hypothesis* is that both types of aid have had similar effects at the sub-national as at national level, however these effects may have manifested more quickly. This is because administrative regions should be large enough to capture general equilibrium effects and should therefore support the national level findings, but because production and labour can reallocate more quickly within regions than within countries, it is expected that this will be reflected in a more

[3] Arndt et al. (2010) confirm the persistence of the micro-macro paradox in the aid effectiveness literature in recent years, noting continued highly positive impact evaluations of specific aid projects (Cohen & Soto 2007; Banerjee & Duflo 2009) in the same time period when most rigorous macro-level analysis found null or even negative effects (Gong & Zou 2003; Rajan & Subramanian 2008).

rapid reallocation response to aid inflows. The results in section 5 collectively represent an empirical test of these three hypotheses.

3 Data and Sources

The national level analysis is performed on a panel of 18 Sub-Saharan African [SSA] countries[4] of the Economic Transformation Database [ETD] (de Vries et al. 2021). As the ETD prioritized primary source data, with each country individually investigated so as to retrieve sectoral data directly from the NSIs, it automatically represents an improvement on secondary sources such as the ILO sectoral employment estimates. The ETD covers the time period 1990 - 2018; however in some cases, the time period on which analysis can be performed is restricted by the aid inflow data. The analysis of the effects of DAC aid at the national level covers the entire time period 1990 - 2018; the analysis of the effects of World Bank aid at the sub-national level covers the time period 1995 - 2014; the analysis of the effects of Chinese aid at both the national and sub-national levels covers the time period 2000 - 2014. In all cases, the sample period is the maximum possible given the source data.

The sub-national level analysis is performed on a panel of SSA regions of the Sub-national Economic Transformation Database [SETD], which is constructed specifically for this paper. The SETD comprises a total of 122 different African regions[5] across 8 countries[6] in SSA. The sample period, 1990 - 2018, and the sector disaggregation correspond precisely to the parent ETD. Appendix A presents the SETD in some detail and provides some discussion of limitations and biases. The ETD provides the dependent variable data for all of the national level specifications of this paper, the SETD provides the dependent variable data for all of the regional level specifications.

The independent variables of interest are the flows of aid from varying sources, drawn from foreign aid databases. Data for total DAC aid by recipient country is from the OECD Statistics database. As the OECD does not provide DAC aid data disaggregated at the regional-recipient level, sub-national analysis of the effects of

[4] Burkina Faso, Botswana, Cameroon, Ethiopia, Ghana, Kenya, Lesotho, Mozambique, Mauritius, Malawi, Namibia, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Uganda, and Zambia.

[5] Official administrative regions at the lowest level possible depending on the primary source data.

[6] Botswana, Ghana, Mauritius, Namibia, Nigeria, Rwanda, Tanzania, and Zambia.

'traditional' aid is done using World Bank aid, which is a component of total DAC aid. The data source for this is the "World Bank Geocoded Research Release, Version 1.4.2" (AidData 2017b), which is a database of individual World Bank aid projects geolocated to precise recipient locations, with disbursement amounts. Similarly, all data for Chinese aid comes from the "Geocoded Global Chinese Official Finance Dataset version 1.1.1" database (AidData 2017a; Bluhm et al. 2018; Dreher et al. 2021), which is a database of individual Chinese aid projects geolocated to precise recipient locations, with disbursement amounts, and individually verified to ensure the project was genuine and this disbursement actually took place. In both cases, the individual projects were aggregated upwards by hand such that they correspond to the recipient regions of the SETD; in the case of the Chinese aid data, this was then additionally aggregated upwards to the recipient country level.

It is necessary to briefly discuss the Chinese aid data. First, as the Chinese aid data-set was compiled by hand of specific aid projects which were individually verified by Aid Data lab researchers, this data is not equivalent to official Chinese aid statistics and instead includes only *genuine* and *verified* Chinese aid flows. Second, as specific detail of the nature and financing structure of each individual aid project is included, it is possible to filter the Chinese aid data such that it is directly comparable to DAC aid. That is, only 'ODA equivalent' aid projects are included in the analysis. ODA equivalent aid means only cash grants, soft loans, or in-kind gifted resources are taken into account (Fuhrer 1996). Therefore, the analysis of Chinese aid *does not* include Chinese FDI, or other forms of investment marked as aid, nor does it involve aid as explicit barter, nor does it include aid in the form of loans at market rates. This paper therefore captures as far as possible the effects of Chinese *pure aid* on the structure of the economy, and is deliberately silent regarding the effects of Chinese investment.

The new instrumental variables developed in this paper exploit exogenous variation in the frequency and severity of natural disasters occurring in *donor countries*. The source of natural disaster data is the "Emergency Events Database" (EM-DAT) maintained by the Université Catholique de Louvain; this provides a complete list of all natural disasters recorded in each country, along with statistics related to their severity. This data was used to construct two types of natural disasters variable. Measures of the *frequency* of natural disasters occurring per year in China and each donor country of the DAC[7] are a pure count of the number of disasters occurring in each country. Measures of the *severity* of all natural disasters occurring per year in China and each donor country of the DAC include the total number of deaths due to natural disasters, the total value of damage from natural disasters in constant US dollars, and the total number of people rendered homeless by natural disasters.

Controls are selected on the following bases: a) other theoretically established drivers of structural change; and b) recurring controls from past aid effectiveness regressions. There is some overlap between the two control sets. Income per capita and population are among the most common controls in aid effectiveness regressions[8]. This data comes from the Penn World Tables [PWT]. Changes in relative sectoral productivity/prices is proxied by the ratio of manufacturing to agricultural sector productivity, which is calculated from the ETD. This is similar to the 'Unbalanced Productivity Growth' indicator of Mensah (2020). Change in comparative advantage is proxied by the ratio of total trade (imports plus exports as a share of GDP) in merchandise to total trade in services, which is calculated using variables drawn from the World Bank Development Indicators [WBDI]. Additional controls include a conflict dummy constructed using data from the "Armed Conflict Dataset version 20.1" (Gleditsch et al. 2001, Pettersson & Öberg 2020); and oil rents as a share of GDP, from the WBDI.

The sub-national level controls are Sub-national Human Development Index [SHDI], as a measure for regional level of development, and regional population, both from the "Global Data Lab Area Database version 3.6.0" [GDL]. Due to a lack of SSA regional data availability, there are fewer controls at the sub-national level. In particular, it is not possible to include the aforementioned drivers of structural change at the sub-national level. Whether or not this is important depends on the extent to which these drivers differ between regions within the same country. Production technology, and therefore relative sectoral productivity, might be expected to be fairly constant across regions due to technological diffusion.

[7]The DAC contains 30 full members, one of which is the European Union, which in turn contains several smaller members. The DAC disaster index, construction details of which can be found in section 5, therefore utilizes natural disasters data for a total of 37 countries. The full list of DAC donor countries, along with rules and requirements for DAC aid, can be found in OECD (2021). China is not and has never been a member of the DAC.

[8]As this purpose of this paper is not to trace out the 'inverted U-Shape' a la Rodrik (2016), the quadratic of income per capita is not part of the standard set of controls, however most findings are robust to its inclusion.

Nevertheless, Bloom et al. (2012) show that there can be significant heterogeneity between productivity levels at different manufacturing plants in developing country contexts. However, the SHDI implicitly controls for all of income level, education (human capital) and health status, so the set of controls is larger than it may appear.

3.1 Descriptives

Table 1 presents summary statistics of the manufacturing shares[9], agricultural shares, the logarithms or inverse hyperbolic sines [ihs] of the DAC and Chinese aid variables, and the controls at the national-recipient level.

Table 1: Summary Statistics; *National Level Data 1990-2018*

	Mean	S.D.	Min	Max
Manu Share [EMP]	0.073	0.055	0.001	0.315
Manu Share [VAQ]	0.112	0.048	0.026	0.290
Agri Share [EMP]	0.579	0.228	0.067	0.949
Agri Share [VAQ]	0.230	0.147	0.021	0.696
DAC Aid (ln)	5.89	1.17	0.20	9.28
Chinese Aid (ihs)	1.68	2.88	0	11.16
GDP per capita (ln)	20.84	1.01	18.91	23.04
Population (millions)	26.88	33.77	1.06	190.9
Relative Prod (Man/Agr)	7.9	4.77	0.77	23.79
Relative Trade (Goods/Serv)	4.08	2.28	1.14	14.73
Conflict	0.20	0.40	0	1
Observations	501	(Chn:	250)	

Notes: Summary statistics for dependent variable, independent variables of interest and all control variables used in the National Level Analysis. All units and data sources are as collated in Appendix B. Observations refers to country-years, sample is Sub-Saharan African countries from 1990 - 2018.

As Table 1 averages over both countries and time periods, much information is lost in aggregation. Nevertheless, some important insights can be gleaned. The average manufacturing share of value added is greater than the average share of employment, whereas the average agriculture share of employment is (much)

[9]For reasons of brevity, only the employment and real value added share statistics are shown.

greater than the average share of value added. This indicates the vast productivity difference between the two sectors, which is confirmed by the average relative productivity ratio. Despite this, the average share of persons employed in agriculture is much larger than of manufacturing, denoting the misallocation of labour and the potential surplus employment in agriculture necessary in Lewis (1954) and other two-sector models. Note that, as the sum of the average shares of manufacturing and agriculture are far below one for both employment and VA, the average country year also has other relatively large sectors including trade services, public sector, transportation, etc.

The average DAC annual aid flow to a recipient country is considerably larger than the average Chinese aid flow, and the DAC has provided at least some aid to every sample country in every sample year, whereas China has not. Despite this, the standard deviation of Chinese aid flows is greater than of DAC aid, as is the maximum aid disbursement, suggesting that Chinese aid flows are much more volatile, and can be of an economic magnitude greater than the DAC. It seems therefore that China is more specific in providing aid, and generally provides smaller amounts of aid than the DAC, but can on occasion provide very large flows. There is great heterogeneity in terms of the population sizes of the countries in the sample, less in terms of GDP per capita, and, somewhat soberingly, 20% of country-years saw some form of conflict.

Table 2 presents summary statistics of the manufacturing shares and agricultural shares of employment, the inverse hyperbolic sines of the WB and Chinese aid variables, and the controls at the regional-recipient level. The statistics are for the largest time period available, and therefore do not always correspond; the WB aid covers the time period 1995 - 2014, the Chinese aid 2000 - 2014. It can be seen that Word Bank aid flows to regions are considerably higher than Chinese, both on average, and at the maximum. Chinese regional aid flows can be sizeable, but are on average quite small. Unlike at the national level, there are regions at the lower bound in terms of manufacturing and agriculture share (note that, as employment is measured in thousands, a share of zero does not denote precisely zero workers). The average manufacturing and agriculture shares are comparable to those at the national level.

Figure 1 presents an ascending bar chart of the average labour productivity levels at the national level in 11 sectors of the ETD, omitting real estate, in the style of McMillan & Harttgen (2014). The width of the bars represent the average share of employment in each sector, and the dashed horizontal line is the total average labour productivity. Average productivity is constructed directly from

Table 2: Summary Statistics; *Subnational Level Data*

	Mean	S.D.	Min	Max
Manu Share [EMP]	0.064	0.070	0	0.370
Agri Share [EMP]	0.559	0.282	0	0.980
WB Aid (ihs)	4.86	7.46	0	19.80
Chinese Aid (ihs)	0.64	1.76	0	7.83
SHDI	0.51	0.08	0.33	0.72
Population (millions)	1.71	1.54	0.04	9.29
Observations	2413 (SETD)	1880 (WB)	765 (Chn)	

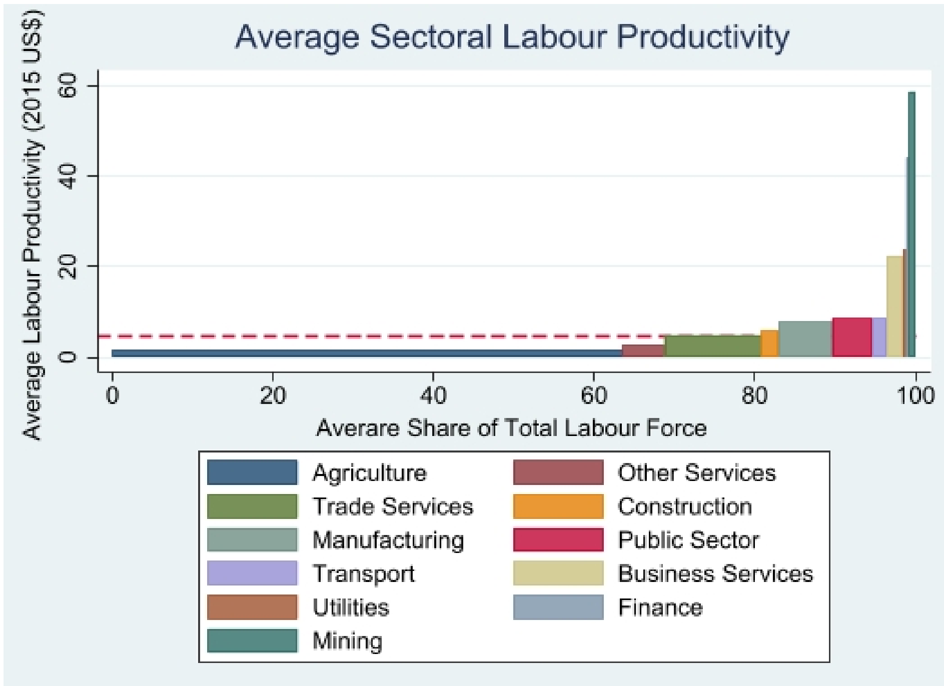
Notes: Summary statistics for dependent variable, independent variables of interest and all control variables used in the Sub-National Level Analysis. All units and data sources are as collated in Appendix B. Observations refers to region-years, sample is Sub-Saharan African countries from 1990 - 2018, with the World Bank and Chinese aid averages calculated from subperiods thereof.

the ETD with VA converted to US dollars at average annual exchange rates as in Rodrik (2013); the scale is therefore in thousands of US dollars per worker per year.

From Figure 1 it can be seen that the average productivity of manufacturing is above average, considerably higher than that of agriculture, and somewhat higher than trade services. Manufacturing is by no means one of the highest productivity sectors. Nevertheless, most sectors to the right of manufacturing in the bar chart are very limited in their capacity to absorb labour, as illustrated by the relative thinness of their bars. Utilities is a publicly funded natural monopoly, mining is highly capital intensive, and business services and finance require high levels of human capital. For workers wishing to 'move right' from agriculture or trade services, it is hard to envision that they could get much further than manufacturing or transport, given their skills and human capital level and the labour demand of the other sectors. The figure demonstrates the fact that deindustrialization will be average productivity reducing, unless the displaced workers are able to move to the industries on the right-hand side of the bar chart.

Figure 2 illustrates the fundamental heterogeneity between Chinese and DAC aid. This figure presents scatterplots and best fit lines between a) DAC aid, and b) Chinese Aid, and manufacturing share at the national level, across all three manufacturing share measures (employment, nominal value added, and real value added). The zero-aid-flows are omitted from the Chinese scatterplots, their inclusion does not materially affect the trends of the best fit lines. From Figure 2,

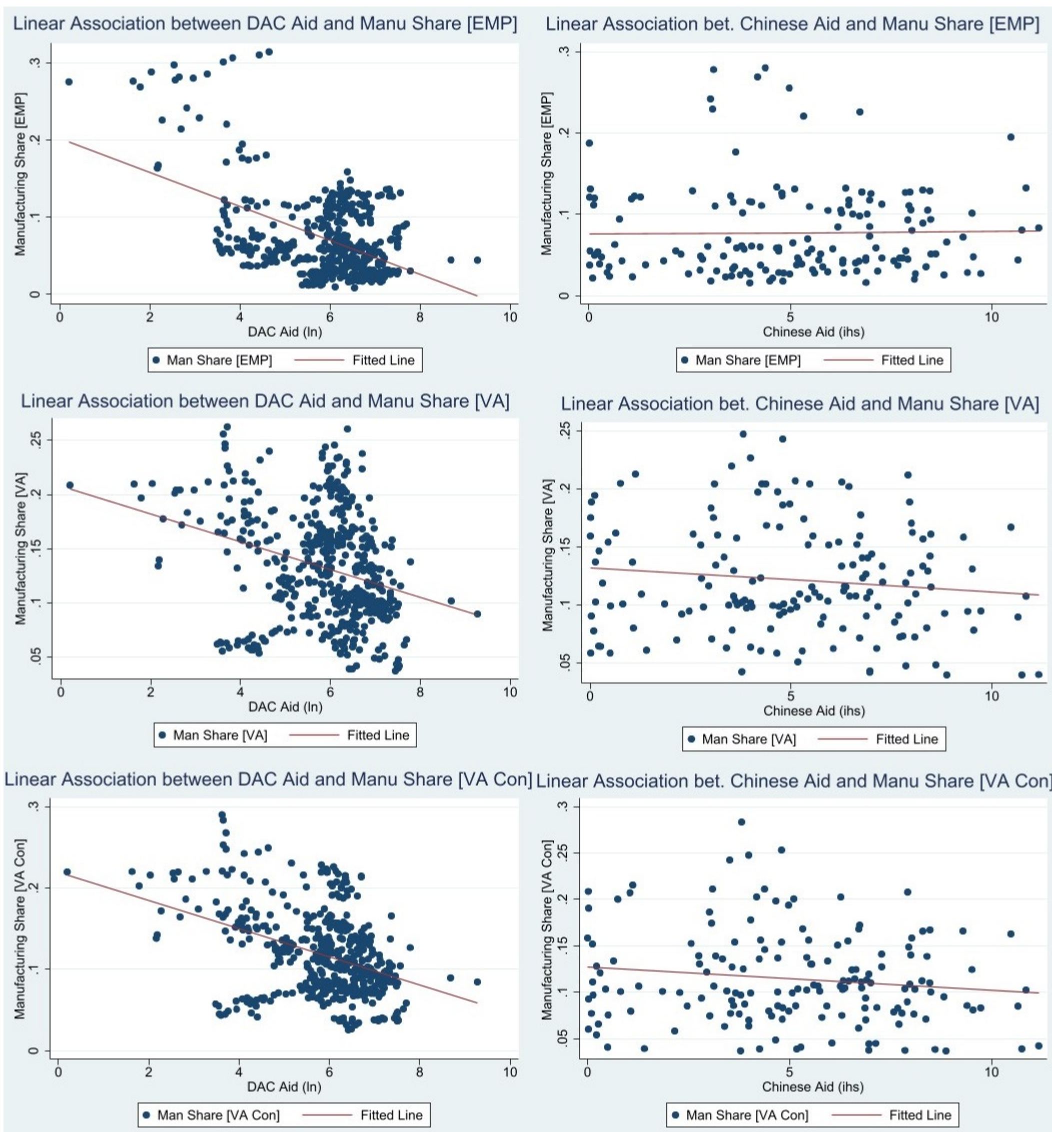
Figure 1: Average Labour Productivity by Sector; *National Level*



it can be seen that there is a *strong negative association* between DAC aid and manufacturing share both in terms of employment and both types of value added. No such association can be observed with the Chinese aid, or at best a much more gentle negative association in the case of the VA shares. These associations tell us nothing of the causal impact of aid types on manufacturing due to the likely presence of reverse causality. Nevertheless, the difference between the patterns of DAC and Chinese aid are very important, regardless of the explanation. *Either* Chinese aid is not nearly so targeted at less industrialized economies as DAC aid, *or* Chinese aid has less of a causal impact on industrialization, or some combination thereof. Therefore, Chinese aid is either differently targeted or different in impact as compared to DAC aid, and there is a *fundamental heterogeneity* between aid from these two different sources.

Appendix B collates a full list of all variables, units, and sources to act as a reference point for interpretation of forthcoming regression results.

Figure 2: Linear Associations between a) DAC Aid, and b) Chinese Aid and Manufacturing Share of i) Employment, ii) Current Price Value Added, and iii) Constant Price Value Added in SSA Sample; Zero Aid Flows excluded.



4 Empirical Methodology

The baseline specifications of this paper are panel fixed effects regressions. By exploiting the panel structure of the data and lagging the independent variable of interest, many sources of endogeneity bias will already be mitigated in these baseline specifications. The basic structural equation is as follows:

$$IndShare_{i,j,k,t} = \beta_1 Aid^{tr}_{i,t-n} + \Psi \boldsymbol{X^{Dr}_{i,t}} + \gamma \boldsymbol{X^{Oth}_{i,t}} + c_i + \delta_t + \epsilon_{i,t} \tag{1}$$

where the dependent variable $IndShare_{i,j,k,t}$ is the share of industrial sector $j \in (MAN, AGR)$[10] in total aggregate $k \in (EMP, VA, VAQ)$, at time t in country or region i. The dependent variable of interest is $Aid^{tr}_{i,t-n}$, which is the nth lag of the transformed dollar flow of DAC or Chinese Aid to which a logarithmic or inverse hyperbolic sine transformation has been applied. The estimated coefficient β_1 will therefore be the point estimate for the effect of aid on the relative size of the dependent variable sector. The term c_i captures the individual country or region fixed effects and δ_t is a full set of annual time dummies with the first year excluded as the baseline. The vectors $\boldsymbol{X}^{Dr}$ and $\boldsymbol{X}^{Oth}$ collectively represent the full set of controls; the former vector contains theoretically established drivers of structural change which are useful for benchmarking effects in addition to refining the consistency and prescision of the point estimates.

The dependent variable, sector shares, is a decimal percentage, and is therefore bounded between zero and one. This is similar to the case in Hamilton et al. (2021), where the dependent variable was the urbanization rate expressed as a percentage, and in Mensah (2020), which also explored the manufacturing share of the economy. The former used a two-limit tobit model, censored both from below and above (Cameron & Trivedi 2006), and the latter used the robust fractional response method (Papke & Wooldridge 2008) as checks against the results in the linear main specifications. In both cases, the results from these alternative methods were extremely similar to the linear results. Few observations are at the extreme bounds of the unit interval rendering linear estimation appropriate (von Hippel 2005). Therefore, this paper opts to proceed exclusively with the linear panel fixed effects model. The data required to calculate two-limit tobit estimations can be provided on request.

[10]Whilst all the regressions in the main body of this paper utilize the manufacturing or agriculture shares, some unreported regressions may be mentioned or discussed which explore other sectors, in which case the sector set k expands.

Finally, the decision was taken to set the appropriate lag length for the main specifications of this paper to $n = 4$, i.e. to model the effects of aid on the structure of the economy four years later. The issue of appropriately modelling the timing of aid effects is thoroughly explored by Clemens at al. (2011). Structural change takes time; workers cannot switch jobs instantly, and physical capital and plant require time to purchase, build, and install. Using the lags of aid as the independent variable also helps mitigate endogeneity biases arising from reverse causality. However, all output tables for the panel fixed effects estimations will also present the contemporaneous results, and in no case does the coefficient on the fourth lag qualitatively differ from that on the third or fifth.

There are three potential sources of endogeneity bias in these panel FE regressions: reverse causality, omitted variable bias, and measurement error. Reverse causality would occur when changes in the manufacturing share *cause* changes in the inflows of aid, rather than the other way around. This is highly plausible in the case of both DAC and Chinese aid, as aid could be targeted specifically at countries with a lower manufacturing share. This is even more likely to occur at the regional level, whereby regions with underdeveloped industry are likely to be preferred for aid projects. Omitted variable bias occurs when there is a latent third variable which causally drives both aid disbursement and the manufacturing share; for example recipient country political policy or even political competence. Measurement error occurs when either the dependent variable or the independent variable of interest are measured imprecisely. In terms of aid flows, measurement error is unlikely to be a large issue with the DAC aid flows or with the World Bank regional aid data, but there may be an issue with the Chinese aid data. To the extent that such resulting measurement error represents classical measurement error, this would lead to attenuation bias (Schennach 2016). This may imply that findings of null effects in fact mask small but true effects; the fact that there is a higher potential for measurement error in the Chinese than DAC aid data might therefore be one explanation for why the best fit lines in Figure 2 are flatter for Chinese aid. There may also be some measurement error which is non classical; for example if smaller aid projects are more likely to be misreported or are more difficult to trace and verify than large ones.

4.1 A New Instrument for Aid

Panel fixed effects regressions are often insufficient on their own to provide unambiguously causal estimates of independent variable effects as they do not remove biases from time-variant country/region heterogeneity; e.g. changes in political leadership or specific climate events. It is for reasons such as these that instrumental variable strategies have become standard practice in the aid effectiveness literature. This paper utilizes different instruments for DAC and Chinese aid, which are both 'supply-side instruments' (Deaton 2010; Chauvet 2015) based on the same principle and the same sources of exogenous variation, but are constructed differently. This difference in construction is necessitated by the facts that a) China is a single donor country, whereas the DAC is a large set of geographically diffuse donor countries, and b) there are many recipient country-years in which China did not provide any aid, whereas the DAC provided at least some aid to every country in the sample in every year. The instrument for Chinese aid was first presented in Hamilton et al. (2021), and is based on the methodology established by Nunn & Qian (2014) and further developed by Dreher & Langlotz (2017). The instrument for DAC aid is entirely new, and is constructed for and presented in this paper for the first time.

Both the instrument sets for Chinese and DAC aid rely on the same basic concept in terms of their construction - exploiting exogenous variation in the frequency and severity of natural disasters in *donor* countries as a means to introduce truly random variation in aid flows, and interacting with a source if inter-recipient variation as in Nunn & Quian (2014). That is, it is proposed that randomly occurring natural disasters in donor countries affects their *supply* of aid to developing countries, in terms of volume, independent of any conditions within the recipient countries themselves. Supply-side instruments used in the past for DAC aid have often related to political conditions or policy changes in donor countries (Morrissey 1991; Rajan & Subramanian 2008), historical or past-colonial features of donor countries (Dalgaard et al. 2004), or total donor aid budgets prior to specific allocation (Frot & Perrotta 2009). Past supply-side instruments for Chinese aid have included production measures of various Chinese commodities as it is believed that these directly impact the amount of aid China has to disburse (Dreher & Langlotz 2017; Dreher et al. 2019; Bluhm et al. 2020; Cruzatti et al. 2020; Dreher et al. 2021). All of these Chinese aid papers introduce inter-recipient variation in the IV via interaction with the recipient-country probability of receiving aid; 'shift-share' instruments of this type were pioneered by Nunn & Qian (2014), and first applied to Chinese aid by Dreher & Langlotz (2017). It is these instruments which inspired Hamilton et al. (2021). The new instrument presented for DAC also utilizes a 'shift-share' structure, but deviates from the Chinese aid instruments in the method of construction.

The Chinese aid instruments are constructed using a procedure precisely analogous to that of Nunn & Qian (2014). Panel (inter-recipient) variation in the instrument is introduced by interacting the *disaster* variables with the *probability* that a country will receive aid from China in a given year based on past receipts of aid; this probability is calculated as the proportion of the sample years for which the country has received at least some aid. The disaster variables are as collated in Appendix B; a total of four different measures of the frequency and severity of natural disasters in China have been compiled. Each of these is separately interacted with the recipient country aid probability yielding an *instrument set* of four disaster based instruments for Chinese aid. Multiple instruments for a single independent variable allows for performing the Sargan-Hansen test of overidentifying restrictions (Sargan 1958, Hansen 1982), which can provide some supportive evidence against certain types of violation of the exclusion restriction[11]. The four instruments which comprise the instrument set for Chinese aid are constructed separately as follows:

$$I_{i,t}^{CHN} = P_i * Z_t = \frac{1}{T}\sum_{t=1}^{T} D_{i,t} * Z_t \tag{2}$$

where Z_t is the frequency or severity measure of natural disasters occurring in China in year t. P_i is the probability of recipient country i receiving Chinese aid in any year based on past receipts of aid, and is calculated as the share of the total sample years for which the country or region received a positive quantity of Chinese aid - $\frac{1}{T}\sum_{t=1}^{T} D_{i,t}$, where $D_{i,t}$ is a dummy variable indicating whether or not country i received any aid from China in year t. The result is therefore time constant, is bounded $P_i \in [0,1]$ and is recipient country specific. The interaction between Z_t, which varies only with time, and P_i, which varies only with recipient country, results in the instrument $I_{i,t}$ which exhibits both forms of variation and is therefore suitable for panel IV analysis. The first stage equation for Chinese aid is therefore:

$$\widehat{Aid_{i,t}} = \gamma_0 + \boldsymbol{\gamma_1' I_{i,t}^{CHN/DAC}} + \delta_t + [\boldsymbol{\Psi X_{i,t}}] + \omega_{i,t} \tag{3}$$

where the inverse hyperbolic sine transformation of Chinese aid flows is predicted by a vector of the full set of Chinese disaster based instruments, $\boldsymbol{I_{i,t}^{CHN}}$; a set of time dummies δ_t; and a vector of the full set of controls, $\boldsymbol{\Psi X_{i,t}}$ as collated in Appendix B. The control vector is bracketed because, when an instrument set is truly exogenous and satisfies both conditions for instrument validity, regression will yield a consistent coefficient of the parameter of instrument even in the absence

[11]Although this test is not strictly a test of the exclusion restriction, it can at least reduce the scope of potential violations under the assumption of homogeneous effects.

of controls (Angrist & Pischke 2009). The coefficients $\boldsymbol{\gamma_1'}$ in the first stage can be used to test the strength/relevance of the instrument set, as will be discussed in the next subsection. The structural equation is:

$$IndShare_{i,j,k,t} = \beta_1 \widehat{Aid_{i,t-n}} + c_i + \delta_t + \boldsymbol{\Psi X_{i,t}} + \upsilon_{i,t} \tag{4}$$

with variables and subscripts defined analogously to equation (1), and β_1 again capturing the coefficient of interest.

Constructing the disaster-based instrument for DAC aid is a more complex task for three reasons. First, unlike China which is a single country, the DAC is a large and geographically diffuse set of countries which spans much of the globe. Therefore, any disaster-based instrument for DAC aid must take into account the frequency of severity of domestically occurring natural disasters in *all* of the DAC countries. Second, the members of the DAC vary widely in terms of the volume of their contribution to the overall DAC aid flow, with very large donors such as the USA providing contributions which are a factor of several hundred of those of the smallest contributors such as Luxembourg or Liechtenstein. Therefore, any instrument must be weighted so that this differential contribution is taken into account. Third, whilst China did not provided aid to every country in every sample year, the DAC did. Therefore, if the instruments for DAC aid were constructed as those for Chinese aid in equation (4), it will be the case that $P_i = 1$ for all recipient countries and there will be no panel variation. An alternative method of introducing inter-recipient variation is therefore necessary.

The approach taken to solving these three issues is as follows. A set of *weighted indices* of the frequency and severity of natural disasters in the DAC countries is constructed, with the weights dictated by the total share of aid contributions of each donor country to each recipient country. Fortunately, issues two and three can be solved simultaneously. By weighting in this manner, disasters occurring in the larger donors influence the first stage more than those occurring in the smaller donors, proportionate to their contributions. Additionally, as the weights differ for each recipient, inter-recipient variation is introduced. The construction of each of the DAC instruments is as follows:

$$I_{i,t}^{DAC} = \sum_{j=1}^{J} [D_{j,t} * w_{i,j,t}] \tag{5}$$

where, for example, the number of natural disasters in each donor country j in year t, $D_{j,t}$, is multiplied with the total share of aid provided by that donor country j to recipient country i in year t, $w_{i,j,t}$. As these are shares, $w_{i,j,t} \in [0,1]$. The instrument is then the total sum of these weighted disaster counts across all donors, and takes the form of a weighted average index of disaster frequency or severity across the entire DAC, with the weights dictated by share of aid contribution. Due to the time intensity of constructing such instruments, only two are used in the DAC instrument set - the frequency of natural disasters and the severity of natural disasters as measured by deaths. The first stage and structural equations are then identical to equations (3) and (4) for Chinese aid, save that the instrument set is now the DAC disaster indices and the instrumented variable is now the logarithm of the flow of DAC aid.

In the context of the instruments used in this paper, instrument relevance requires that the frequency and severity of natural disasters in donor countries has a *sufficiently strong* influence on the volume of their foreign aid disbursements. The theoretical argument for this first stage relationship incorporates the following mechanisms. First, from a purely practical level, domestically occurring natural disasters impose large costs to the donor countries, both in terms of economic damage due to the disasters and the post-disaster recovery costs. This may reduce the volume of funds available for foreign aid disbursement. Disaster relief can be thought of as a form of 'domestic aid', and whilst domestic aid and foreign aid disbursements are not zero-sum[12], an increase in one is likely to yield an at least partial reduction in the other. Second, the occurrence of natural disasters may affect the *tastes* of donor country citizens and legislators for aid disbursement. Intense media coverage of a domestic natural disaster may lead to public demand for foreign aid to be reduced such that such funds can instead be used at home. Alternatively, a visceral and proximate experience of a domestic natural disaster may increase public preference for aid disbursement more generally, including foreign aid. The question of whether a first stage relationship is sufficiently strong is ultimately a statistical one, however it can be seen from the arguments above that it is reasonable to expect this strong relationship to hold.

Table 3 presents the first stage equations with accompanying F-Statistics for establishing instrument strength. It can be seen that the F-Statistics of both instrument sets surpass the Staiger & Stock (1997) rule of thumb of 10, although the Chinese aid instruments do not quite pass the most stringent Stock & Yogo (2005) critical values.

[12]There may even be some forms of aid disbursements which are zero sum; for example if a donor country has only a set number of public health experts or temporary shelter engineers, a disaster occurring at home may see such people recalled from serving on foreign aid projects abroad.

Table 3: OLS Panel FE Estimates of First Stage Relationships between DAC and Chinese Aid and Natural Disaster Instruments; *National Level Data*

	(1) [OLS FE] $lnDACAid_{i,t-4}$	(2) [OLS FE] $ihsCHNAid_{i,t-4}$
$\mathrm{I}_{i,t-4}^{DACFreq}$	-0.0203***	
	(-5.54)	
$\mathrm{I}_{i,t-4}^{DACDamage}$	-2.78*10^{9}	
	(-0.41)	
		-1.19*10^{4}
$\mathrm{I}_{i,t-4}^{CHNFreq}$		(-0.51)
$\mathrm{I}_{i,t-4}^{CHNDeaths}$		5.24*10^{7***}
		(4.62)
$\mathrm{I}_{i,t-4}^{CHNAffected}$		-5.14*10^{7***}
		(-4.25)
$\mathrm{I}_{i,t-4}^{CHNDamage}$		1.27*10^{7}
		(0.66)
Controls	Yes	Yes
Time Dummies	Yes	Yes
N	387	291
F-Statistic	65.68	13.12

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: OLS Panel Fixed Effects estimations of first stage relationships. Dependent variables are transformed aid flows. Independent variables are interacted frequency and severity measures of natural disasters in DAC and China, with inter-recipient variation introduced as detailed in section 4.

It should be noted that panel IV regressions commonly exhibit lower F-Statistics than traditional cross-sectional IVs. The signs of the individual instruments are not all negative as per the expectation, but this is likely due to *ceteris paribus* interpretations of the individual first stage coefficients. The final results tables show the Kleibergen–Paap rk statistics as opposed to these traditional Wald statisics, which are slightly more rigorous but still surpass 10 in both cases.

Whilst many of the supply-side instruments used previously in the literature are credible sources of exogenous variation, they still may suffer from the fact that they are for the most part essentially *controlled variables.* For example, all of the donor country political or policy based instruments result from decisions made by the donor country executive, legislators, or electorate. Such decisions will be influenced by a plethora of competing factors, but without a thorough decomposition which is beyond the scope of any economics paper, it is often difficult to rule out that conditions in developing countries may have played a role. Whilst such exclusion restriction violations may be minor or even implausible in certain situations, it seems wise to utilize instruments which abstract from choice altogether. If an instrument cannot be chosen, it cannot be influenced, and even such small exclusion restrictions are not plausible.

It is this line of thinking which influenced the decision to utilize donor-country natural disasters as the source of inter-temporal exogenous variation in aid flows - surely few forms of random assignment can be more plausible than the occurrence and severity of natural disasters, except potentially through a global climate change mechanism. There is a scientific consensus that natural disasters in the modern era are, to some extent, self determined through the mechanism of climate change (van Aalst 2006). From a modelling perspective, it could therefore be considered that donor country governments choose levels of CO_2 emission on the basis of optimizing between economic growth and potential climate disruption (Nordhaus 2001). In this case, natural disasters might be thought of as a choice variable. However, whilst global temperature and other forms of global climate change may be partially controllable variables, the precise nature and timing of natural disasters resulting from these changes is not. Furthermore, China has always experienced a large number of natural disasters dating back to the pre-industrial era (Elvin 1998), implying that at least a sizeable component of natural disasters are purely exogenous and not determined by climate change.

In order for the exclusion restriction to be violated, it would be necessary that the frequency or severity of natural disasters in China and the DAC could influence the structure of economies in Sub-Saharan Africa. The most clear cut example of such a violation would be a natural disaster so large that it impacted both some subset of donor countries and the African continent. None of the DAC countries are located in Africa, and China is also geographically far. Table 7 presents the raw correlation coefficients between the annual number of natural disasters in the ten largest countries of the DAC in terms of aid volume. As can be seen from the table, with the exception of the correlation between the geographically joined Germany and Netherlands, and geographically very proximate Netherlands and United Kingdom, all of the correlation coefficients are below 0.5. If the frequencies of natural disasters are so uncorrelated even between the major DAC countries, many of which are on the same continent, then they are surely uncorrelated between the DAC countries, China, and the much more geographically distinct countries of Sub-Saharan Africa.

Table 4: Corrlation Coefficients between Natural Disaster Frequency in key DAC Countries.

# Disasters	DEU	ESP	FRA	GBR	ITA	JPN	KOR	NLD	NOR	USA
DEU	1.000									
ESP	0.072	1.000								
FRA	0.362	0.181	1.000							
GBR	0.343	0.378	0.495	1.000						
ITA	0.101	0.050	0.339	0.294	1.000					
JPN	-0.331	-0.057	-0.200	-0.009	-0.019	1.000				
KOR	-0.175	0.241	0.108	0.277	0.097	0.325	1.000			
NLD	0.581	0.018	0.338	0.525	-0.104	-0.217	0.006	1.000		
NOR	0.079	-0.121	0.387	0.255	-0.116	-0.207	0.225	0.482	1.000	
USA	-0.188	-0.130	-0.003	0.158	0.098	0.191	0.152	0.028	0.007	1.000

Notes: Table of raw correlation coefficients between the annual number of natural disasters in the ten largest countries of the DAC in terms of aid volume. Coefficients below 0.5 suggest a very low correlation.

Indirect violations of the exclusion restriction could occur if natural disasters in donor countries impact the structure of economies in SSA through channels other than aid. An example of this might be if disasters did such significant damage to, for example, agricultural production in large donor countries that these countries had to significantly increase their volume of agricultural imports. This could in turn increase the relative share of agriculture in the economies of SSA through a demand-side mechanism. Note however that the lagged structure of the main specifications of this paper would imply that this impact would have to still be felt four years on, which would seem like a sufficient time period for most developed countries to restore lost production capacity from all but the worst natural disasters. Additionally, the low correlations between natural disasters in the DAC observed in Table 4 would suggest that such demand-side effects channels will be limited, as agricultural production disruptions are likely to be concentrated only in a subset of the DAC at any one time. The inclusion of controls, recipient country fixed effects, and time dummies in the IV specifications, and the fact that all estimations pass the Sargan-Hansen test, should further relax any lingering doubts regarding potential exclusion restriction violations.

Angrist et al. (1996) provide a thorough discussion of the fact that most IV estimates in fact capture merely a local average treatment effect [LATE], rather than an average treatment effect which applies across the full distribution of the independent variable[13]. Not all types of aid may have the same effects, even from the same source, and the types of aid which may change as a result of natural disasters in donor countries may not be representative of the full spectrum of aid. Therefore, what is causally identified by the IV specifications is not the average effects of *all* types of aid from the relevant source, but merely the local average effects of the *specific* types of aid more likely to vary in response to variation in the instrument. For example, if demands on domestic resources are such that aid is cut as a result of severe domestic disasters, it is likely to be the least effective projects which will be cut first, potentially leading to attenuation bias in the IV estimations; $LATE < ATE$. Similarly, the issue of heterogeneous effects broadens when considering the instrument for DAC aid. The DAC aid instrument is a weighted index of the frequency and severity of natural disasters in all of the donor countries of the DAC. However, some of the donor countries will have much more volatility in terms of their natural disasters than others. For example, the USA and Japan experience many more, and much more severe, natural disasters than Germany and Switzerland. This means that more of the instrumented variation in *aid flows* will be variation in aid flows from the volatile climate countries. If the effects of DAC aid are homogeneous, this will not matter, and it is likely that aid effects across the DAC are more homogeneous than, say, between DAC and Chinese aid, because of common DAC standards and central disbursement authorities.

[13] These issues were respectively raised to the author by Axel Dreher and Andreas Fuchs, for which the author is extremely grateful.

5 Results

5.1 National Level

Tables 5 through 8 present the results of panel fixed effects estimations of various permutations of equation (1). All standard errors are clustered at the country level, and all estimated models include time dummies and the full set of controls as detailed in Appendix B. Table 5 presents the results for DAC aid and the manufacturing share. Odd numbered columns show the contemporaneous relationship, $n = 0$, and even numbered columns show the effect after a lag of four years, $n = 4$. The first pair of columns show the effect on the manufacturing share of employment $k = EMP$; the second pair of columns show the effect on the manufacturing share of nominal value added $k = VA$, and the third pair of columns show the effect on the manufacturing share of real value added $k = VAQ$. The estimated coefficients on the set of controls which are previously established drivers of structural change are shown in the table so as to facilitate benchmarking the effect of aid. *RelProd* is the relative productivity and $RelTrade$ is the relative trade shares; other variable labels should be self explanatory, but all are as defined in Appendix B. All of the results are qualitatively robust to the inclusion of the quadratic of income.

From Table 5 it can be seen that, in all six columns, the coefficient on the flow of DAC aid is negative, and in the even numbered column where the fourth lag is considered, it is significantly so. These results show a consistent story of a *negative* effect of DAC aid on the relative size of the manufacturing sector across both employment and value added share - in other words, that DAC aid caused deindustrialization, *ceteris paribus*. The coefficients on the contemporaneous effect, in the odd numbered columns, are of a similar magnitude, but less significant. The economic interpretation of the coefficients from the lagged specifications is as follows: a ten percent increase in the flow of DAC aid led to an approximately 0.093 percentage point decrease in the relative size of the manufacturing share of employment, a 0.066 percentage point decrease in the relative size of the manufacturing share of nominal value added, and a 0.083 percentage point decrease in the relative size of the manufacturing share of real value added, *ceteris paribus*. In terms of benchmarking the result against the other drivers of structural change, it can be seen that the effect size is more regularly significant than the effect of changes in income per capital, population, relative productivity, and relative trade; the latter two of which have the expected signs and significance, although the coefficient magnitudes are not directly comparable due as the aid flows are in logarithms whilst the relative productivity and trade are ratios.

Table 6 presents the results of estimation precisely analogous to those of table 5, except that the dependent variable is now the Agriculture share $k = AGR$. Table 6 shows that the coefficients of the effect of DAC aid on the agricultural share of both employment and value added are all positive, and significant in some cases. Especially the effect of aid on agricultural share of real value added is significantly positive in both the contemporaneous and lagged relationship. Additional regressions show that DAC aid had null effects on the relative sizes of the trade services and public sector; these are omitted for reasons of brevity but are available on request. This latter result is especially interesting as it contradicts the notion that DAC aid is used to swell the public sector which is prone to cronyism and rent extraction.

Table 7 repeats the estimations of Table 5 exactly, except now the independent variable of interest is the inverse hyperbolic sine transformation of the flows of Chinese aid. Therefore, Table 7 captures the effects of Chinese aid on the manufacturing share. Table 7 shows that the point estimates of the effects of Chinese aid on the relative share of manufacturing are all positive, but of very small economic magnitude and for the most part insignificant. This is in sharp contrast to DAC aid which appears to have had a strongly negative effect. Finally, Table 8 repeats the estimations of table 7, but now with the agricultural share as the dependent variable. Thus, table 8 captures the effects of Chinese aid on the agriculture share. Chinese aid does not appear to have had a significant effect on the agricultural share of either employment or VA, either contemporaneously or with a lag. These null effects of Chinese aid on the agricultural share, and null to very modest effects on the manufacturing share, contrast with the other drivers of structural change - all of income, relative productivity, and relative trade have statistically significant effects on either the manufacturing or agriculture shares in at least some specifications.

Table 5: Panel FE Estimates of Effect of DAC Aid on Manufacturing Share; *National Level*

	(1) [OLS FE] $ManEMP_t$	(2) [OLS FE] $ManEMP_t$	(3) [OLS FE] $ManVA_t$	(4) [OLS FE] $ManVA_t$	(5) [OLS FE] $ManVAQ_t$	(6) [OLE FE] $ManVAQ_t$
$lnDACAid_{i,t}$	-0.0074***		-0.0080		-0.0059	
	(0.002)		(0.005)		(0.004)	
$lnDACAid_{i,t-4}$		-0.0093***		-0.0066**		-0.0083***
		(0.003)		(0.002)		(0.003)
lnGDPpc	-0.0422	-0.4300	-0.0030	-0.0090	-0.0127	-0.0411
	(0.066)	(0.061)	(0.033)	(0.030)	(0.042)	(0.034)
Pop	0.0008	0.0011	0.0001	0.0002	-0.0001	0.0006
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
RelProd	-0.0021	-0.0023*	0.0028**	0.0032***	0.0017	0.0026**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RelTrade	0.0038	0.0042*	0.0035	0.0040**	0.0039*	0.0042***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	445	387	445	387	445	387
R^2	0.123	0.098	0.118	0.045	0.100	0.096

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS Panel Fixed Effects estimations of equation (X) for the National Level Data, with controls and time dummies. Odd numbered columns display the contemporaneous effect, even numbered columns show the effect after a lag of four years. Dependent variables: share of total employment which is in manufacturing sector, share of total nominal value added which is in manufacturing sector, share of total real value added which is in manufacturing sector, all expressed as decimal percentages. Independent variables of interest: logarithm of real dollar flow of DAC aid, or fourth lag thereof. Significant negative coefficients suggest DAC aid had a negative effect on the relative size of the manufacturing sector. All variables, controls, units and data sources are as collated in Appendix B.

Table 6: Panel FE Estimates of Effect of DAC Aid on Agriculture Share; *National Level*

	(1) [OLS FE] $AgrEMP_t$	(2) [OLS FE] $AgrEMP_t$	(3) [OLS FE] $AgrVA_t$	(4) [OLS FE] $AgrVA_t$	(5) [OLS FE] $AgrVAQ_t$	(6) [OLE FE] $AgrVAQ_t$
$lnDACAid_{i,t}$	0.0103***		0.0050		0.0110**	
	(0.003)		(0.005)		(0.005)	
$lnDACAid_{i,t-4}$		0.0072		0.0026		0.0068**
		(0.006)		(0.005)		(0.002)
lnGDPpc	0.0075	-0.0031	-0.1522***	-0.0890***	-0.0172***	-0.1637***
	(0.052)	(0.060)	(0.036)	(0.028)	(0.052)	(0.037)
Pop	-0.0009	-0.0011	-0.0010	-0.0010	-0.0010	-0.0004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RelProd	0.0101***	0.0105***	-0.0013	-0.0007	-0.0020	-0.0011
	(0.003)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)
RelTrade	0.0009	-0.0011	-0.0030**	-0.0040**	0.0013	-0.0030
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	445	387	445	387	445	387
R^2	0.007	0.010	0.592	0.472	0.680	0.736

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS Panel Fixed Effects estimations of equation (X) for the National Level Data, with controls and time dummies. Odd numbered columns display the contemporaneous effect, even numbered columns show the effect after a lag of four years. Dependent variables: share of total employment which is in agriculture sector, share of total nominal value added which is in agriculture sector, share of total real value added which is in agriculture sector, all expressed as decimal percentages. Independent variables of interest: logarithm of real dollar flow of DAC aid, or fourth lag thereof. Insignificant coefficients suggest DAC aid had no effect on the relative size of the agriculture sector. Significant positive coefficients suggest DAC aid had a positive effect on the relative size of the agriculture sector. All variables, controls, units and data sources are as collated in Appendix B.

Table 7: Panel FE Estimates of Effect of Chinese Aid on Manufacturing Share; *National Level*

	(1) [OLS FE] $ManEMP_t$	(2) [OLS FE] $ManEMP_t$	(3) [OLS FE] $ManVA_t$	(4) [OLS FE] $ManVA_t$	(5) [OLS FE] $ManVAQ_t$	(6) [OLE FE] $ManVAQ_t$
$ihsCHNAid_{i,t}$	0.0007		0.0001		0.0008**	
	(0.004)		(0.0004)		(0.0004)	
$ihsCHNAid_{i,t-4}$		0.0005		0.0003		0.0003
		(0.0004)		(0.0004)		(0.0003)
lnGDPpc	-0.0331	-0.0013	-0.0646	-0.0850*	-0.0732**	-0.0656*
	(0.055)	(0.047)	(0.037)	(0.041)	(0.034)	(0.036)
Pop	0.0008	0.0007	0.0012	0.0015	0.0010	0.0014
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RelProd	0.0025**	0.0035**	0.0046**	0.0032*	0.0035*	0.0028
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
RelTrade	0.0035	0.0020	0.0003	0.0001	0.0030	0.0019
	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	250	190	250	190	250	190
R^2	0.120	0.001	0.100	0.110	0.149	0.172

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS Panel Fixed Effects estimations of equation (X) for the National Level Data, with controls and time dummies. Odd numbered columns display the contemporaneous effect, even numbered columns show the effect after a lag of four years. Dependent variables: share of total employment which is in manufacturing sector, share of total nominal value added which is in manufacturing sector, share of total real value added which is in manufacturing sector, all expressed as decimal percentages. Independent variables of interest: inverse hyperbolic sine of real dollar flow of Chinese aid, or fourth lag thereof. Insignificant coefficients suggest Chinese aid had no effect on the relative size of the manufacturing sector. Significant positive coefficients suggest Chinese aid had a positive effect on the relative size of the manufacturing sector. All variables, controls, units and data sources are as collated in Appendix B.

Table 8: Panel FE Estimates of Effect of Chinese Aid on Agriculture Share; *National Level*

	(1) [OLS FE] $AgrEMP_t$	(2) [OLS FE] $AgrEMP_t$	(3) [OLS FE] $AgrVA_t$	(4) [OLS FE] $AgrVA_t$	(5) [OLS FE] $AgrVAQ_t$	(6) [OLE FE] $AgrVAQ_t$
$ihsCHNAid_{i,t}$	-0.0002		0.0008		-0.0003	
	(0.001)		(0.001)		(0.000)	
$ihsCHNAid_{i,t-4}$		-0.0007		0.0008		0.0002
		(0.001)		(0.000)		(0.0003)
lnGDPpc	-0.0067	-0.0470	-0.0156	-0.0901**	-0.1176***	-0.1553***
	(0.068)	(0.081)	(0.038)	(0.042)	(0.033)	(0.028)
Pop	-0.0017	-0.001	-0.0001	-0.0007	-0.0003	-0.0006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RelProd	0.0101**	0.0102**	-0.0001	-0.0002	-0.0014	-0.0005
	(0.004)	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)
RelTrade	-0.0061	-0.0045	-0.0090***	-0.0061**	0.0007	0.0026
	(0.004)	(0.005)	(0.003)	(0.002)	(0.002)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	250	190	250	190	250	190
R^2	0.002	0.155	0.006	0.464	0.728	0.641

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS Panel Fixed Effects estimations of equation (X) for the National Level Data, with controls and time dummies. Odd numbered columns display the contemporaneous effect, even numbered columns show the effect after a lag of four years. Dependent variables: share of total employment which is in agriculture sector, share of total nominal value added which is in agriculture sector, share of total real value added which is in agriculture sector, all expressed as decimal percentages. Independent variables of interest: inverse hyperbolic sine of real dollar flow of Chinese aid, or fourth lag thereof. Insignificant coefficients suggest Chinese aid had no effect on the relative size of the agriculture sector. All variables, controls, units and data sources are as collated in Appendix B.

Moving to the preferred 2SLS estimations, table 9 estimates structural equation (7) for the effects of DAC aid. The instrument set is as in the first column of the first stage table 2. As can be seen from table 9, the effect of DAC aid on the manufacturing share of employment at the fourth lag remains negative and statistically significant, with a coefficient which is in fact somewhat larger than that in the panel FE estimation. The economic interpretation is that a ten percent increase in the flow of DAC aid led to an approximately 0.142 percentage point decrease in the relative size of the manufacturing share of employment, *ceteris paribus*. Based on the average manufacturing share of employment of 6.9 percentage points, this represents a 2.1% decrease in the manufacturing share of the average country-year. The coefficients for the effects of DAC aid in the other columns are now all insignificant, suggesting that the deinstrustrialization effect was concentrated on the employment rather than the VA share. The effects on the agricultural share are no longer significant.

Table 10 presents the IV results for the Chinese aid flows, with instrument set as in the second column of the first stage table 2. When Chinese aid is instrumented, the coefficients on the effect of aid on the manufacturing share remain positive, as was the case in the panel FE regressions, but become economically larger and more statistically significant. The IV results suggest that Chinese aid has in fact had a *positive* causal effect on the relative size of the manufacturing share across both employment and value added, although the value added coefficients are significant only at 10%. The economic magnitude of the positive effect of a 10% increase in Chinese aid on manufacturing share of employment is about one half to one third of the size of the negative effect on the manufacturing share of employment caused by a 10% increase in DAC aid. There is also now a significant negative effect on the agricultural share of employment and constant VA. Comparable to Table 2, the K-P F-statistics for the DAC instrument set is very high, at 63.2; this is not the case for the Chinese instrument set, at 11.9, which surpasses the Staiger & Stock (1997) rule of thumb of 10, but is not larger than the most stringent of the Stock & Yogo (2005) critical values. This means that a small amount of bias may still be present in the IV coefficients for Chinese aid. It is therefore understandable if the more cautious reader would prefer to interpret the body of the results for the effects of Chinese aid on the manufacturing share as simply non-negative. This is still an important finding considering the contrast with the effects of DAC aid. On the other hand, probable measurement error in the Chinese aid data likely led to attenuation bias in the panel FE estimates, which may explain why they are smaller and less significant than the IV results. In terms of the Sargan-Hansen statistics, all specifications for both DAC and Chinese aid fail to reject the null that all instruments are valid.

Table 9: IV Estimates of Effect of DAC Aid on Manufacturing and Agriculture Shares; *National Level*

	(1) [IV FE] $ManEMP_t$	(2) [IV FE] $ManVA_t$	(3) [IV FE] $ManVAQ_t$	(4) [IV FE] $AgrEMP_t$	(5) [IV FE] $AgrVA_t$	(6) [IV FE] $AgrVAQ_t$
$lnDACAid_{i,t-4}$	-0.0142**	-0.0062	0.0025	-0.0011	-0.0128	-0.0017
	(0.006)	(0.004)	(0.013)	(0.017)	(0.012)	(0.010)
lnGDPpc	-0.0406	-0.0092	-0.0464	0.0010	-0.0814***	-0.1595***
	(0.055)	(0.029)	(0.032)	(0.056)	(0.031)	(0.033)
Pop	0.0013	0.0002	0.0003	-0.0009	-0.0005	-0.0001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
RelProd	-0.0024**	0.0032***	0.0027**	0.0104***	-0.0008	-0.0012
	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)
RelTrade	0.0043*	0.0040**	0.0040***	-0.0010	-0.0037***	-0.0028
	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	387	387	387	387	387	387
R^2	0.281	0.084	0.127	0.088	0.127	0.489
K-P F-Stat	63.2	63.2	63.2	63.2	63.2	63.2
Sargan-Hansen	0.035	0.499	0.056	0.208	1.074	0.165
P-Value	0.85	0.48	0.45	0.65	0.30	0.68

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: IV Panel Fixed Effects estimations of equation (X) for the National Level Data, with controls and time dummies. Dependent variables: share of total employment which is in manufacturing or agriculture sector, share of total nominal value added which is in manufacturing or agriculture sector, share of total real value added which is in manufacturing agriculture sector, all expressed as decimal percentages. Independent variables of interest: logarithm of real dollar flow of DAC aid, or fourth lag thereof. Insignificant coefficients suggest DAC aid had no effect on the relative size of the sector in question; significant negative coefficients suggest DAC aid had a negative causal effect on the relative size of the sector in question. Instruments are the weighted indices of the frequency and severity of natural disasters in the DAC. K-P F-Stats above 10 suggest instrument set is sufficiently strong, Sargan-Hansen test p-values above 0.10 provide supportive evidence for the validity of the exclusion restriction. All variables, controls, units and data sources are as collated in Appendix B.

Table 10: IV Estimates of Effect of Chinese Aid on Manufacturing and Agriculture Shares; *National Level*

	(1) [IV FE] $ManEMP_t$	(2) [IV FE] $ManVA_t$	(3) [IV FE] $ManVAQ_t$	(4) [IV FE] $AgrEMP_t$	(5) [IV FE] $AgrVA_t$	(6) [IV FE] $AgrVAQ_t$
$ihsCHNAid_{i,t-4}$	0.0052**	0.0060*	0.0058*	-0.0020	0.0168***	-0.0102***
	(0.003)	(0.004)	(0.003)	(0.005)	(0.012)	(0.003)
lnGDPpc	-0.0488	-0.0806**	-0.0882**	0.0125	-0.1629**	-0.0860**
	(0.039)	(0.035)	(0.037)	(0.063)	(0.073)	(0.036)
Pop	0.0007	0.0009*	0.0009**	-0.0017*	-0.0014*	-0.0003
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
RelProd	-0.0019**	0.0041***	0.0038***	0.0088***	0.0008	-0.0017
	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)
RelTrade	0.0033	0.0028	0.0035	-0.0046	-0.0067**	-0.0006
	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	291	291	291	291	291	291
R^2	0.296	0.453	0.433	0.400	0.696	0.030
K-P F-Stat	11.9	11.9	11.9	11.9	11.9	11.9
Sargan-Hansen	2.006	3.255	1.383	2.668	0.971	2.978
P-Value	0.57	0.35	0.71	0.45	0.81	0.40

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: IV Panel Fixed Effects estimations of equation (X) for the National Level Data, with controls and time dummies. Dependent variables: share of total employment which is in manufacturing or agriculture sector, share of total nominal value added which is in manufacturing or agriculture sector, share of total real value added which is in manufacturing agriculture sector, all expressed as decimal percentages. Independent variables of interest: inverse hyperbolic sine of real dollar flow of Chinese aid, or fourth lag thereof. Insignificant coefficients suggest Chinese aid had no effect on the relative size of the sector in question; significant positive coefficients suggest Chinese aid had a positive causal effect on the relative size of the sector in question. Instruments are the frequency and severity measures of natural disasters in China interacted with the recipient country probability of receiving aid. K-P F-Stats above 10 suggest instrument set is sufficiently strong, Sargan-Hansen test p-values above 0.10 provide supportive evidence for the validity of the exclusion restriction. All variables, controls, units and data sources are as collated in Appendix B.

5.2 Results at the Subnational Level

As the set of countries from which the regions of the SETD are drawn is quite small, and the aid flows to regions exhibit less variation, it was unfortunately not as yet possible to construct a sufficiently strong instrument set for either World Bank or Chinese aid at the subnational level. Nevertheless, as this is the first time such analysis has been performed at the regional level for Sub-Saharan Africa, providing panel fixed effect estimations for the effects of both World Bank and Chinese aid on structural change at the regional level is of value.

Tables 11 and 12 repeat the estimates of equation (1), except that now i represents recipient regions rather than recipient countries. As the SETD only contains data on sectoral employment at the regional level, $k = EMP$ in all specifications. Table 11 presents the results for panel fixed effects estimations of the effects of World Bank aid on the manufacturing and agricultural employment shares; the odd numbered columns show the contemporaneous effect ($n = 0$), and the even numbered columns show the lagged effect ($n = 4$). The only controls, SHDI and population, are included in the regression output as they can proxy for the demand side drivers of structural change. All specifications contain time dummies, and standard errors are clustered at the *country* level, following the guidance of Bottomley et al. (2016) to cluster at the highest level of potential within-group autocorrelation.

From tables 11 and 12 it can be seen that the results at the sub-national level in terms of the effect of aid on the manufacturing share of employment support those at the national level for the contemporaneous effect, but not for the lagged effect. World Bank aid has a small but statistically significant negative effect on the regional manufacturing share of employment in the year of aid disbursement, but no effect four years on. Chinese aid has a small but statistically significant positive effect on the regional manufacturing share of employment in the year of aid disbursement, but this effect turns significantly negative four years on. No significant effects are found for either WB or Chinese aid on the agricultural share of employment. One brief point of note is that, as the sectoral employment figures were constructed from census and labour force survey microdata, they *do not* include foreign workers sent from donor countries to work on aid projects, so such international workers cannot explain the uncovered sectoral employment effects.

Table 11: Panel FE Estimates of Effect of World Bank Aid on Manufacturing and Agricultural Employment Share; *Sub-National Level*

	(1) [OLS FE] $ManEMP_t$	(2) [OLS FE] $ManEMP_t$	(3) [OLS FE] $AgrEMP_t$	(4) [OLS FE] $AgrEMP_t$
$ihsWBAid_{i,t}$	-0.0003**		-0.0001	
	(0.000)		(0.004)	
$ihsWBAid_{i,t-4}$		0.0001		0.0000
		(0.000)		(0.000)
SHDI	-0.08230	-0.0390	-0.0134	0.0806
	(0.082)	(0.070)	(0.082)	(0.066)
Pop	-0.0036**	-0.0019*	-0.0126**	-0.0103***
	(0.001)	(0.001)	(0.004)	(0.002)
Controls	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
N	1880	1504	1880	1504
R^2	0.003	0.000	0.043	0.034

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS Panel Fixed Effects estimations of equation (X) for the Sub-national Level Data, with controls and time dummies. Odd numbered columns display the contemporaneous effect, even numbered columns show the effect after a lag of four years. Dependent variables: share of total employment which is in manufacturing sector, share of total employment which is in agricultural sector, all expressed as decimal percentages. Independent variables of interest: inverse hyperbolic sine transformation of real dollar flow of World Bank aid, or fourth lag thereof. Insignificant coefficients suggest WB aid had no effect on the relative size of the sector in question; significant negative coefficients suggest WB aid had a negative effect on the relative size of the sector in question. All variables, controls, units and data sources are as collated in Appendix B.

Table 12: Panel FE Estimates of Effect of Chinese Aid on Manufacturing and Agricultural Employment Share; *Sub-National Level*

	(1) [OLS FE] $ManEMP_t$	(2) [OLS FE] $ManEMP_t$	(3) [OLS FE] $AgrEMP_t$	(4) [OLS FE] $AgrEMP_t$
$ihsCHNAid_{i,t}$	0.0005**		0.0004	
	(0.000)		(0.001)	
$ihsCHNAid_{i,t-4}$		-0.0005**		0.0012
		(0.000)		(0.001)
SHDI	-0.0780	0.0207	0.3857***	-0.0374
	(0.048)	(0.140)	(0.060)	(0.354)
Pop	-0.0024	-0.0001	-0.0199***	-0.0210***
	(0.002)	(0.001)	(0.003)	(0.001)
Controls	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
N	765	561	765	561
R^2	0.200	0.038	0.063	0.074

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS Panel Fixed Effects estimations of equation (X) for the Sub-national Level Data, with controls and time dummies. Odd numbered columns display the contemporaneous effect, even numbered columns show the effect after a lag of four years. Dependent variables: share of total employment which is in manufacturing sector, share of total employment which is in agricultural sector, all expressed as decimal percentages. Independent variables of interest: inverse hyperbolic sine transformation of real dollar flow of Chinese aid, or fourth lag thereof. Significant negative coefficients suggest Chinese aid had a negative effect on the relative size of the manufacturing sector. All variables, controls, units and data sources are as collated in Appendix B.

5.3 Discussion of Results

The body of results presented in this section collectively represent empirical testing of all three of the hypotheses developed in section 2. Hypothesis one is strongly supported by the evidence of tables (5), (6), and (9). The panel FE and IV estimations tell a consistent story of negative causal effect of DAC aid on the manufacturing share of employment. The panel FE results suggest additionally that this deindustrializing effect of DAC aid may carry to the manufacturing share of value added, although the IV analysis does not support this. Similarly, the panel FE results suggest that the displaced manufacturing share may have relocated to agriculture, but again this is not supported by the IV results which show a null effect of DAC aid on the agriculture share.

Hypothesis two is weakly supported by the evidence of tables (7), (8), and (10). The panel FE results hint at a small positive effect of Chinese aid on the manufacturing share, but are generally not significant. The IV results are less ambiguous, indicating a significant positive causal effect of Chinese aid on the manufacturing share across both employment and VA. However, the coefficients in the VA regressions are significant only at ten percent. The decision as to whether to err on the side of collectively interpreting these results as a null effect or a positive effect of Chinese aid on industrialization is somewhat subjective. What can, however, be unambiguously declared is that, unlike DAC aid, Chinese aid has played no role in driving *deindustrialization* during the sample period.

Finally, hypothesis three is supported by the evidence of tables (11) and (12). The contemporaneous effects of DAC and Chinese aid on the manufacturing share of employment at the regional level are significant, and operate in the same direction as their national level counterparts, albeit with smaller economic magnitude. For Chinese aid the effect seems to reverse after a lag of four years, with Chinese aid having a *significantly negative* effect on the manufacturing share at the regional level after a lag of four years, whilst the effect of DAC aid after four years is not significant. This implies that, at the sub-national level, the effects of aid on the structure of the economy diffuse more quickly and may revert in the case of Chinese aid. The latter result may be due to the fact that Chinese aid to regions of often 'one-shot' and not sustained over multiple years.

In terms of links to the previous literature, the micro-level study of Ahlerup (2019) found that foreign aid in Uganda caused a reallocation of working hours towards agriculture. This is consistent with the results of this paper, which shows a positive effect of DAC on the agriculture share in some specifications, and also as a reallocation to agriculture would imply deindustrialization, which is the main result of this paper. Page (2012) presented descriptive evidence that DAC aid had not been sufficiently targeted at projects which were supportive of industry, and therefore predicted a deindustrializing, or at least no industrializing, effect of aid. The results of this paper confirm his expectations.

6 Conclusion

This paper has shown that DAC and Chinese aid have meaningful, and meaningfully different, causal effects on the structure of recipient country economies. Since 1990, DAC aid has had a *significant negative effect* on the share of employment in manufacturing in a large sample of SSA, and may also have had a negative effect on the manufacturing share of VA. Conversely, Chinese aid has had no negative effects, in the shorter sample period since 2000, and seems in fact to have had a significant positive effect on the manufacturing share of employment. These effects operate in the same direction at the sub-national level, although they diffuse more quickly. Where there has been deindustrialization in some SSA countries, DAC aid appears to have contributed to it, whilst Chinese aid acted against it.

This paper does not claim to tell the full story of either aid effectiveness or of structural change. The process of deindustrialization, and its reversal in the most recent years as documented by Kruse et al. (2021) in the form of a "manufacturing renaissance", is surely multifaceted. Similarly, foreign aid affects many aspects of recipient country economies. Nevertheless, it is proposed both that foreign aid has been neglected as a driver of structural change, and that structural change has been neglected as an effect of foreign aid. It is the aim of this paper to rectify this neglect and, in doing so, to form a link between the aid effectiveness and structural change literatures.

In terms of development policy, many implications stem from these results. Average productivity for this sample is far lower in both agriculture and trade services than in manufacturing, therefore if employment relocated from manufacturing to either of these sectors, the total effect of DAC aid on structural change was harmful for overall productivity. The results suggest DAC aid causes a concomitant rise in the agricultural share of employment, although it is not proven that this is a relocation of the same displaced manufacturing workers. There remains a strong implication that any *within sector* productivity growth caused by aid was mitigated by negative *between sector* productivity growth, which may contribute to the explanation for why many studies find small, negative, or null effects of aid on growth. Furthermore, to the extent that the structure of the economy is path dependent, the deindustrializing effects of DAC aid may have sparked long term trends in manufacturing decline with further negative impacts.

The finding that Chinese aid did not have a comparable deindustrializing effect may provide some reassurance. It is by no means claimed that Chinese aid is normatively superior to DAC aid on aggregate; the structural change element is just one component of aid effectiveness, and industrialization is just one element of development. Nevertheless, Chinese aid focuses more on infrastructure and other projects which seem to conform more closely with the industry-supporting aid projects advocated by Page (2012); it can therefore be inferred that such targeting of aid can be more successful in terms of sparking industrialization. Moving forward, it may be that the DAC policymakers face a difficult trade off: whilst it is of paramount importance to support agricultural workers and rural dwellers, who are usually amongst the poorest in any society, this may come at the cost of contributing to deindustrialization. An alternative strategy which instead boosts industrialization, giving those agricultural workers and rural dwellers higher paying manufacturing jobs to move to, may be considered more optimal from a long-run macroeconomic perspective. Such an aid strategy is further supported by the important recent finding that industrialization in Sub-Saharan Africa reduces overall poverty levels (Erumban & de Vries 2021). The contemporary policy discussion seems already to be moving towards a consideration of these trade-offs; a 2019 UNIDO event entitled 'Africa Industrialization Day' incorporated panel discussions on the need to strengthen the link between aid and industrial investment, and the Aid-for-Trade Global Review (OECD 2019) contains a full chapter on "promoting economic diversification and structural transformation through industrialization".

In terms of future research, this paper begs the question of which *mechanisms* drive the link between aid and economic structure. The real exchange rate and the urbanization effect are two potential channels, however a deeper exploration of these and other mechanisms will be required in order to fully understand empirically both why aid alters the structure of recipient country economies, and exactly why the effects of Chinese aid and DAC are so different. Furthermore, whilst the SETD represents a considerable advance in terms of sub-national analysis, it is still not as comprehensive in terms of country coverage as compared to the ETD, and expanding it to be more representative of the full set of SSA economies is necessary in order to confirm sub-national results. Additionally, a quality IV estimation procedure of the sub-national effects should further resolve the extent to which the aid effects remain the same at increasingly smaller levels of aggregation.

Appendices

A The Sub-National Economic Transformation Database

In order to facilitate the sub-national analysis of structural change, this paper constructs and presents the Sub-national Economic Transformation Database Beta version [SETD]. The SETD is inspired by, and an offshoot of, the Economic Transformation Database [ETD] (de Vries et al. 2021), and follows many of the same construction principles. The twelve ISIC.4 broad industry sectors and the time period correspond precisely. However, unlike the ETD, it contains only data related to share of persons employed in each of the twelve sectors, as quality value added data for even a modest set of SSA countries at the regional level is still a holy grail[14] Additionally, the SETD relies more on primary source microdata, as NSI census and survey publications and reports rarely present sectoral employment data by region.

Full details as to the construction of the SETD can be found in the sources and methods documentation (Hamilton & de Vries 2021). This includes a complete list of all benchmark sources by country[15]. However, the general construction procedure for the SETD is as follows. First, countries were selected to form the SETD Beta version on the basis of their statistical capacity and openness with regards to publishing data. For each country, a set of candidate benchmark years were identified in which either population censuses or comprehensive[16] labour force surveys were conducted. Each benchmark year was then rigorously investigated in an attempt to find regional sectoral employment data. A country was only included in the SETD if a minimum of three such benchmark years could be found, with reasonable temporal interspacing. In some cases this procedure involved direct

[14]Common practice is to proxy regional income levels and growth with lights data (Henderson et al. 2012), which have been shown to correlate with income growth quite well (Pinkovskiy & Sala-i-Martin 2016); however, attempting to unpick this lights data into different industries would suffer from obvious externality issues, and whilst light intensity might be considered a reasonable proxy for growth in the modern sector, it is unclear what would form the denominator of the ratio in order to compare the *relative* size of the modern and traditional sectors.

[15]All primary source data has been stored and is available on request, although as some data was privately provided by NSI staff, NSI permission may need to be sought for re-use in other databases.

[16]I.e., labour force surveys which incorporated the informal sector and demonstrated a reasonable degree of stratification.

contact with representatives of NSIs[17]. Generally speaking, the benchmark data came in one of three forms, listed in order of preference: population census or survey microdata obtained directly from the NSI, which was then aggregated and tabulated by region and industry of employment; population census or survey published or unpublished reports, some of which contained tables of employment by industry at the regional level; and IPUMS population census microdata samples. IPUMS microdata samples were used only when there were no other options, and no country contains exclusively IPUMS benchmarks. Of the 26 total benchmark sources, eleven are from NSI microdata, six are from published reports, three are from unpublished reports or tables direct from the NSI, and six are from IPUMS.

Once data sources were established for a minimum of three, well spaced benchmark years for each country, the *regional share of each sector's total employment* was calculated on the basis of these sources. For example, in 2000 in Ghana, 10.4% of total persons engaged in agriculture were based in Western region, 15.8% were based in Greater Accra, etc. These *regional shares* were then applied to the *national level totals* for persons employed in that sector-year from the ETD. Therefore, the sum of the persons employed in agriculture in each region of, for example, Ghana year 2000 in the SETD precisely equals the total persons employed in agriculture in Ghana year 2000 in the ETD. This procedure is identically so for all of the twelve sectors. In between benchmark years, the sectoral employment levels were then interpolated using the *national level employment trends* for each sector. This means that inter-regional variation is imposed only from the benchmark years, although between benchmark years there is still variation between regions of different countries. Whilst imperfect, this was the only option as there are no sources for providing regional sector employment trends outside of the constructed benchmark years. The interpolation and extrapolation formulas are exactly as in de Vries et al. (2021). Researchers have the option of using the SETD either as an unbalanced panel, with only the benchmark years, or a balanced panel with the interpolations. It should be noted that the interpolations may introduce attenuation bias into statistical inference performed on the full sample due to artificially smoothing the relative trends. This paper utilizes the full SETD, including the interpolated years.

In addition to the aforementioned potential for attenuation bias, there are two other issues to be aware of when making use of the SETD. First, the sample of countries included in the SETD may not be representative of SSA as a whole. As is commonly the case with such databases, reliance on a certain level of NSI sta-

[17]In particular, this paper would like to thank Narainee Devi Gujadhur of the Mauritius NSI, and Salmon Uulenga and his wonderful colleagues at the Namibia NSI.

tistical capacity tends to bias the sample towards relatively more developed SSA countries (Diao et al. 2018). Whilst the ETD succeeded in including a broader set of SSA countries in terms of income level, many of these countries do not have sufficient primary source data at the regional level to allow for inclusion in the SETD. Similarly, as much of the construction of the SETD required deep reading of NSI documents and sources, and in some cases communication with NSI staff, and as the author is not a French or Portuguese speaker, the sample is biased towards anglophone or formerly anglophone countries. Second, the quality of the primary source data is not the same for every country and benchmark year. Almost all countries in the SETD contain at least some extremely reliable benchmark sources (full population censuses or large scale labour force surveys), however this may not be true of Nigeria.

During the sample period, Nigeria conducted only one full population census in 2006, and this was fraught with a variety of issues (Akinyemi 2020). Therefore, the Nigerian regional data benchmark years utilize exclusively survey microdata; either from labour force surveys or more general household surveys, and in the case of the earliest benchmark year (2003), industry is mapped from occupation. This means that surveys of around 30,000 respondents are aggregated up to conclusions about a country with a population of 200 million. In and of itself, this is not unusual - similarly sized labour force surveys are often used to discuss countries as a whole, and the Central Limit Theorem [CLT] removes many statistical fears. However, as the samples are split by region across Nigeria's 37 federal states, and across the twelve sectors of the SETD, it may be that in the case of some region-industry shares, it is not appropriate to rely on the CLT, especially in the case of the smaller industries. Ultimately, the decision as to whether or not to include the Nigerian regional data must be made by the individual researcher, and will depend on the research question at hand. It is probably more reliable for the broader, primary sectors than the smaller sub-sectors, for the southern and central geopolitical zones rather than the north, and for the latter half of the sample period. As such a large SSA country in terms of both population and GDP, it was considered necessary to include Nigeria in the SETD in the best form which could be managed; however, inferences drawn from the SETD data which are not robust to the exclusion of Nigeria may be driven more by measurement error than by actual relationships, and researchers should be aware of this.

Despite these shortcomings and caveats, it is still claimed that the SETD represents a very considerable advance in terms of available sub-national structural change data in Sub-Saharan Africa, opening the door to analysis of shifting sectoral employment shares at the regional level beyond single country case studies for the first time. The total panel contains 122 separate regions across 29 years, a total of almost 4000 region-years; a sizeable panel on which to perform statistical inference. Restricted even to only the benchmark years, there are around 400 unique region-year observations. Attempts will be made to expand the country coverage of the SETD in forthcoming versions.

The full list of primary sources used in the SETD can be found in Table 13.

Table 13: SETD Primary Sources

Country	Benchmark Sources	Source Type
Botswana	1991 Population Census	IPUMS
	2001 Population Census	IPUMS
	2006 Labour Force Survey	NSI Microdata
	2011 Population Census	IPUMS
Ghana	2000 Population Census	NSI Microdata
	2010 Population Census	NSI Microdata
	2015 Labour Force Survey	NSI Microdata
Mauritiua	1991 Population Census	NSI Report
	2000 Population Census	NSI Direct Contact
	2011 Population Census	NSI Report
Namibia	2001 Population Census	NSI Direct Contact
	2011 Population Census	NSI Microdata
	2018 Labour Force Survey	NSI Microdata
Nigeria	2003 National Living Standards Survey	NSI Microdata
	2008 General Household Survey	NSI Microdata
	2018 General Household Survey	NSI Microdata
Rwanda	2002 Population Census	IPUMS
	2012 Population Census	IPUMS
	2018 Labour Force Survey	NSI Report
Tanzania	2002 Population Census	IPUMS
	2006 Labour Force Survey	NSI Microdata
	2014 Labour Force Survey	NSI Microdata
Zambia	1990 Population Census	IPUMS
	2008 Labour Force Survey	NSI Report
	2014 Labour Force Survey	NSI Report
	2018 Labour Force Survey	NSI Report

Notes: Reference table of benchmark years, primary sources, and source types used in the construction of the Sub-National Economic Transformation Database beta version.

B Full list of variables, units, and sources.

As this paper contains a lot of different variables from a lot of different data sources, Table 14 presents a concise list of all variables, their units (pre-transformation) and their sources to allow the reader to easily keep track.

Table 14: All Variables, Units and Sources

Variable	Units	Source
National Level		
Dependent Variables		
Industry Share of Employment	Decimal Percentage	ETD
Industry Share of Nominal Value Added	Decimal Percentage	ETD
Industry Share of Real Value Added	Decimal Percentage	ETD
Independent Variables		
DAC Aid	Millions of US$ (Constant)	OECD Stat
Chinese Aid	Millions of US$ (Constant)	AidData
Instrument Components		
Natural Disasters	Count	EM-DAT
Deaths Due to Disasters	Count	EM-DAT
Homeless Due to Disasters	Count	EM-DAT
Total Cost of Disasters	Thousands of US$ (Constant)	EM-DAT
Controls & Drivers		
GDP Per Capita	Millions of US$ (Constant)	World Bank
Population	Millions	PWT
Relative Sector Productivity	Ratio	ETD
Relative Trade	Ratio	World Bank
Oil Rents as Share of GDP	Percentage	World Bank
Conflict	Binary Indicator	UCDP/PRIO
Sub-national Level		
Dependent Variable		
Industry Share of Employment	Decimal Percentage	SETD
Independent Variables		
Chinese Aid	Millions of US$ (Constant)	AidData
World Bank Aid	Millions of US$ (Constant)	AidData
Controls		
SHDI	Index	GDL
Population	Millions	GDL

Notes: Reference table of all variables used in this paper alongside units and data sources. More detail regarding the sources and source citations can be found in the text of section 3.

C Replications: Aid, Growth, and Deindustrialization

The purpose of this appendix is to demonstrate that aid likely had a null effect on growth within the ETD sample of SSA countries, and that deindustrialization appears to have taken place for at least part of the sample period. This establishes that the dual phenomena which motivate this a paper - disappointing effects of aid on growth, and underwhelming industrial performance/deindustrialization - are present in the sample analyzed by this paper. These are not replications in the most rigid sense, there is no precise reconstruction of the empirical work of previous researchers. Tsang & Kwan (1999) make the point that replications differ in their tools, their approach and, as a result, the kind of check upon and insight into the original results which the provide, offering a typology of replication studies. This paper uses different methods, databases, and time-periods to check previously developed findings, and therefore can be considered an empirical generalization, within the Tsang & Kwan (1999) replication framework.

First, panel fixed effects and IV regressions are run on the national level sample to demonstrate that aid likely did not positively impact growth within the ETD SSA sample and time period. Second, trends are presented which demonstrate that deindustrialization, or at least no industrialization, likely took place in this sample and time period, although regressions similar to those performed by Rodrik (2016) suggest that the premature deindustrialization trend may be reversing.

C.1 Foreign Aid and Growth in the ETD Dataset

A standard aid effectiveness fixed effects regression is as follows:

$$dlny_{i,t} = \alpha_1 + \beta_1 lnXXXAid_{i,t-n} + \Gamma \boldsymbol{X_{i,t}} + c_i + \delta_t + \epsilon_{i,t} \tag{6}$$

where $dlny_{i,t}$ is the difference log of income per capita, i.e. the growth rate, of country i at time t, $lnXXXAid_{i,t-n}$ is the nth lag of the log of the aid flow from source $XXX \in (DAC, CHN)$, $\Gamma \boldsymbol{X_{i,t}}$ is a vector of controls, c_i is country fixed effects, and δ_t is set of time dummies. The sign and significance of the coefficient β_1 allows appraisal of whether aid has had a negative, positive, or null effect on average across the sample and time period.

An IV version of the standard aid effectiveness regression is:

$$dlny_{i,t} = \alpha_1 + \beta_1 lnX\widehat{XXAi}d_{i,t-n} + \boldsymbol{\Psi} \boldsymbol{X_{i,t}} + \upsilon_{i,t} \tag{7}$$

where the first stage is:

$$lnXX\widehat{XXAi}d_{i,t-n} = \gamma_0 + \boldsymbol{\gamma_1' I_{i,t}^{Dis}} + + \boldsymbol{\Psi X_{i,t}} + \omega_{i,t}$$

and the variables are all as in the fixed effects regression, but where $\boldsymbol{\gamma_1' I_{i,t}^{Dis}}$ is a vector of instruments.

Equations (8) and (9) are estimated on the full set of ETD SSA countries for the time period 1990 - 2018, with the results presented in Table 15. The fourth lag of aid is used so as to appropriately model the timing of aid effects, as discussed by Clemens at al. (2011). However the findings are not materially different for the contemporaneous effect ($n = 0$). For further discussion, please see the presentation of the main specifications in section 4. The instruments are the 'disasters based' instruments presented and discussed in section 4; all discussions regarding exogeneity, instrument construction, instrument validity, and the identifying assumptions of both FE and IV regressions are delayed until this section. Rather than the difference log of income, the dependent variable utilizes the growth rates directly from the World Bank Development Indicators [WBDI]. The controls are not the same as in Table 14, as the 'strucutural change driver' controls are of little relevance to a growth regression, they are omitted and replaced with geographic size.

From Table 15, it can be seen that the empirical regularity of 'disappointing effects of aid on growth' is observable in the ETD sample. The coefficients from the fixed effects regressions are both positive but insignificant and of small economic magnitude, the coefficient from the IV regression of the effects of DAC aid is negative and significant at the 5% level. The coefficient from the IV regression of the effects of Chinese aid is insignificant; however it is positive, of larger economic magnitude, and is 'almost significant', as $p = 0.142$. In summation, these finds suggest that DAC aid had certainly no positive effect on growth, and probably had a negative effect, for the ETD sample of 18 SSA countries across the period 1990-2018. The picture is not quite so bad for Chinese aid, however there is no solid evidence to suggest any better than a null effect. As these findings are estimated with new instruments, they can be added to the large set of aid effects on growth findings, albeit specific to SSA and a relatively recent time period.

Table 15: Panel FE and IV Estimates of Effect of DAC and Chinese Aid on Annual GDP Growth; *National Level*

	(1) [OLS FE] $GDPGrow_t$	(2) [OLS FE] $GDPGrow_t$	(3) [IV FE] $GDPGrow_t$	(4) [IV FE] $GDPGrow_t$
$lnDACAid_{i,t-4}$	0.2208		-1.5558**	
	(0.421)		(0.770)	
$lnCHNAid_{i,t-4}$		0.0490		1.1044
		(0.069)		(0.752)
Controls	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
K-P F-Stat	-	-	34.8	16.7
Sargan-Hansen	-	-	2.40	1.08
P-Value	-	-	0.30	0.58
N	428	429	404	405
R^2	0.217	0.217	-	-

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS Panel Fixed Effects estimations of equation (1), and IV Panel Fixed Effects estimation of equation (2), for the National Level Data, with controls and time dummies. Odd numbered columns display the lagged effects of DAC aid, even numbered columns show the lagged effects of Chinese aid. Dependent variable: growth rate of income per capita. Independent variables of interest: fourth lag of logarithm of real dollar flow of DAC aid, fouth lag of inverse hyperbolic sine of real dollar flow of Chinese aid. Insignificant coefficients suggest a null effect of aid on growth, significant negative coefficients suggest a negative causal effect of aid on growth. All variables, controls, units and data sources are as collated in Appendix B.

C.2 Deindustrialization and 'Lost Growth'

There are various ways to model (de)industrialization trends, and results can vary depending on the method used. Figure 5 plots the annual average manufacturing share of a) employment, b) current price value added, and c) constant price value added across the ETD SSA sample. The averages are *weighted by total value added*, such that the larger economies exert more influence over the average. Weighting instead by population yields very similar pictures[18]. Figure 5 suggests a pattern of deindustrialization in the early part of the sample period for all three manufacturing share indicators, although the timing at which the deindustrialization trend is arrested is earlier for the manufacturing share of employment than for value added. However, in all three indicators, the period 1990-2010 is characterized by either continuous deindustrialization or a combination of deindustrialization and no industrialization. Things improve somewhat from 2010, with a considerable surge in the manufacturing share of employment, and at least an end of the declines of manufacturing shares of nominal and constant value added. This is indicative of the "manufacturing renaissance" discovered and presented by Kruse et al. (2021).

Figure 6 plots the annual average manufacturing share of employment at the regional level, from the SETD. As there is not reliable regional GDP data for the full sample, and as the regions are closer in size than the countries, the averages are unweighted. From Figure 6 can be observed a clear trend of decline in the manufacturing share of employment at the regional level until as late as 2010, when the trend appears to reverse and a decade of regional reindustrialization begins. It would appear that the "manufacturing renaissance" documented by Kruse et al. (2021) may also be occurring at the regional level. It bears repeating that the sample of countries from which the regions are drawn is smaller than the national level sample, which may in part explain the stronger and more monotonic deindustrialization trend until 2010 - the set of countries is much closer to that of Rodrick (2016) than of Mensah (2020).

[18]Unweighted averages yields a better picture in terms of manufacturing share of employment, with a positive upward trend across the time period, but no such equivalent for manufacturing share of VA, which exhibits a continuous downward trend.

Figure 3: Trends in Average Manufacturing Share of a) Employment, b) Current Price Value Added, and c) Constant Price Value Added in SSA Sample, Weighted by Total Value Added.

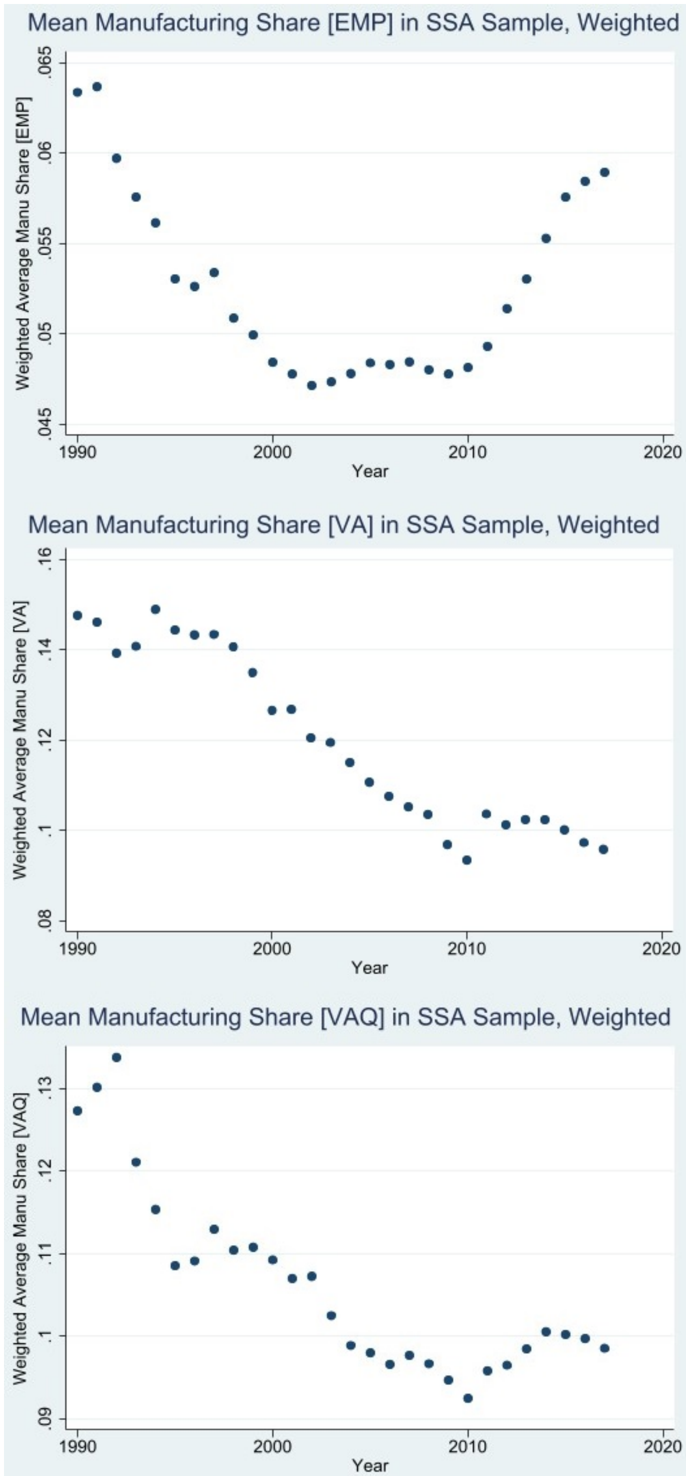
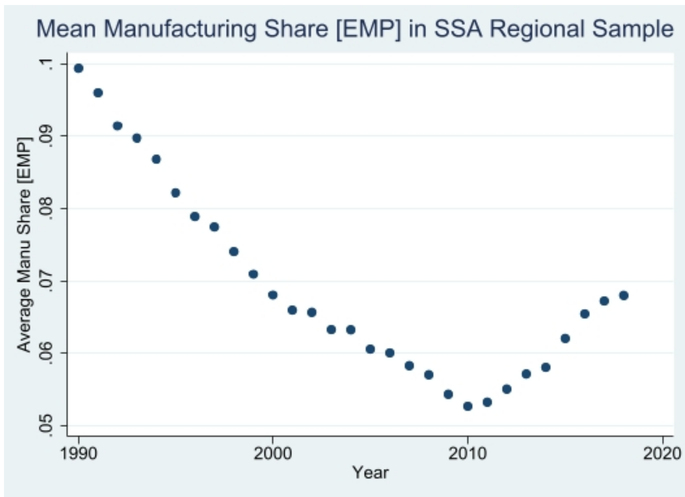


Figure 4: Trends in Average Manufacturing Share of Employment in SSA Regional Sample, Unweighted.



Finally, a version of the 'premature deindustrialization' regression of Rodrik (2016) was performed on the full ETD sample, to explore the extent to which industrialization has been shifting earlier - becoming more premature - across the sample period. The specification is:

$$ManShare_{i,t,k} = \alpha_1 + \beta_1 ln(pop_{i,t}) + \beta_2 ln(pop_{i,t})^2 + \beta_3 ln(y_{i,t}) + \beta_2 ln(y_{i,t})^2 + c_i + \sum^{T} \psi_T PER_T + \epsilon_{i,t}$$

where $ManShare_{i,t,k}$ is the manufacturing share of $k \in (EMP, VA, VAQ)$; the main regressors are the logs of population and income per capita with their quadratics, c_i is country fixed effects, and $\sum_{t=2}^{T} \psi_T PER_T$ is a set of period dummies for each decade or partial decade of the sample, in this case the excluded benchmark period is 1990-99, the first dummy is 2000-09, and the second dummy is 2010-18. The quadratics allow for capturing the 'inverted U-Shape' of the deinstrustrialization hypothesis. The signs of the coefficients on the dummies indicate whether the deindustrialization has been stronger or weaker in later decades as compared to the first decade of the sample. The specification differs from that of Rodrik (2016) in two regards, a) whilst Rodrik utilizes specific country dummies for each country of the sample, this specification uses standard country fixed effects in a panel regression, and b) whilst Rodrik uses the logs of population in pure levels, this estimation prefers the convention of measuring population in millions. Table 16 presents the results of the estimation of the above specification on the full ETD sample, for the manufacturing share of each of employment, nominal VA, and real VA.

The picture which emerges from Table 16 is mixed. The first thing to note, however, is that in all specifications the coefficient on income is strongly significantly positive, and the coefficient on the income quadratic is strongly significantly negative, suggesting the presence of the 'Inverted U-Shape' in the ETD data. Looking now at the coefficients on the decade dummies, it can be seen that they are *significantly positive* in the specification for manufacturing share of employment, suggesting the deinstrustrialization has been *less severe* in more recent decades as compared to the 1990s. In the specification of manufacturing share of nominal value added, they are significantly negative, which represents a continuation of the findings of Rodrik (2016); however, as this is nominal value added, it is likely confounded by price effects. In the specification of manufacturing share of real value added, they are weakly significantly positive in the case of the 2000s dummy, and insignificant in the case of the 2010s dummy. The suggests that (de)industrialization has been neither more nor less strong in recent decades since the 1990s, once income and population changes (and country fixed effects) are accounted for.

The findings are broadly in line with those suggested by Figure 3, and also with those of Mensah (2020), which argues that in a large sample of SSA countries, Africa is not deindustrializing prematurely, and that industrialization performance in terms of real value added continues to be slugglish into the 21st century, but is not necessarily declining. It is not possible to conclude that, within this sample which contains only the most recent three decades, premature deindustrialization is taking place in SSA. What is being dealt with, then, is a pattern of deindustrialization, but not necessarily premature deindustrialization; and furthermore is a pattern which may be beginning to reverse in the most recent time period(s). The main empirical section of this paper will go on to explore the role of foriegn aid from different sources on this deindustrialization process.

Table 16: Panel FE Regressions of Manufacturing Share on Income, Population, and Period Dummies; *National Level*

	(1) [OLS FE] $ManEMP_t$	(2) [OLS FE] $ManVA_t$	(3) [OLS FE] $ManVA_Qt$
$ln(pop_{i,t})$	0.011	0.045***	0.035***
	(0.013)	(0.013)	(0.012)
$ln(pop_{i,t})^2$	-0.001	-0.012***	-0.011***
	(0.002)	(0.002)	(0.002)
$ln(y_{i,t})$	0.992***	0.397***	0.834***
	(0.073)	(0.084)	0.076
$ln(y_{i,t})^2$	-0.025***	-0.010***	-0.020***
	(0.002)	(0.002)	(0.002)
Period00_09	0.006**	-0.007**	0.005*
	(0.003)	(0.003)	(0.003)
Period10_18	0.021***	-0.027***	0.002
	(0.005)	(0.005)	(0.005)
N	501	429	405
R^2	0.213	0.217	-

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS Panel Fixed Effects estimations of manufacturing share in a) employment, b) nominal value added, c) real value added, on income, population, quadratics thereof, and decade period dummies, for the National Level Data. Significant positive decade dummies suggest less deindustrialization than the benchmark decade (90s); significant negative decade dummies suggest more deindustrialization than the benchmark decade (90s). All variables, controls, units and data sources are as collated in Appendix B.

D DAC vs Chinese Aid: A Horse-race

The main empirical results of this paper suggest that DAC and Chinese aid have had effects on industrialization which acted in opposition directions; this begs the question of the extent to which they may have mitigated each other, and which effect was dominant. It would seem to be the case that Chinese aid at best only partially mitigated the deindustrializing effects of DAC aid. This conclusion is complicated by the fact that the sample periods are different due to data limitations. However, the finding that the magnitude of the positive coefficient of the effect of Chinese aid on the manufacturing share of employment is less than half that of the negative coefficient of the effect of DAC aid, combined with the fact from the summary statistics that average Chinese aid flows are considerably smaller than average DAC aid flows, suggests that the industrializing effects of Chinese aid have not been large enough to mitigate the deindustrializing effects of DAC aid. To further support this point, table 17 puts the effects of DAC and Chinese aid in a basic horse-race with each other, where both are entered simultaneously into the panel FE regression with the full set of controls and time dummies. The specification tested is therefore:

$$\begin{aligned} IndShare_{i,j,k,t} = \alpha_1 + \beta_1 lnDACAid_{i,t-n} + \beta_2 ihsCHNAid_{i,t-n} + \\ \Psi \boldsymbol{X_{i,t}^{Dr}} + \Gamma \boldsymbol{X_{i,t}^{Oth}} + c_i + \delta_t + \epsilon_{i,t} \end{aligned}$$

where $n = 4$ and $j = MAN$ in all regressions. All controls are included but the coefficients are omitted from the regression output for reasons of brevity. From Table 17 it can be seen that the fourth lags of both DAC and Chinese aid on the manufacturing shares enter the equations with the expected signs, consistent with the main analysis of this paper. However, whilst the negative effect of DAC aid is highly significant in all three specifications, the positive effect of Chinese aid is significant only on the manufacturing employment share. Furthermore, the economic magnitudes of the positive coefficients on Chinese aid are in all cases considerably smaller than those of the negative coefficients on DAC aid. The result of this horse race would seem to be that DAC aid has a stronger deindustrializing effect that Chinese aid has an industrializing effect, and therefore that Chinese aid did not fully mitigate the deindustrializing effect of DAC aid across the sample period.

Table 17: Panel FE 'Horse-Race' Between Effects of DAC and Chinese Aid on Manufacturing Share of Employment, Nominal VA, and Constant VA; *National Level*

	(1) [OLS FE] $ManEMP_t$	(2) [OLS FE] $ManVA_t$	(3) [OLS FE] $ManVAQ_t$
$lnDACAid_{i,t-4}$	-0.0094***	-0.0067***	-0.0084***
	(0.003)	(0.002)	(0.003)
$ihsCHNAid_{i,t-4}$	0.0011**	0.0004	0.0007
	(0.001)	(0.000)	(0.000)
Controls	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes
N	387	387	387
R^2	0.110	0.040	0.101

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS Panel Fixed Effects estimations of horse-race equation for the Subnational Level Data, with controls and time dummies. Dependent variables: share of total employment which is in manufacturing sector, share of total nominal value added which is in manufacturing sector, share of total real value added which is in manufacturing sector; all expressed as decimal percentages. Independent variables of interest: fourth lags of logarithm of real dollar flow of DAC aid and inverse hyperbolic sine transformation of real dollar flow of Chinese aid. All variables, controls, units and data sources are as collated in Appendix B.

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