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FOREIGN AID AND STRUCTURAL CHANGE

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Abstract

This paper examines the impact of aid on industrialization in 18 Sub-Saharan African countries from 1990-2018. I employ a Two-Stage Least Squares (2SLS) regression approach, leveraging a novel Shift-Share Instrumental Variable (IV) strategy to identify the effects of DAC aid. This method exploits exogenous variations in donor country aid budgets resulting from the occurrence of natural disasters within those countries. The findings suggest that DAC aid reduces the manufacturing share of employment in recipient countries, increases the agriculture share of employment, and has no effect on non-government services. On average, a ten percent increase in aid causes an estimated 0.09 percentage point decrease in the manufacturing employment share after three years. Results using a novel sub-national dataset corroborate the findings at the national level. Aid from China, a non-DAC source, does not exhibit the same deindustrializing effects observed with DAC aid.

Keywords— development aid, structural change, manufacturing.

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1 Introduction

Inter-sectoral structural change, and particularly shifts from agriculture to manufacturing, plays a major role in the process of economic development (Diao & McMillan, 2018; Gollin, 2014; Herrendorf et al., 2014; Sen, 2023).[1] This is because, in contexts of large productivity gaps between sectors, such industrialization can significantly boost average labour productivity growth (Gollin et al., 2013; McMillan et al., 2014). Despite this, support for industrialization and structural change remains a low priority in international development aid allocation, at least from conventional OECD donors (Desai et al., 2024; Dreher et al., 2024; Kaya et al., 2013; Page, 2012). This is especially noteworthy in the context of sub-Saharan Africa [SSA] where, compared to other developing regions, sub-optimal trends in structural change and industrialization is a particular policy concern (McMillan et al., 2014; Rodrik, 2016; Stiglitz, 2021; Wood, 2019).[2] Industrialization has failed to take-off, or is

[1] In this paper, the term structural change is used specifically to denote between-sector reallocations of this type. This differs somewhat from usage elsewhere in the literature, whereby for example Herrendorf et al. (2014) favour the term structural transformation. The term structural change is preferred here to emphasize that such changes may or may not be 'transformative' in terms of development impact, and that this paper concerns a narrower definition that the wider concept of structural transformation as advocated by Gollin and Kaboski (2023).

[2] SSA is not the only developing region which may have experienced sub-optimal structural change; for example, Hamilton and de Vries (2023) showed that the former-Soviet transition economies were actually the worst-performing developing region in terms of structural change contribution to growth in the period since 1990.

only just taking-off, across large swathes of the African continent (Kruse et al., 2023). It is of course understandable that foreign aid practioners may have other and more pressing aims than structural change; be they poverty alleviation, disaster relief, rural subsistence support, etc. (Dreher et al., 2024; Kanbur & Sumner, 2012). Nevertheless, aid which does not consider structural change may still have substantial indirect effects upon it, and against a backdrop of slow industrial development in SSA, this potential effect is a major yet underexplored concern.

This paper positions itself at the intersection of the structural change and aid effectiveness literatures to ask the question: what is the effect of official development assistance [ODA] aid on structural change, and particularly on the manufacturing share of employment and real value added in SSA? My aim is to identify this reduced form relationship using a novel identification strategy, and provide evidence that the findings are a specific feature of recent DAC aid in recent years rather than a general consequence of all types of aid. I hypothesize a negative impact of DAC aid on the relative size of the manufacturing sector in recipient SSA countries. This is because theoretical work into large revenue inflows to developing countries predicts a suppression of the manufacturing sector when these revenues are not used to bolster manufacturing productivity (Adam, 2013; Adam & Bevan, 2006; Diao & McMillan, 2018; Gollin et al., 2016; Sala-i-Martin & Subramanian, 2013). Most of this literature focuses on natural resource rents, but Diao and McMillan (2018) explicitly anticipate a comparable effect for foreign aid, and Rodrik (2008) speculates that such a deindustrializing effect may be a mechanism through which aid impacts growth. It has been shown that DAC aid reduces manufacturing competitiveness in recipient countries whilst increasing recipient country consumption, with this increase being almost entirely made up of imports (Rajan & Subramanian, 2011; Temple & Van de Sijpe, 2017). Both empirical and policy-report evidence suggests that the manufacturing sector is a very low priority for DAC aid, implying that a large boost to manufacturing productivity from aid is unlikely (Dreher et al., 2024; Kaya et al., 2013; Pöntinen, 2014). I also show empirically this limited impact of DAC aid on manufacturing productivity, and that aid increases the relative size of agriculture but has no effect on non-government services.

In order to answer this research question with a claim to causality, I employ a novel Shift-Share Instrumental Variables [SSIV] identification strategy with panel and time fixed effects which exploits intertemporal variation in the total volume of DAC aid driven by the frequency of natural disasters occurring in the DAC donor countries. I argue that natural disasters occurring in donor countries (negatively) influence aid budgets both by diminishing the resources available to give as foreign aid and by influencing citizen preferences away from international relief efforts. Cross-sectional variation is introduced on the basis of each recipient country's exposure to exogenous shocks to aid flows from each DAC donor. The interaction of these two sources of variation yields an instrument for DAC aid which exhibits full panel variation. In short, identification manifests as follows: natural disasters in donor countries shock their overall aid budgets, and the degree to which these shocks differentially impact aid to recipient countries depends on their level of exposure to aid from that specific donor. This SSIV is inspired by those of Nunn and Qian (2014), Dreher and Langlotz (2020), and Dreher et al. (2021), but utilizes an entirely new source of exogenous intertemporal variation (natural disasters) and a different construction approach. As discussed by Borusyak et al. (2022) and Goldsmith-Pinkham et al. (2020), the plausibility of the exclusion restriction in such SSIV instruments increases with the degree of exogeneity in the intertemporal component; I argue that my natural disaster based instrument offers a high degree of such exogeneity. Data for the relative sector sizes come from the new Economic Transformation Database [ETD] from UNU-WIDER and the Groningen Growth and Development Centre [GGDC] (de Vries et al., 2021; Kruse et al., 2023) which provides sectoral employment and VA data for a set of 18 SSA countries for the period 1990-2018.

The results show that DAC aid has had a negative impact on recipient country industrialization in SSA over the sample period from 1990. DAC aid is estimated to have reduced the relative manufacturing share of the economies of Sub-Saharan Africa in terms of employment; these effects are statistically significant and economically meaningful. According to the preferred SSIV specification, a ten percent increase in the flow of DAC aid causes an approximately 0.09 percentage point decrease in the manufacturing share of employment after three years. Regressions on the manufacturing employment totals suggest that these relative results stem at least in part from a negative impact on the level of manufacturing employment, rather than from disproportionately positive impacts on other sectors. Regressions for the impact of aid on manufacturing labour productivity shows a likely null effect. I provide some evidence that DAC aid may also have reduced the manufacturing share of real value added, although these negative coefficients are statistically significant only in OLS panel FE regressions and not in the preferred SSIV specifications. I show, by contrast, that DAC aid increases the relative size of the agriculture sector in terms of employment, and has no impact on the relative size of the non-government services sector. The estimated impact of a 10 percent increase in aid is a 0.19 percentage point increase in the agriculture share of employment, and no effect on the services share of employment. This suggests that workers displaced from manufacturing may be relocating to the lower-productivity agriculture sector, and that in addition to not supporting agriculture-to-manufacturing routes to structural transformation, aid has also not contributed to alternative agriculture-to-services routes.

To shed further light on these results, I also investigate the impact of aid from the largest non-DAC donor - China - on the manufacturing shares of employment and real value added and find a non-negative effect. The reason for analyzing the effects of aid from China is to support the argument that the negative industrialization effect of DAC aid is more likely a feature of specific DAC allocation priorities rather than an inherent feature of all aid. China is the largest non-DAC donor and as such is not subject to the same allocation priorities, and there is substantial evidence that Chinese aid is disbursed very differently from DAC aid (Anaxagorou et al., 2020; Brazys et al., 2017; Dreher & Fuchs, 2015; Dreher et al., 2019). The finding that Chinese aid does not suppress the African manufacturing share suggests that a negative impact on manufacturing is not an inevitable consequence of any large cash inflows in the form of aid, but rather a specific consequence of the composition of DAC aid over recent decades.

Finally, I also explore the impact of a subset of ODA - World Bank Aid - on the manufacturing share of the employment at sub-national (regional) level and show a significant negative association from OLS panel fixed effects regressions. To make possible this analysis, I extend the ETD to present a new Sub-national 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 regional level. A 'micro-macro' paradox in aid effectiveness research has emerged from the fact that the impacts of aid on various outcomes can appear very different at different levels of aggregation (Addison et al., 2017; Arndt et al., 2010); therefore a finding that sub-national results do not contradict those of the national level analysis provides some support as to their generality. I also show that Chinese aid has a significant, positive association with the manufacturing share of employment at the sub-national level. This is again in-line with the national level results.

This 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. I contribute the finding that DAC aid has at least not helped to promote manufacturing growth in Africa in recent decades, and has in fact likely acted as an impediment. Despite the importance of this research question, attempts to answer it have emerged only very recently, and to my knowledge this is the first paper to tackle the question with a causal identification strategy other than GMM. Tékam Oumbé et al. (2024) explore the link between aid and industrialization in terms of value added in Africa using GMM and find a negative association in line with the results of this paper, and Asiama and Nell (2024) employ a VAR and show that aid 'Granger-causes' manufacturing growth, but do not attempt causal identification.[3] Rajan and Subramanian (2007) show that higher aid inflows are subsequently associated with a lower share of manufacturing in recipient country GDP, and Rajan and Subramanian (2011) found DAC aid cause a lower relative growth rate of exportable as compared to non-exportable manufacturing production. I contribute causally identified results for the impact of aid on the manufacturing share of employment as well as the employment shares of other main sectors, in addition to updated results on the impact of aid on the manufacturing share of value added which go beyond panel fixed effects. I further contribute analysis of the impact of aid on within-sector productivity growth, comparative analysis with the impact of aid from an alternative source (China), and results at the regional level based on a novel sub-national database.

In terms of the aid effectiveness literature, this paper contributes to the expanding set of research exploring the impact of aid on a broader set of macroeconomic outcomes, and particularly to outcomes which may act as alternative mechanisms through which aid can contribute to growth (Andersen et al., 2022; Jones & Tarp, 2016; Temple & Van de Sijpe, 2017). I do not intend this paper as a fundamental critique of aid *per se*, but instead to alert both aid practitioners and promoters of structural transformation to an important side-effect of the current set of aid allocation priorities and the possible need for mitigation. The comparative analysis on the impacts of Chinese aid contributes to the nascent literature

[3]In contrast to this paper, both Tékam Oumbé et al. (2024) and Asiama and Nell (2024) consider industrialization almost exclusively in terms of value added share, although Tékam Oumbé et al. (2024) do use the employment share in one robustness check. The Asiama and Nell (2024) finding of Grander-causality implies only that increased aid flows tend to precede industrialization episodes chronologically.

on Chinese and Chinese vs DAC aid effects (Anaxagorou et al., 2020; Dreher et al., 2019, 2021; Isaksson & Kotsadam, 2018), and the quantification of the impact of aid on the manufacturing share contributes to the literature establishing the empirical drivers of structural change and industrialization in Africa (Mijiyawa, 2017; van Neuss, 2019). I also make a technical contribution in the form of new SSIV strategy for identifying aid effects, and a significant data contribution in the form of the first database of regional sectoral employment data in Sub-Saharan Africa which utilizes national statistical institute [NSI] primary sources and microdata and yields a complete, balanced panel for almost three decades.[4]

The remainder of this paper will proceed as follows. Section 2 provides further framing of the expected links between aid and structural change and evidence of the low priority of industrial-sector support in DAC aid allocation. Section 3 compiles data, sources, and descriptive statistics. Section 4 outlines the empirical strategies and introduces the new instrumental variable approach. Section 5 presents and discusses the main results of the impact of DAC aid on manufacturing at the national level. Section 6 explores the results further via a discussion of alternative outcomes on which aid has had a positive impact, a comparative analysis with the effects of Chinese aid, and analysis at the subnational level. Section 7 concludes.

2 Foreign Aid and Structural Change

Structural change in the form of industrialization and the reallocation of economic activity towards the manufacturing sector is seen as a key ingredient of the recipe for rapid economic development, both in the actualized growth experiences of development success stories in East Asia and elsewhere, and as a potential source of growth in currently lower-income countries (Herrendorf et al., 2014; Timmer, 2000; Young, 1995). This is because manufacturing generally operates at considerably higher average labour productivity than other labour-intensive sectors such as agriculture and trade services, and therefore the movement *en masse* of workers to these sectors from agriculture can rapidly raise aggregate labour productivity (Diao & McMillan, 2018; Gollin, 2014; McMillan et al., 2014). For this reason,

[4]The important paper of Baccini et al. (2023) explores structural change in SSA at the subnational level and makes a series of valuable data contributions, but their employment data comes only from IPUMS census samples which usually have no more than two benchmark years per country and provides sporadic coverage of the 1990s and early 2000s.

there is considerable interest in understanding the determinants and impediments of such structural change, particularly on the African continent where rapid and sustained economic growth remains elusive in many countries (Diao et al., 2017; Fosu, 2018; Rodrik, 2018a). Optimism over recent improvements in the rates of growth in Africa is often tempered by the observation that it is occurring in the absence of transformative industrialization.

Many countries in SSA are either yet to experience industrialization of any scale, or have started industrializing only very recently (Kruse et al., 2023). Of the relatively richer countries in the region, many appear to have already begun a process of deindustrialization from comparatively low peaks in manufacturing share of employment and GDP (Rodrik, 2016). In cases where African countries are experiencing relative manufacturing growth, this is often characterized by lower-productivity informal manufacturing activities (Diao et al., 2024; Kruse et al., 2023; McMillan & Zeufack, 2022), and in cases where African countries are experiencing growth-enhancing structural transformation, it is frequently occurring in the absence of industrialization, with labour moving from agriculture to services rather than to manufacturing (Mensah et al., 2023; Rodrik, 2018b; Sen, 2019). Attention in the literature is increasingly turning to whether services can offer a viable alternative to manufacturing as a driver of structural transformation (Atolia et al., 2020; Baldwin & Forslid, 2023; Rodrik, 2018b; Sen, 2023). Various drivers and explanations have been proposed for these non-transformative industrialization trends in Africa, including globalization, labour-saving technological progress, labour costs, factor endowments, lack of policy dedication, and exchange rate overvaluation (Austin et al., 2017; Gelb et al., 2013; Mijiyawa, 2017; Rodrik, 2016). In particular, Gollin et al. (2016) place emphasis on revenue inflows in the form of natural resource rents as a major determinant of the nature of structural transformation, arguing that these inflows appreciate the real exchange rate without stimulating manufacturing productivity, causing recipient countries to lose manufacturing competitiveness and gain comparative advantage in consumption services.

There is reason to expect that foreign aid may also influence structural change and the relative size of the manufacturing sector in recipient countries. Evidence suggests that DAC aid flows exert an adverse effect on manufacturing competitiveness in recipient countries and can reduce relative growth of exportable manufacturing production (Rajan & Subramanian, 2011). This effect was attributed to an appreciating impact of aid on the real exchange rate.[5] Furthermore, there is a high degree of domestic absorption of aid whereby aid inflows increase imports almost one-for-one, and have a much larger positive impact on consumption than on investment as shares of GDP (Temple & Van de Sijpe, 2017). Whilst aid is therefore increasing the consumption levels of recipient country citizens, this increase in consumption appears to take the form of imported manufactured goods and domestically produced non-tradeables. This comes alongside a negative impact on the competitiveness of domestic manufacturing. Furthermore, aid generates a productivity bias in favour of domestic non-tradable vs tradable production via spillover effects when it stimulates public infrastructure spending (Adam & Bevan, 2006), which Donaubauer et al. (2016) show that it does. This is because public infrastructure investment has a double-gain for non-tradable sectors because not only can they make use of it to facilitate their production and distribution, it also allows for more consumers to reach them at lower costs. There is also evidence that aid increases the relative sizes of certain non-manufacturing sectors such as the public sector (Boone, 1996), and the informal consumption services sector (Chatterjee et al., 2022), which may result in the relative contraction of other sectors including manufacturing. Finally, it has been shown that aid targeted at rural and agricultural areas can act as a 'pull-factor' for internal migrants towards the agriculture sector (Lanati et al., 2023), and that such rural and agricultural targeted aid is an increasingly large component of the overall DAC aid mix (Kaya et al., 2013). Within rural areas, aid increases the proportion of time individuals spend working in agriculture and decreases time spent working in non-agriculture sectors (Ahlerup, 2019).

On these bases, I hypothesize that aid of this type exerts a deindustrializing effect on structural change and therefore has a negative impact on the relative share of manufacturing in employment and economic activity in recipient countries in SSA. This is the main hypothesis which I test empirically in this paper. I also test whether DAC aid has had a negative effect on the levels of manufacturing employment, so as to show that any reduction in the share stems from a negative impact to manufacturing rather than disproportionately positive impacts on other sectors, and whether DAC aid has had an impact on the shares of agricultural and services employment, to provide an indication of where workers may be relocating or remaining instead of manufacturing. I further test the additional hypothesis

[5] In addition to Rajan and Subramanian (2011); Addison and Baliamoune-Lutz (2017), Elbadawi et al. (2012), and Nowak-Lehmann et al. (2012) all show empirically that aid appreciates the real exchange rate. In contrast, Jarotschkin and Kraay (2016) do not find such an effect in the short run, but explicitly warn against ruling out a longer run appreciation.

that aid does not have a sizeable impact on manufacturing productivity, which would imply any loss in manufacturing competitiveness as a result of aid is not mitigated by gains in efficiency. Finally, as I discuss in the next sub-section, I propose that any deindustrializing effect of aid is a specific feature of the recent and current DAC aid mix and is therefore not an inevitable side-effect of all foreign aid. I illustrate this by testing the hypothesis that an alternative source of aid - aid from China - which is not subject to DAC allocation priorities does not have the same negative impact on the manufacturing share.

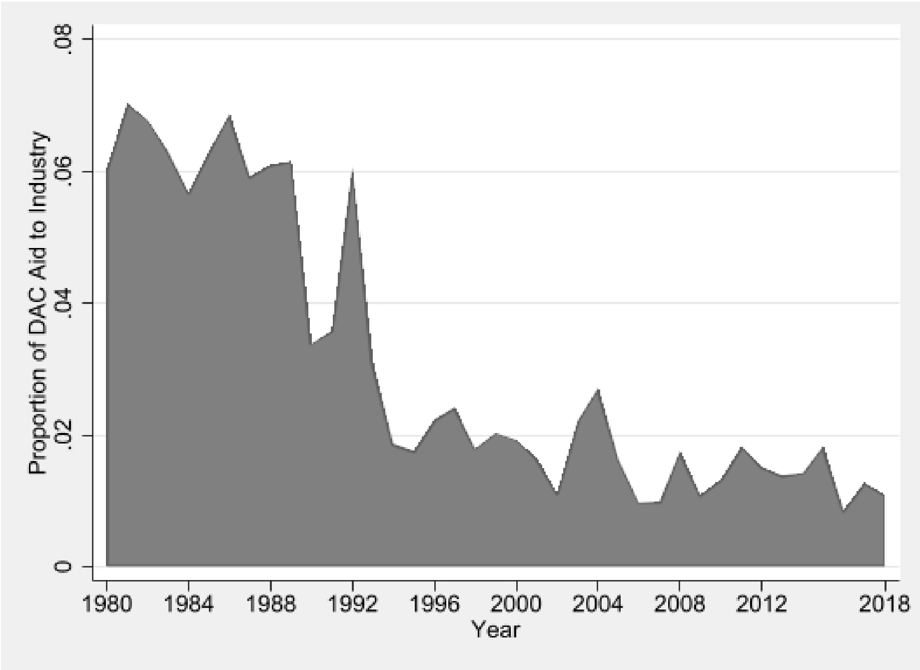
2.1 Empirical Background

In recent decades, DAC aid specifically has placed a low and diminishing emphasis on supporting the manufacturing sector which would render it likely that this aid did not have a pro-industrializing effect. Figure 1 presents data on aid by sector from the official OECD aid statistics for the period 1980 to 2018. This is for a longer period than that of the main empirical analysis, which runs from 1990, but the preceding decade is included so as to illustrate the change from 1990. Panel A shows the proportion of total ODA which was directed explicitly at supporting industry. Since around 1992, this proportion has been very low, usually below two percent of total ODA and frequently as low as one percent. This was not always the case; in the years before 1992, this share was consistently around six percent - at least three times larger than in almost every post-1992 year. To place this share in a broader context, panel B shows the total ODA budget since 1980, normalized to one and segmented by sector/use. Industry is at the bottom of the figure, with Agriculture immediately above it. For the entire period, Agriculture received as least twice as much ODA as Industry. Both of these sectors are dwarfed in recent years by Humanitarian Aid, which has greatly expanded since 1990, by Economic Infrastructure and, most notably, by aid to the Social Sector - including public sector activities such as education, healthcare, sanitation, and government - which reached 45% of overall ODA in 2018.

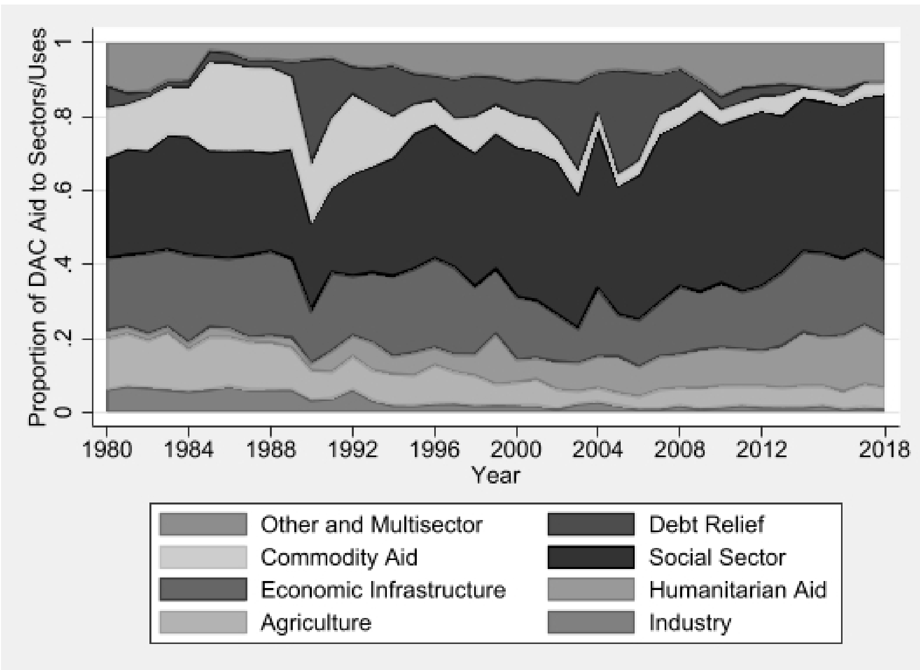
Figure 1 demonstrates that, not only is aid to industry a low priority for the DAC, it has greatly decreased in relative terms since the 1990s. Furthermore, this share is consistently dwarfed by those to other sectors of economic activity and employment, such as agriculture,

Figure 1: DAC Aid to Industry and Other Sectors as Shares of Total Aid

(a) DAC Aid to Industry



(b) Total DAC Aid by Sector



Note: Panel A shows the share of total ODA which was directed to Industry as a percentage of total aid for the time period 1980-2018; Panel B shows the shares of total ODA which were directed to each sector or use for the time period 1980-2018. Sectors or uses are the official ODA sector classifications. *Source:* Authors calculations from OECD Aid Statistics. Creditor Reporting System database.

the public sector, and construction (which drives most economic infrastructure projects).[6] Not only is a larger proportion of aid targeted explicitly at agriculture and rural support than at industry, there is also evidence to suggest that *within* other aid categories such as social sector support and infrastructure, priority has further shifted over time towards impoverished rural settings (Gomanee et al., 2005). Page (2012) provides extensive descriptive evidence of the lack of attention paid by ODA to industry and other 'high value added' sectors in SSA, and predicts negative consequences for structural change. In particular, he notes that to the extent that aid since 1990 has considered the private sector, the focus has been only on the 'investment climate' in terms of regulatory and institutional environment, rather than on technology and productivity-enhancing investments themselves. A recent and highly extensive review of the modern aid effectiveness literature by Dreher et al. (2024) makes the case that aid projects should be evaluated in line with donor motives rather than macroeconomic aggregates, and shows that research which evaluates aid in this way tends to find more significantly positive outcomes. Of particular relevance to my hypotheses outlined above is that, according to their overview, these donor motives very rarely incorporate industrialization or structural change. The most consistent positive impacts found are along the dimensions of human development and health, conflict reduction, migration reduction, and strengthening of political ties. The implication is that these are the most common achievements of ODA because these are the most common intentions, and that structural transformation plays a much smaller or even negligible role in DAC donor motivations.

3 Data and Descriptives

My focus in this paper is on sub-Saharan African [SSA]. For data on the relative size of manufacturing and other sectors in SSA, I use the Economic Transformation Database [ETD] from the Groningen Growth and Development Centre [GGDC] which provides the broadest coverage of employment and real value added by sector for the region (de Vries et al., 2021; Kruse et al., 2023). The ETD provides consistent data on employment, real, and nominal value added [VA] by twelve ISIC 4 industry sectors in 18 SSA economies for the period

[6] Pöntinen (2014) provides an alternative sectoral breakdown of ODA and also explicitly notes the diminishing importance of industry, providing an explanation of why this was the case in the form on a diminishing reliance on older, 'savings-investment-gap' development models. Frot and Santiso (2010) also highlight and document this shift from production to social sectors in DAC aid priorities and date the change at around 1990, and Kaya et al. (2013) note a shift in aid priorities towards alleviating subsistence poverty in rural and therefore non-industrial areas.

1990-2018.[7] The ETD or its precursor databases from the GGDC have underpinned influential analyses of structural transformation in SSA (Diao et al., 2017; Kruse et al., 2023; McMillan & Rodrik, 2011; McMillan & Zeufack, 2022; Rodrik, 2016). The high degree of internal, inter-temporal, and international consistency in the ETD renders it preferable for comparative analysis of structural change in value added as compared with, for example, composite measures of UN value added over GDP, and it is the largest source of sectoral employment data drawn from primary sources as opposed to modelled estimates. My sample is therefore restricted to these 18 countries, which account for 73% of the GDP and more than half of the population of SSA.[8] The sample period, 1990-2018, corresponds well with the period of reduced prioritization of industry in the DAC aid mix as illustrated in section 2.

Data on official development assistance (aid) is from the OECD Aid Statistics database in constant 2017 US dollars and represents the total flows of aid from the DAC donors to each recipient country in each year. ODA is (donor) government aid which is disbursed with the explicit intention of promoting development and welfare in developing countries. Only grants and soft (low or zero interest) loans qualify as ODA, and the common DAC framework imposes both a common set of priorities and a harmonized and reliable reporting system (Scott, 2018). Nevertheless, the dates from the OECD Aid Statistics are those of disbursement which might therefore be slightly earlier than when the money is actually spent at the project level. This is one reason for considering the lagged effect of aid as discussed in section four (Clemens et al., 2012). The DAC includes a total of 32 donor countries including Australia, Canada, Japan, New Zealand, South Korea, the UK, the USA, and the countries of the European Union. All DAC donor countries are democratic states and OECD members. The five largest DAC donors in terms of total volume of aid since the foundation of the DAC are, in order: the USA, Germany, the UK, Japan, and France. These remain the five largest donors in the final year of my sample, 2018.

Controls are drawn from the structural change and aid effectiveness literatures. Controlling for income and population is standard practice because of the influence of demand on

[7]The 18 countries are Burkina Faso, Botswana, Cameroon, Ethiopia, Ghana, Kenya, Lesotho, Mozambique, Mauritius, Malawi, Namibia, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Uganda, and Zambia.

[8]Authors calculations based on the Penn World Table version 10.0 in the final sample year, 2018.

the reallocation of economic activity (Comin et al., 2021; Rodrik, 2016).[9] I also control for oil rents as they represent an alternative large revenue inflow which may impact economic structure (Sala-i-Martin & Subramanian, 2013). I construct controls for relative sectoral productivity and comparative advantage of trade as additional drivers of structural change (van Neuss, 2019). These are the ratio of manufacturing to agricultural productivity and the ratio of trade in merchandise to trade in services, respectively.[10] Finally, as conflict can be very destructive to manufacturing and other capital-intensive sectors (Binetti, 2023), a conflict dummy is included taking the value one in years when a country experienced conflict.[11]

This paper also makes novel contributions in terms of methods and sub-national data. The new SSIV strategy, detailed in section four, exploits exogenous intertemporal variation in the frequency of natural disasters occurring in donor countries. The source of natural disaster data is the Emergency Events Database [EM-DAT] of the Université Catholique de Louvain (Delforge et al., 2023); the main variable used is the number of natural disasters in a donor country in each year. Sub-national level analysis is performed on a panel of SSA regions of a new Sub-national Economic Transformation Database [SETD]. The SETD comprises a total of 122 different African regions across 8 countries in SSA.[12] The sample period, 1990 - 2018, and the sector disaggregation correspond precisely to the parent ETD. Appendix A presents the sources and methods of the SETD and discusses limitations. Finally, comparative analysis in section 6 seeks to demonstrate that not all aid necessarily suppresses the manufacturing sector by comparing DAC aid with aid from China; data for aid from China is from the Geocoded Global Chinese Official Finance Dataset version 1.1 constructed by Dreher et al. (2021) and Dreher et al. (2022) for the period 2000-2014. The implications of using this data are discussed in section 6.

[9] The main specifications do not include quadratics of the income per capita and population controls as in Rodrik (2016), Kruse et al. (2023), Baccini et al. (2023), etc., because the purpose of those regressions are to establish trends in manufacturing rather than causal impacts. Nevertheless, robustness checks are performed whereby the log of aid flows is included in Rodrik (2016)-style regressions with quadratics.

[10] The relative trade variable is not included in the main specifications as it is available for fewer country-years and reduces the sample size, however all main results are robust to its inclusion.

[11] Data on GDP, oil rents, and relative trade are constructed from the World Bank Development Indicators [WBDI], population is from the Penn World Table [PWT] version 10.0 (Feenstra et al., 2015), relative productivity is calculated from the ETD, and conflict is from the Armed Conflict Dataset version 20.1 of the Uppsala Conflict Data Program (Gleditsch et al., 2002; Pettersson & Öberg, 2020).

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

Table 1 presents summary statistics of the manufacturing shares of employment and real value added, the agricultural shares, the logarithm of DAC aid flows, and relevant controls at the (recipient)country-year level. The average manufacturing share of value added is greater than the average share of employment, whereas the average agriculture share of employment is (much) greater than the average share of value added. This indicates the vast labour productivity difference between the two sectors, which is confirmed by the average productivity ratio. Sectoral differences in average labour productivity are discussed further below. Each country in the sample received at least some DAC aid in each sample year. It is not therefore necessary to perform any manipulations to account for zeros in the log transformation. The average annual aid flow to each country was $361 million, and the largest was over $10 billion. Relatively large standard deviations in the manufacturing and agriculture shares show that there is considerable variation in the structures of the economies in the sample; and in some cases the manufacturing shares of employment and value added are close to the lower bound of zero.

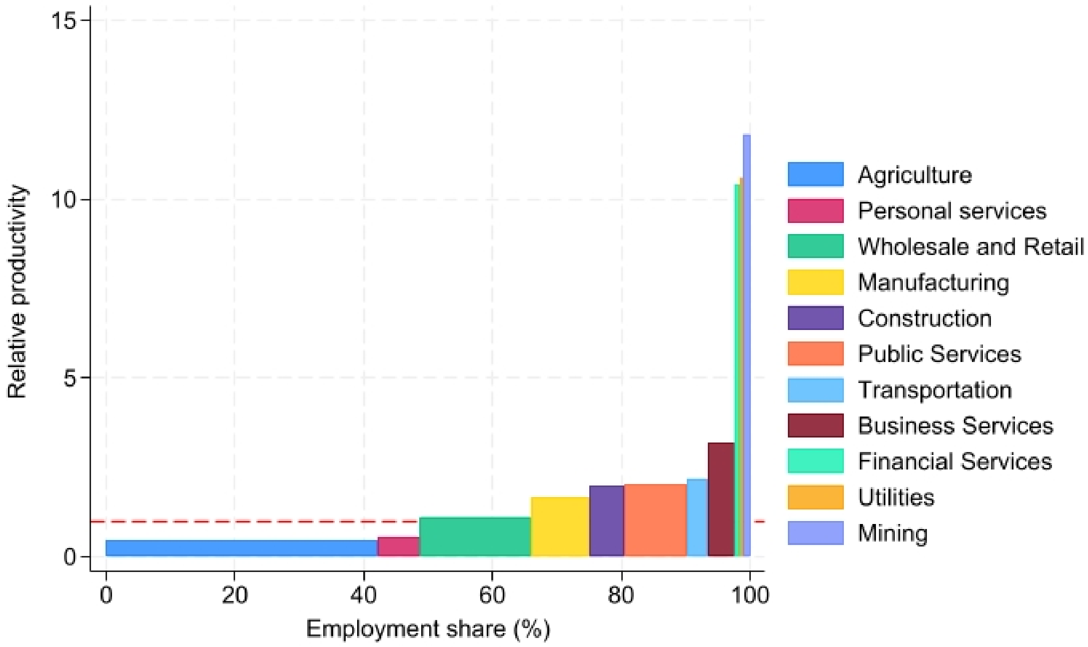
Table 1: Summary Statistics; *National Level Data 1990-2018*

	Mean	S.D.	Min	Max	N
Man Share [EMP]	0.073	0.055	0.001	0.315	501
Man Share [VAQ]	0.112	0.048	0.026	0.290	501
Agri Share [EMP]	0.579	0.228	0.067	0.949	501
Agri Share [VAQ]	0.230	0.147	0.021	0.696	501
DAC Aid (ln)	5.89	1.17	0.20	9.28	501
GDP p.c. (ln)	7.02	0.95	5.31	9.24	501
Population (millions)	26.88	33.77	1.06	190.9	501
Relative Prod (Man/Agr)	7.9	4.77	0.77	23.79	501
Conflict	0.20	0.40	0	1	501

Notes: Summary statistics for main dependent variables, independent variable of interest and key control variables used in the main specifications. Observations refers to country-years, sample is Sub-Saharan African countries from 1990 - 2018.

Figure 2 shows the average sectoral structure of the SSA sample in terms of employment shares and average sector labour productivity in the final sample year of 2018, as unweighted averages. The width of the bars shows employment in each sector as a share of total persons employed, and the height shows the ratio of sector labour productivity to average labour productivity across all sectors.[13] Labour productivity is calculated as constant VA per worker per annum in each sector, and then normalized to the average labour productivity in each country before taking the unweighted average across the eighteen SSA countries.

Figure 2: Average Labour Productivity and Employment Share by Sector, 2018



Note: Figure shows the unweighted average of 18 SSA Countries; width of bars denotes share of persons employed in each sector in 2018, height of bars denotes labour productivity of the average worker in each sector relative to the aggregate labour productivity which is normalized to one. *Source:* Authors calculations from ETD.

Figure 2 demonstrates that the manufacturing sector operates at above-average labour productivity in the typical SSA country. Around 65% of the workforce in the average SSA country are working in sectors with lower average productivity levels than manufacturing, and of the 24% working in higher productivity sectors (sectors to the right of manufacturing

[13]Real Estate sector is excluded because of the distortionary impact of imputed rents on productivity calculations.

in Figure 2), a large proportion are in the public sector for which there is not a clear labour productivity definition (Diewert, 2011). Most of the other sectors to the right of manufacturing in the productivity distribution are either extremely capital intensive (in the case of Mining and Utilities), or require high-skilled labour (in the case of Business Services and Financial Services), and are therefore very limited in their capacity to absorb labour at scale. The implication of Figure 2 for the argument of this paper is as follows: if DAC aid is found to be displacing workers from manufacturing, these displacements will be on average detrimental to aggregate productivity growth if these workers relocate in any of the sectors to the left of manufacturing in the figure, by far the largest of which is agriculture.[14] Given the nature of the sectors and their capacity to absorb labour, and the relative sizes of the lower productivity sectors, such a movement is the most likely direction for displaced manufacturing workers.

Finally, Figure 3 illustrates the conditional linear association between DAC aid and the manufacturing share of recipient country employment and production in the ETD sample of 18 SSA countries for the period 1990-2018. The figure shows the added variable plots of the relationship between the log of annual aid inflows and the manufacturing shares of a) employment, and b) real value added, conditional on the set of control variables described above and with time and panel fixed effects. The decision to show the conditional associations was taken in order to maintain comparability with Rajan and Subramanian (2007) who apply a similar approach, and with the forthcoming results tables. Nevertheless, the unconditional plots are qualitatively very similar and are available on request. Figure 3 shows that countries which receive more aid have smaller manufacturing shares of employment and value added, although the latter association for value added is not quite statistically significant.[15] Rajan and Subramanian (2007) also showed a negative association between aid and the share of manufacturing in GDP for an earlier time period, but did not explore the manufacturing share of employment.

[14]Not only is agriculture the sector with the lowest average productivity level in 2018, there is also evidence that smallholder agriculture in Africa has experienced productivity declines rather than productivity growth for at least the last decade (Wollburg et al., 2024).

[15]The two outliers on the right hand side of the distribution in Figure 3 are Nigeria in 2005 and 2006 when the country received a very high volume of aid as part of a debt relief agreement (Odusanya et al., 2011). The outlier on the left hand side is Mauritius in 1996. Since these represent genuine aid flows, I do not exclude them from the analysis, but the correlations in figure 3 and subsequent results are robust to their exclusion. The significant negative relationship remains when either Mauritius or Nigeria are dropped from the sample entirely.

4 Methodology and Identification

As a baseline specification, I perform OLS panel regressions with time and country fixed effects and standard errors clustered at the recipient country level. The time and country fixed effects mitigate endogeneity biases which stem from country specific, time-invariant variables (for example, colonial history or legal system), and from time-variant, non-country specific variables (for example, trends in the global economy). They will not mitigate omitted variable biases which stem from country specific, time-variant variables (for example, changes in governing party ideology). In the case of the effect of aid on structural change, omitted variable biases of this latter type are plausible as, for example, changes in the quality of economic governance could impact both economic structure and ability to attract aid. Nevertheless, the OLS FE model serves as a useful benchmark. I use a model comparable with those across the aid effectiveness literature, which as Doucouliagos and Paldam (2009) noted exhibits a high degree of formal homogeneity in terms of econometric models. In particular, the model specification mirrors that of Dreher et al. (2021) which regresses the outcome variable of interest on the log of aid flows, a control set, and time and country fixed effects. The equation is as follows:

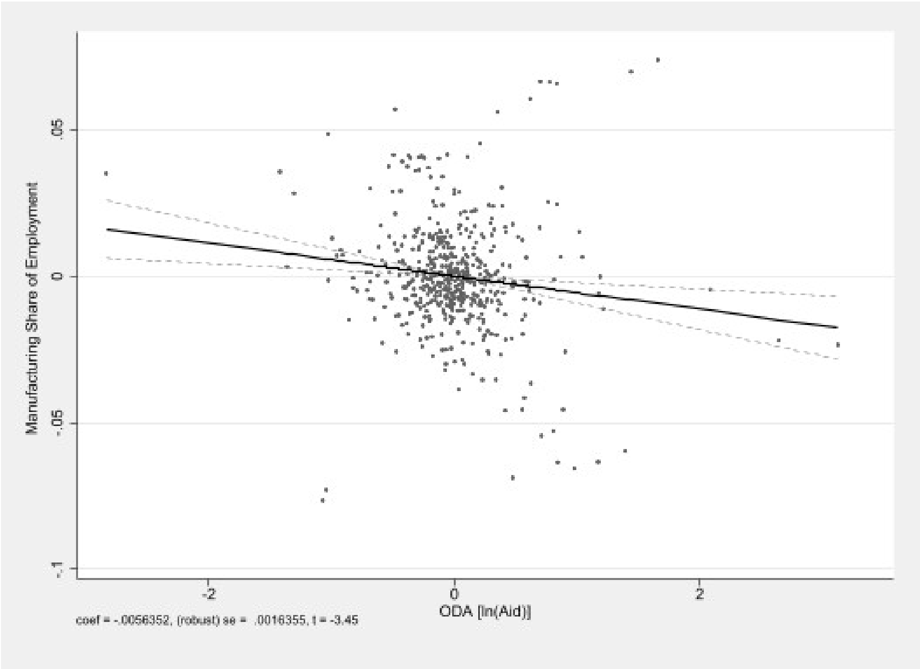
$$IndShare_{i,t} = \beta_1 lnAid_{i,t-n} + \Psi \boldsymbol{X_{i,t}} + c_i + \delta_t + \epsilon_{i,t} \tag{1}$$

where the dependent variable $IndShare_{i,k,t}$ is the share of real value added or employment in the sector under analysis at time t in country i.[16] In the main specifications, the sector under analysis is the manufacturing sector. In some additional specifications, alternative dependent variables are used such as the levels of manufacturing employment or sectoral labour productivity; these are detailed in the relevant results sections. The independent variable of interest is $lnAid_{i,t-n}$, which is the nth lag of the log of the dollar flow of

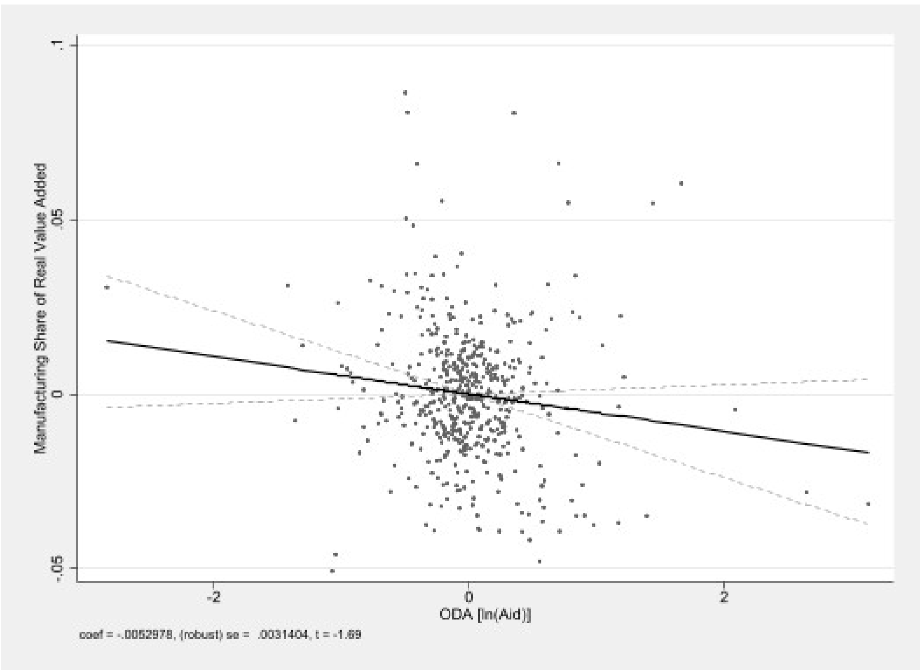
[16]The dependent variable, sector shares, is a decimal percentage, and is therefore bounded between zero and one. In such cases, linear estimation techniques are appropriate when there are few observations at the extreme bounds of the unit interval (Papke & Wooldridge, 2008). This is the case in this sample. Nevertheless, main results are robust to the use of a two-limit tobit model, censored both from below and above, the results of which are available on request.

Figure 3: Manufacturing and Aid in Sub-Saharan Africa Between 1990 and 2018

(a) Aid and Manufacturing Share of Employment



(b) Aid and Manufacturing Share of Value Added



Note: These plots represent the conditional relationship between the relative size of the manufacturing sector and the annual volume of aid flows in recipient SSA countries between 1990 and 2018. They are based on the results of a panel regression of the share of a) employment, and b) real value added (in constant 2015 prices) on the log of DAC aid flows received with controls and time and country fixed effects. Dashed lines are linear plots of the bounds of the 95% confidence intervals.

DAC Aid.[17] In the preferred specifications, the lag length of the aid inflows is three years, to give the effects of aid on structural transformation time to manifest. This is both because there will inevitably be a delay between the disbursement of aid funds and the actual commencement and completion of projects, and because reallocation between industries as a response to these projects will also not be instantaneous (Clemens et al., 2012). Robustness checks are performed for a variety of alternative lag lengths. β_1 is the point estimate for the effect of aid on the relative size of the dependent variable sector and has a partial elasticity interpretation, this estimate will suffer from downward bias if omitted variables which are not absorbed into the country or time fixed effects contribute both to higher aid flows and lower industry shares. c_i captures the country fixed effects and δ_t is a set of annual time dummies with the first year excluded as baseline. The vector $\boldsymbol{X_{i,t}}$ represents the full set of controls.

4.1 A New Shift-Share Instrument for Aid

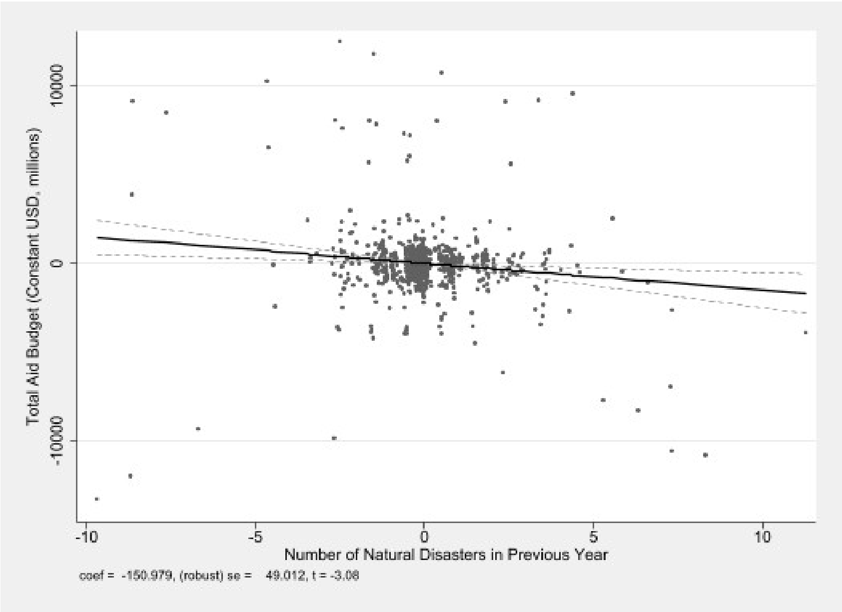
OLS panel FE regressions alone are unlikely to alleviate all forms of omitted variable bias in the relationship between aid and structural change. Therefore, as a preferred specification I employ a novel Shift-Share Instrumental Variables [SSIV] identification strategy with panel and time fixed effects which exploits inter-temporal variation in the total volume of DAC aid driven by the frequency of natural disasters occurring in the DAC donor countries. The frequency of natural disasters is measured by the number of natural disasters occurring in a donor country per year according to EM-DAT (see data section above). I argue that the frequency of natural disasters in donor countries can exogenously influence aid budgets through at least two channels: a tightening of budget constraints as a result of a negative economic shock to donor countries, and a shift in citizen preferences away from international relief efforts. To allow these two channels time to manifest in changes to aid budgets, I lag the instrumental variables one year behind the aid volume variables in the first stage regressions.

[17]There is some divergence in the aid effectiveness literature over whether or not aid should be normalized by recipient country GDP (Doucouliagos et al., 2021; Roodman, 2008). Annen and Kosempel (2018) demonstrated through simulations that normalization by GDP can introduce bias because aid itself influences GDP, and Dreher et al. (2021) argue that normalization by GDP or population unnecessarily constrains the effect of aid to move one-to-one with that of the denominator. I follow Ahmed (2016), Dreher et al. (2019), Dreher et al. (2021), etc. in using the log of aid flows with gdp per capita and population as separate controls in the preferred specifications and providing robustness checks with the logs of aid normalized by both recipient country GDP and population.

Regarding the first channel, natural disasters have sizeable adverse effects on the macroeconomy and fiscal conditions of the countries in which they occur, including in advanced economies and in the short-run, and the magnitudes of these impacts have increased in recent years (Botzen et al., 2019; Hallegatte & Ghil, 2008; McDermott et al., 2014). Donor aid budgets are known to depend strongly on their fiscal and economic conditions (Faini, 2006; Fuchs et al., 2014), including short-run business cycle downturns (Dabla-Norris et al., 2015; Frot, 2009; Gravier-Rymaszewska, 2012). It is therefore plausible to expect natural disasters to exert a negative economic impact on donor countries and, *inter alia*, an exogenous shock to aid budgets. In DAC donors, aid budgets are commonly set as a fixed proportion of GDP, therefore in these cases if GDP drops as a result of natural disasters, aid budgets will drop automatically. Regarding the second channel, there is considerable evidence that conditions and citizen preferences within donor countries exert influence over their aid budgets, especially when donor countries are democracies as all DAC donors are. Chong and Gradstein (2008), Paxton and Knack (2012), Greene and Licht (2018), Heinrich et al. (2018), Kaufmann et al. (2019), and others have all shown that citizen characteristics, preferences, and voting choices exert influence on aid budgets in DAC donor countries. In particular, unanticipated crises occurring in donor countries have been shown to reduce public support for foreign aid, for example in the case of the Covid-19 pandemic (Kobayashi et al., 2021), and major domestic news events such as natural disasters in donor countries crowd out citizen interest in aid-recipient countries with a negative impact on actual aid volumes (Eisensee & Strömberg, 2007). Heinrich et al. (2016) argue that the public support channel actually explains more of the decline in aid in the aftermath of economic shocks to donors than the budgetary constraints themselves.

The negative relationship between natural disasters and DAC donor aid budgets can also be shown empirically. Figure 4 shows the relationship between total aid disbursements from each donor country and the number of natural disasters in that country in the previous year. The figure accounts for time and donor fixed effects but is otherwise unconditional. It can be seen that a higher number of natural disasters in a donor country is followed by a lower total aid budget in the following year, and this relationship is statistically significant at the 1% level.[18] The correlations between total aid disbursements and the first lag of natural disasters are also negative in all five of the largest donor countries; these results are available on request.

Figure 4: Natural Disasters and Total Aid Budgets in Donor Countries



Note: This plot represents the unconditional relationship between the frequency of natural disasters in donor countries and their total aid budgets (in millions of constant USD) in the following year by DAC donor country for the period 1990-2018. The plot is based on a panel regression of total ODA disbursements on the first lag of the number of natural disasters in each donor country with time and donor fixed effects and clustered standard errors, but no other controls. Dashed lines are linear plots of the bounds of the 95% confidence intervals.

This source of inter-temporal variation - frequency of natural disasters in donor countries - is common to all recipient countries in the sample. For this reason, I introduce

[18]Figure 4 is not a graphical representation of the first stage relationship. In the first stage equation, panel variation is across recipient countries and panel variation is introduced to the instrument via recipient country specific exposure weights as shown in equation (2). In figure 4, panel variation is across the donor countries and the aim is to show empirically that higher numbers of natural disasters are followed by lower aid budgets on a donor-by-donor basis. Results from the full first stage estimation are shown at the bottom of table 4, and show a significantly negative coefficient on the instrument.

cross-sectional variation via a shift-share design. This involves the deployment of recipient-country specific weights such as to establish their separate degrees of exposure to exogenous shocks in aid budgets from each of the donor countries. For each recipient country, the weights are the share of aid to that country on average across the sample period. The weights are therefore constant over time. Countries which historically received a larger share of aid from a specific donor are more exposed to ongoing exogenous shocks in aid flows from that donor as compared to countries which historically received a lower share. In short, identification manifests as follows: natural disasters in donor countries shock their overall aid budgets in the following year, and the degree to which these shocks differentially impact aid to recipient countries depends on their level of exposure to aid from that specific donor. These exposure weights are not exogenous; as per the taxonomy of SSIVs discussed by Borusyak et al. (2022) and Goldsmith-Pinkham et al. (2020), this is an SSIV with a high degree of plausible exogeneity in the inter-temporal component, endogenous exposure weights, and large and repeated inter-temporal variation across the sample period.[19]

Mathematically, the instrumental variable is constructed as follows:

$$I_{i,t} = \sum_{j=1}^{J} [D_{j,t} * w_{i,j}] \tag{2}$$

where $D_{j,t}$ is the number of natural disasters in each donor country j, in year t, and is multiplied by the total share of aid provided by that donor country j to recipient country i in the average sample year, $w_{i,j}$. The number of natural disasters reflects the extent to

[19]SSIV designs of this form are usually first attributed to Bartik (1991), and were brought to the aid effectiveness literature by Nunn and Qian (2014). They are now used regularly for particularly Chinese aid by Dreher and Langlotz (2020), Dreher et al. (2021), etc. However, not all such instruments are alike. The original Bartik (1991) instruments employed inter-temporal and cross-sectional variation which are both likely endogenous, relying on the shift-share interaction to place the burden of exogeneity on the differential impact across the more or less exposed units as per the weights. The Goldsmith-Pinkham et al. (2020) econometric review of Bartik-style designs focuses mostly on SSIVs of this 'double-endogenous' type. My instrument, by contrast, exhibits a high degree of exogeneity in the inter-temporal component as natural disasters in donor countries are random, and unrelated to conditions in recipient countries. The set-up therefore more closely resembles those SSIVs analysed by Borusyak et al. (2022) which are effectively continuous difference-in-difference estimations, whereby the effect of changes in the independent variable of interest (aid) are captured by the difference in response to exogenous shocks to the trending variable between the more- and less-exposed observational units. Other examples of recent, novel SSIV use in the aid effectiveness literature include Doucouliagos et al. (2021), Minasyan and Montinola (2022) and Ferrière (2024).

which each donor country has been exposed to negative social and economic shocks as a result of randomly occuring natural disasters in each year. The shares of aid from the donor country to the recipient country in the average sample year represents the prominence of each recipient country in the aid budget of each donor country on average across the sample period, and therefore captures the degree of exposure of recipient countries to exogenous shocks to the aid budget of that donor country. The instrument is then the total sums of these weighted disaster measures across all donors, and takes the form of a weighted average index of disaster frequency across the entire DAC.

This instrument then fits into the first stage equation for predicting the aid flows to each recipient country as follows:

$$ln\hat{Aid}_{i,t} = \gamma I_{i,t-1} + X_{i,t}\psi + \alpha_i + \delta_t + \epsilon_{i,t} \tag{3}$$

where $I_{i,t-1}$ is the instrument for aid constructed as per equation (2). The coefficient γ gives the direction of the first stage relationship which should be negative according to the argument made for the impact of natural disasters on aid budgets. The vector of controls, $X_{i,t}\psi$, is identical to the control set used in the panel FE regressions. Finally, the predicted values of the aid flows enter into the structural SSIV equation as follows:

$$IndShare_{i,t} = \beta_1 \widehat{lnAid_{i,t-n}} + \Psi \boldsymbol{X_{i,t}} + c_i + \delta_t + \epsilon_{i,t} \tag{4}$$

with variables and subscripts defined analogously to equation (1), except that now the independent variable of interest $\widehat{lnAid_{i,t-n}}$ is the predicted values of aid flows on the basis of the first stage equation (3). β_1 captures the coefficient of interest and is expected to be negative.

Since Nunn and Qian (2014), the use of SSIV instruments in the aid effectiveness and other literatures has come under some scrutiny. In particular, a critique by Christian and Barrett (2017) discussed the possibility for instrument strength to be driven by spurious correlations in such set-ups when the variables under consideration are trending variables. Furthermore, the work of Angrist et al. (1996) onwards has drawn attention to the fact that most IV estimates capture merely a local average treatment effect [LATE], rather than an average treatment effect [ATE] which applies across the full distribution of the independent variable, and this has implications for the type of aid which is varying in response to shocks to the instrument. Appendix B therefore provides a deeper discussion of the SSIV strategy performed in the context of this paper against a backdrop of Christian and Barrett (2017), Goldsmith-Pinkham et al. (2020), and Borusyak et al. (2022), including placebo tests and an examination of trends. The results of this appendix suggest that the main findings of this paper are not driven by spurious correlation. The appendix also provides a discussion over potential differences between the LATE and the ATE in the context of my IV results, and the implications of this.

5 Main Results

5.1 Aid and Manufacturing

Table 2 reports the results of the empirical estimations of the effect of aid on the manufacturing share of employment in sub-Saharan Africa. Columns (1) and (2) show the results from the OLS panel fixed effects regression as per equation (1), columns (3) and (4) show the results from the SSIV regression as per equation (4). Even numbered columns include the full sets of controls and time dummies, odd numbered columns include no controls but do include time dummies.[20] The coefficients of interest on $lnODA_{i,t-3}$ capture the effect of a one percent change in aid on the share of employment in manufacturing expressed as a percentage after three years.

From Table 2, the consistent, negative, and statistically significant impact of aid on the manufacturing share of employment can be observed across all specifications. The preferred specification is that of column (4), the SSIV with full set of controls and time dummies. The interpretation of this result is that a one percent increase in the flow of DAC aid leads to a decrease in the manufacturing share of total employment of 0.009 percentage points after three years, significant at the 1% level. To benchmark this effect with a more realistic change in aid of 10 percent, the estimated impact of a 10 percent increase in aid is a 0.09

[20]The smaller sample sizes reported for the SSIV results are due to an additional year of data being lost due to the lagging of the instrument in the first stage as per equation (3), there is no qualitative change in the results when these observations are excluded also from the panel FE regressions (results available on request).

percentage point decrease in the manufacturing share against a sample average manufacturing share of 7.3 percent of total employment - a decline equivalent to 1.2% of the sample average. The result from the Panel FE regression with controls is slightly smaller in absolute magnitude but remains significant at the 5% level. In the SSIV regression without controls in column (3), the coefficient is also negative, statistically significant, and of comparable economic magnitude - this is reassuring from the perspective of identification, because a properly specified IV should yield a consistent point estimate of the instrumented variable with or without controls (Angrist et al., 1996). An improvement in precision does occur when the controls are included in column (4) as is observable from the reduced standard error.[21] The final rows of table 2 provide estimation results for first stage equation (3); in the case both with and without controls, the instrument enters with a negative coefficient as expected, and the Kleibergen-Paap F statistics exceed standard rules-of-thumb including the Stock and Yogo (2005) critical value of 16.38. They differ between the columns due to the inclusion of controls.

Table 3 reports results for the effect of aid on the manufacturing share of real value added (in constant 2015 prices). Whilst the coefficient on aid is negative and statistically significant at the 5% level in the panel fixed effect regression with controls in column (2), it is not statistically significant in the preferred SSIV regression in column (4). There is therefore no consistent evidence that the negative effect of aid on industrialization carries to value added in addition to employment, although there is certainly no positive impact of aid on the manufacturing share of value added. This implies that whilst workers are displaced from the manufacturing sector, production is displaced to a lesser extent, which suggests that some lost labour inputs may be being replaced by capital. These results also suggest that the negative association between aid and the manufacturing share of GDP shown by Rajan and Subramanian (2007) and implied for the more recent sample period by figure 3 may not be causal.

[21]In the OLS panel FE regression without controls in column (1), the coefficient is negative and statistically significant, albeit at the 10% level. When the controls are included in column (2), the economic magnitude and significance of the coefficient increase. This is reassuring from the perspective of omitted variable bias in the OLS FE regressions. As the controls increase the economic magnitude and statistical significance of the point estimate, the exclusion of any omitted variables would have to exert bias not only in the opposite direction of bias due to the exclusion of the controls, but of greater absolute magnitude in order to overturn the result (Altonji et al., 2005; Bezemer et al., 2014). Nevertheless, the preferred specifications remain the SSIV regressions.

Table 4 presents additional results in order to demonstrate that the reductions in the manufacturing share of employment from table 2 are likely due to a negative impact on manufacturing in absolute terms. The dependent variable is the log of the total number of manufacturing workers in recipient countries. The first column shows the results from the OLS panel FE regression and the second column from the SSIV regression. In both cases, the coefficients on aid are negative and of meaningful economic magnitude, although the SSIV results are not quite statistically significant.

Appendix 3 provides a series of robustness checks for the main results of this paper. These include alternative lag lengths of the aid variable (other than three years), an alternative control set (Rodrik (2016) style regressions with population and gdp per capita and their quadratics), and alternative transformations of the aid variable (normalized as aid per capita and over GDP). In all cases the story is consistently one of a negative impact of aid on the manufacturing share of employment.[22] Appendix 3 also shows the results of the main SSIV specification but with an additional instrument added to the instrument set based on the severity of natural disasters as measured by the number of deaths due to natural disasters in donor countries per year. As not all natural disasters are of equivalent magnitude, this additional instrument introduces an adjustment for disaster severity into the first stage. The impact of aid on the manufacturing share of employment remains negative and statistically significant. Furthemore, with two instruments for just one instrumented variable, the specification becomes over-identified which allows for the performance of a Sargan-Hansen test; this test fails to reject the null hypothesis that the over-identifying restrictions are valid, and therefore fails to provide evidence which would lead to the conclusion that the instruments are invalid.

[22]The results for the impact of aid on the agriculture and non-government services sectors, as well as on within-sector labour productivity, qualitatively survive the same robustness checks, the results of which can be provided by the author on request.

Table 2: Panel FE and SSIV Estimates of Effects of DAC Aid on Manufacturing Share of Employment, with First Stage Results.

	(1) [OLS FE] $ManEMP_{i,t}$	(2) [OLS FE] $ManEMP_{i,t}$	(3) [SSIV] $ManEMP_{i,t}$	(4) [SSIV] $ManEMP_{i,t}$
$lnODA_{i,t-3}$	-0.006*	-0.007**	-0.017***	-0.009***
	(0.003)	(0.003)	(0.006)	(0.003)
$lnGDPpc_{i,t}$		-0.026		-0.027
		(0.031)		(0.037)
$lnPop_{i,t}$		0.109		0.105
		(0.119)		(0.109)
$RelProd_{i,t}$		-0.002***		-0.002***
		(0.001)		(0.001)
$Conflict_{i,t}$		-0.002		-0.002
		(0.004)		(0.004)
$OilRent_{i,t}$		0.000		-0.000
		(0.001)		(0.001)
Time Dummies	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
N	446	446	428	428
First Stage:				
$I_{i,t-4}$			-0.046***	-0.047***
			(0.007)	(0.007)
KP F-Statistic			42.7	47.7

Clustered standard errors in parentheses

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

Notes: OLS Panel Fixed Effects estimations of equation (1) and Shift-Share Instrumental Variables estimations of equation (4). Dependent variable: manufacturing as a share of total employment. Independent variable of interest: logarithm of dollar flow of ODA three years prior. All standard errors clustered at country level. The row 'Controls' indicate whether or not controls other than time dummies are included in the regression. Reported F-Statistic is the Kleibergen-Paap rk Wald F statistic from SSIV first stage regressions.

Table 3: Panel FE and SSIV Estimates of Effects of DAC Aid on Manufacturing Share of Real Value Added.

	(1) [OLS FE] $ManVAQ_{i,t}$	(2) [OLS FE] $ManVAQ_{i,t}$	(3) [SSIV] $ManVAQ_{i,t}$	(4) [SSIV] $ManVAQ_{i,t}$
$lnODA_{i,t-3}$	-0.010**	-0.009**	0.004	0.003
	(0.004)	(0.007)	(0.007)	(0.006)
$lnGDPpc_{i,t}$		-0.005		-0.020
		(0.020)		(0.021)
$lnPop_{i,t}$		0.090*		0.096**
		(0.048)		(0.0004)
$RelProd_{i,t}$		0.002***		0.003**
		(0.001)		(0.001)
$Conflict_{i,t}$		0.000		-0.005
		(0.005)		(0.006)
$OilRent_{i,t}$		-0.000		-0.000
		(0.001)		(0.001)
Time Dummies	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
N	446	446	428	428
KP F-Statistic			42.7	47.7

Clustered standard errors in parentheses

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

Notes: OLS Panel Fixed Effects estimations of equation (1) and Shift-Share Instrumental Variables estimations of equation (4). Dependent variable: manufacturing as a share of total real value added (constant 2015 prices). Independent variable of interest: logarithm of dollar flow of ODA three years prior. All standard errors clustered at country level. Reported F-Statistic is the Kleibergen-Paap rk Wald F statistic from SSIV first stage regressions.

Table 4: Panel FE and SSIV Estimates of Effects of DAC Aid on Level of Manufacturing Employment

	(1) [OLS FE] $lnManWRKS_{i,t}$	(2) [SSIV] $lnManWRKS_{i,t}$
$lnODA_{i,t-3}$	-0.107***	-0.063
	(0.040)	(0.049)
$lnGDPpc_{i,t}$	0.291	0.212
	(0.346)	(0.295)
$lnPop_{i,t}$	1.185	1.147
	(1.064)	(0.982)
$RelProd_{i,t}$	-0.044***	-0.044***
	(0.009)	(0.009)
$Conflict_{i,t}$	-0.061	-0.071
	(0.054)	(0.054)
$OilRent_{i,t}$	-0.003	-0.007
	(0.010)	(0.010)
Time Dummies	Yes	Yes
Controls	Yes	Yes
N	446	428
KP F-Statistic		47.7

Clustered standard errors in parentheses

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

Notes: OLS Panel Fixed Effects estimations of equation (1) and Shift-Share Instrumental Variables estimations of equation (4). Dependent variable: total number of manufacturing workers in thousands. Independent variable of interest: logarithm of dollar flow of ODA three years prior. All standard errors clustered at country level. The row 'Controls' indicate whether or not controls other than time dummies are included in the regression. Reported F-Statistic is the Kleibergen-Paap rk Wald F statistic from SSIV first stage regressions.

5.2 Aid and Other Sectors: Agriculture and Services

I now explore the impacts of aid on the relative sizes of other main sectors of the economy. This allows for a more complete picture of the impact of aid on structural change rather than just on industrialization. First, this analysis can provide suggestive evidence as to which sector displaced manufacturing workers may be reallocating into. Second, as practitioners and researchers increasingly look to services as an alternative driver of structural transformation, it is important to also consider the impacts of aid on the services sector (Rodrik, 2018b). Table 5 presents results for the impact of aid on the employment and real value added shares of the agriculture sector, table 6 presents the same for the non-government services sector. The non-government services sector is calculated as the sum of wholesale and retail trade services, transport services, business services, and financial services. Other services are excluded as the development procedure of the ETD means some unclassified workers may have ended up in this sector (de Vries et al., 2021).

The purpose of excluding government services is borne not so much out of a desire to examine only the private sector, but because the government sector has less clear value added and productivity concepts (Diewert, 2011). I focus on the results from the second two columns of tables 5 and 6, as these are from the preferred SSIV specifications.[23] The results show that aid exerts a statistically significant and positive impact on the employment share of agriculture, a statistically insignificant impact on the agriculture share of value added, and exerts no impact on the relative size of the non-government services sector. The estimated impact of a 10 percent increase in aid is a 0.19 percentage point increase in the agriculture share of employment, and no effect on the services share of employment.

The combined evidence of this section therefore shows that the impacts of DAC aid on structural change are a reduction in the manufacturing share of employment, an increase in the agriculture share of employment, no effect on the non-government services share of employment, and that the decline in the manufacturing share also corresponds with a decline in the level of manufacturing employment.

[23]The results are qualitatively similar across the OLS panel FE estimations, although the OLS point estimate for the impact of aid on the agriculture share of employment is statistically insignificant.

Table 5: Panel FE and SSIV Estimates of Effects of DAC Aid on Agriculture Shares of Employment and Value Added.

	(1) [OLS FE] $AgrEMP_{i,t}$	(2) [OLS FE] $AgrVAQ_{i,t}$	(3) [SSIV] $AgrEMP_{i,t}$	(4) [SSIV] $AgrVAQ_{i,t}$
$lnODA_{i,t-3}$	0.003	0.008	0.019**	0.006
	(0.005)	(0.005)	(0.008)	(0.006)
$lnGDPpc_{i,t}$	0.031	-0.182***	0.024	-0.176***
	(0.031)	(0.029)	(0.033)	(0.025)
$lnPop_{i,t}$	-0.250***	-0.175***	-0.240***	-0.173***
	(0.085)	(0.053)	(0.086)	(0.047)
$RelProd_{i,t}$	0.009***	-0.001	0.009***	-0.001
	(0.002)	(0.01)	(0.002)	(0.001)
$Conflict_{i,t}$	0.008	0.020***	0.002	0.021***
	(0.010)	(0.007)	(0.013)	(0.008)
$OilRent_{i,t}$	0.000	-0.001	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Time Dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	446	446	428	428
KP F-Statistic			47.7	47.7

Clustered standard errors in parentheses

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

Notes: OLS Panel Fixed Effects estimations of equation (1) and Shift-Share Instrumental Variables estimations of equation (4). Dependent variables: agriculture as a share of total employment and real value added. Independent variable of interest: logarithm of dollar flow of ODA three years prior. The row 'Controls' indicate whether or not controls other than time dummies are included in the regression. All standard errors clustered at country level. Reported F-Statistic is the Kleibergen-Paap rk Wald F statistic from SSIV first stage regressions.

Table 6: Panel FE and SSIV Estimates of Effects of DAC Aid on (non-Government) Services Shares of Employment and Value Added.

	(1) [OLS FE] $SerEMP_{i,t}$	(2) [OLS FE] $SerVAQ_{i,t}$	(3) [SSIV] $SerEMP_{i,t}$	(4) [SSIV] $SerVAQ_{i,t}$
$lnODA_{i,t-3}$	-0.000	0.009	0.000	-0.006
	(0.005)	(0.007)	(0.006)	(0.013)
$lnGDPpc_{i,t}$	-0.025	0.004	-0.026	0.014
	(0.027)	(0.038)	(0.026)	(0.036)
$lnPop_{i,t}$	-0.133***	-0.092**	-0.133***	-0.099**
	(0.042)	(0.040)	(0.041)	(0.040)
$RelProd_{i,t}$	-0.004***	0.001	-0.004***	0.001
	(0.001)	(0.002)	(0.001)	(0.001)
$Conflict_{i,t}$	0.002	0.003	0.002	0.008
	(0.006)	(0.010)	(0.007)	(0.013)
$OilRent_{i,t}$	0.000	-0.001	0.001	-0.002**
	(0.000)	(0.001)	(0.001)	(0.001)
Time Dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	446	446	428	428
KP F-Statistic			47.7	47.7

Clustered standard errors in parentheses

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

Notes: OLS Panel Fixed Effects estimations of equation (1) and Shift-Share Instrumental Variables estimations of equation (4). Dependent variable: non-government services (trade services + transport services + financial services + business services) as a share of total employment and real value added. Independent variable of interest: logarithm of dollar flow of ODA three years prior. All standard errors clustered at country level. The row 'Controls' indicate whether or not controls other than time dummies are included in the regression. Reported F-Statistic is the Kleibergen-Paap rk Wald F statistic from SSIV first stage regressions.

6 Further Results

In this section I perform additional analysis with the intention of shedding further light on the main results of section 5. First, I explore the impacts of aid on sectoral labour productivity in order to demonstrate that any negative impact on structural change is unlikely to have been mitigated by positive impacts on within-sector productivity growth. I show no impact of aid on labour productivity in either manufacturing, agriculture, or services. Second, I show that aid from the largest non-DAC donor - China - does not appear to be associated the relative size of the manufacturing sector. This suggests that deindustrialization is not a general impact of all types of aid. Third, I provide sub-national analysis at the level of administrative regions to demonstrate that the main results are broadly consistent across different levels of aggregation.

6.1 Aid and Sectoral Labour Productivity

Analyses of structural change tend to decompose aggregate labour productivity growth into two components, between-sector and within-sector productivity growth (de Vries et al., 2015; Hamilton & de Vries, 2023; McMillan et al., 2014; Mensah et al., 2023). The between-sector component represents structural change - such growth occurs when workers move from less-to-more productive sectors, and is negative otherwise. The results presented in section 5 of this paper are indicative of aid contributing negatively to between-sector productivity growth, as manufacturing is a well above average productivity sector and agriculture well below average (see Figure 2), although it is not proven that the same workers being displaced from manufacturing are those sorting into agriculture. If however this is the case, such negative contributions to growth due to structural change could be mitigated if aid is contributing positively to within-sector productivity growth. This is growth due to efficiency gains or technological progress within sectors such that each worker within the sector is more productive.

To explore this possibility, Table 7 presents results from SSIV regressions following equations (2)-(4), but where the dependent variable is now the log of average labour productivity in the manufacturing, agriculture, and non-government services sectors respectively. I do not show the OLS panel FE results as they accord fully with those of the SSIV. Labour productivity is calculated as real value added per worker per annum on the basis of the

ETD. The relative productivity control is excluded from these regressions because it is constructed from the manufacturing and agriculture productivity variables and therefore would represent a bad control (Cinelli et al., 2024); this is why the F-Statistic of the SSIV regression changes slightly. The effect of aid on within-sector productivity is statistically insignificant in all three cases. This suggests that, to the extent that aid has contributed to growth-reducing structural change, it has not mitigated this by also driving productivity growth within sectors. Furthermore, *apropos* of the earlier discussion of aid and other revenues having potential to reduce manufacturing competitiveness, there is no evidence that such an effect was mitigated by any positive impact on manufacturing labour productivity.

Table 7: SSIV Estimates of Effects of DAC Aid a) Manufacturing, b) Agriculture, and c) Non-Government Services Labour Productivity

	(1) [SSIV] $lnManPROD_{i,t}$	(2) [SSIV] $lnAgrPROD_{i,t}$	(3) [SSIV] $lnSerPROD_{i,t}$
$lnODA_{i,t-3}$	0.134	-0.042	-0.022
	(0.083)	(0.048)	(0.069)
$lnGDPpc_{i,t}$	0.756	0.459**	0.887**
	(0.525)	(0.213)	(0.343)
$lnPop_{i,t}$	-0.772	0.623	-0.463
	(0.773)	(0.664)	(0.573)
$RelProd_{i,t}$**	—	—	—
$Conflict_{i,t}$	0.007	0.069	0.080
	(0.076)	(0.075)	(0.061)
$OilRent_{i,t}$	0.011	0.012	0.002
	(0.010)	(0.008)	(0.008)
Time Dummies	Yes	Yes	Yes
Controls	Yes	Yes	Yes
N	428	428	428
KP F-Statistic	50.74*	50.74*	50.74*

Clustered standard errors in parentheses

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

Notes: OLS Panel Fixed Effects estimations of equation (1) and Shift-Share Instrumental Variables estimations of equation (4). Dependent variable: manufacturing as a share of total real value added (constant 2015 prices). Independent variable of interest: logarithm of dollar flow of ODA three years prior. All standard errors clustered at country level. The row 'Controls' indicate whether or not controls other than time dummies are included in the regression. Reported F-Statistic is the Kleibergen-Paap rk Wald F statistic from SSIV first stage regressions. * the slight change in the F-Statistic compared to the other SSIV regressions is due to the slightly different control set. ** The relative productivity control is excluded from these regressions as a bad control.

6.2 Aid from a non-DAC Source: China

The results thus far have all explored the impacts of aid from the Development Assistance Committee [DAC]. I now explore whether these results carry also to non-DAC aid. The empirical background discussed and illustrated in section 2.1 showed that declining industrial sector support was an explicit feature of DAC aid allocation priorities in the period since 1990. As non-DAC donors are not bound by the same priorities and common disbursement framework, there is no *a priori* reason to expect the same effects. On the other hand, if all large revenue inflows in the form of aid contribute to deindustrialization, then the results found above should carry to aid from other donors. This distinction is important from the perspective of policy, because a finding that aid need not necessarily contribute to decreases in the manufacturing share of employment implies that the impacts found in section 5 can be altered if policymakers and aid practitioners wish to do so.

In order to provide suggestive evidence to this question, I present OLS panel FE results for the effect on manufacturing of aid from the largest non-DAC donor: China. Data for Chinese aid comes from the Geocoded Global Chinese Official Finance Dataset version 1.1.1 (Dreher et al., 2022; Dreher et al., 2021), which provides a geolocated dataset of Chinese aid projects for which the amounts and veracity of the disbursements are individually and independently verified. I aggregate the data to the country-year level and filter such that only ODA-equivalent projects are included. I aim to ensure that the comparison between DAC aid and Chinese aid is fair in that only aid offered on comparable terms is included, and the Chinese aid data does not include FDI or other forms of profit-seeking investment. The sample period available for the Chinese aid data is shorter, 2000-2014, and I therefore introduce also DAC aid into the regressions alongside Chinese aid so as to confirm that the DAC aid results still hold in the comparable shorter time period.

Table 8 presents the results from estimating equation (1) with the third lag of the log of Chinese aid rather than DAC aid as the independent variable of interest. The control set is the same, except that in even numbered columns the log of ODA is also included as a control. Table 8 shows no significant impact of Chinese aid on the manufacturing shares of employment or real value added. The impact of DAC aid on the manufacturing share of employment remains negative and statistically significant in this smaller sample period.

Table 8: Panel FE and SSIV Estimates of Effects of Chinese and DAC Aid on Manufacturing Share of Employment, 2000-2014

	(1) [OLS FE] $ManEMP_{i,t}$	(2) [OLS FE] $ManEMP_{i,t}$	(3) [OLS FE] $ManVAQ_{i,t}$	(4) [OLS FE] $ManVAQ_{i,t}$
$lnCHN_{i,t-3}$	0.00004	0.0001	-0.0003	-0.0002
	(0.000)	(0.000)	(0.000)	(0.000)
$lnODA_{i,t-3}$		-0.003**		-0.002
		(0.001)		(0.002)
$lnGDPpc_{i,t}$	-0.004	-0.002	-0.038	-0.038
	(0.024)	(0.024)	(0.027)	(0.027)
$lnPop_{i,t}$	0.189***	0.177***	0.208***	0.204***
	(0.065)	(0.065)	(0.069)	(0.069)
$RelProd_{i,t}$	-0.003***	-0.003***	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
$Conflict_{i,t}$	-0.002	-0.002	0.000	0.001
	(0.002)	(0.002)	(0.004)	(0.004)
$OilRent_{i,t}$	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)
Time Dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	270	270	270	270

Clustered standard errors in parentheses

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

Notes: OLS Panel Fixed Effects estimations of equation (1) and Shift-Share Instrumental Variables estimations of equation (4). Dependent variable: manufacturing as a share of total employment. Independent variable of interest: logarithm of dollar flow of ODA three years prior. All standard errors clustered at country level. The row 'Controls' indicate whether or not controls other than time dummies are included in the regression. Reported F-Statistic is the Kleibergen-Paap rk Wald F statistic from SSIV first stage regressions.

I am not able to provide SSIV results for the impacts of Chinese aid on the manufacturing share of employment as my instrument was constructed for DAC aid, and the instruments for Chinese aid presented by Dreher et al. (2021) are not sufficiently strong when applied in my sample because of the smaller number of SSA countries from the ETD for which sectoral employment data is available. Nevertheless, the findings of null results suggests at the least that the impact on manufacturing is far less than that of DAC aid. This suggests that a reducing effect on relative employment in manufacturing is a specific feature of DAC aid in recent decades rather than a fundamental impact of aid more generally; more rigorous analysis of the impacts of Chinese aid on structural change will be a valuable topic for future research if and when larger databases of sectoral employment in SSA become available.

6.3 Results at the Sub-National Level

It is not uncommon for aid effectiveness results to differ depending on the level of aggregation. This has been dubbed a 'micro-macro' paradox on account of recurring microeconometric evidence that specific aid projects have significant impacts on the individuals that receive them, yet these impacts show up less strongly in national level aggregate analysis (Addison et al., 2017; Arndt et al., 2010; Mosley, 1986). More generally, consistency of results across different levels of aggregation lends support to their credibility, and regional level analysis can bring aggregate results closer to the micro-level (Dreher & Lohmann, 2015). I show in this section that the regional level results for the effects of aid on the manufacturing share of employment broadly do not contradict those at the country level.

In order to demonstrate this consistency, I conduct some exploratory analysis at the level of administrative regions. Multi-country sub-national analysis of structural change in Africa is challenging due to a lack of quality sectoral data at the regional level. Baccini et al. (2023) provide an overview of sub-national trends in African structural transformation, but do so with employment data 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. Other sub-national analyses of structural change in SSA divide only between agriculture and non-agriculture with manufacturing not separately distinguished (Hoekman et al., 2023). Therefore, I perform analysis on the new SETD which is constructed specifically for this paper and is presented in brief in section 3 and in detail in appendix A. Sub-national level ODA aid data is limited; I therefore use data for a subset of DAC aid,

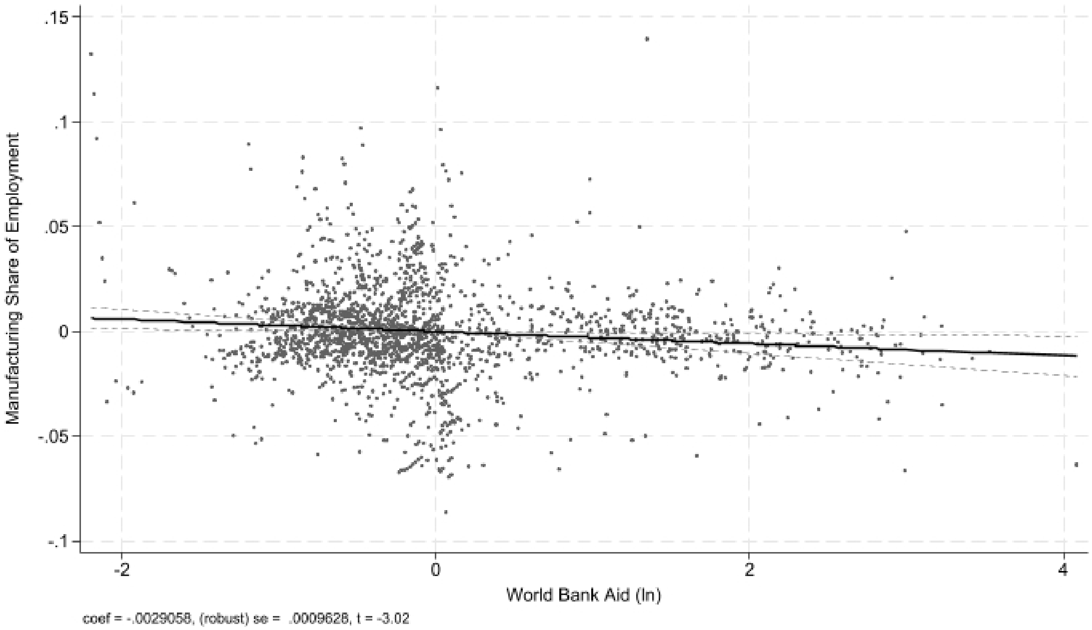
aid from the World Bank [WB], for which full geolocated sub-national data is available from AidData (2017). I aggregate this geolocated data to match the 122 administrative regions of the SETD.

I begin by demonstrating that the negative relationship between aid and the manufacturing share of employment illustrated at the national level by Figure 3 holds also at the regional level. Figure 5 illustrates the conditional linear association between WB aid and the manufacturing share of recipient region employment in the SETD sample of 122 SSA administrative regions for the period 2000-2014. The sample period is constrained by the availability of the WB aid data. The figure shows the added variable plot for the effect of the log of WB aid conditional on controls and with time and panel fixed effects.[24] The figure shows that regions which receive more WB aid have smaller manufacturing shares of employment. This is consistent with the national level relationship.

I next perform OLS panel regressions with controls, time dummies, and region fixed effects using equation (1) but with administrative regions rather than countries. I cluster standard errors at the country level to account for the lack of independence between regions within countries. I include only administrative regions which received aid in at least one year in the sample period, which is 2000-2014. At the sub-national level I have only two controls - the log of population, and the Sub-national Human Development Index (SHDI), both from the Global Data Lab Area Database version 3.6.0 (Smits, 2016). Nevertheless, this specification is less parsimonious than may first appear, because the SHDI variable implicitly controls for levels of health, education, and income. The results from this regression are shown in the first two columns of table 8, where the first column shows the contemporaneous relationship and the second column shows results for the third lag of the aid variable. The coefficient on WB aid in the same year is negative and significant at the 5% level, the third lag of aid is negative but not statistically significant. In order to maintain the comparison with Chinese aid performed at the national level in section 6.2, I present also the results for Chinese aid at the regional level, using the same Chinese aid data as in section 6.2 but now (dis)aggregated to administrative regions. The sample period is the same, 2000-2014, but there are fewer total observations because a larger number of administrative regions received no Chinese aid during the sample period and are therefore

[24]As there are some recipient-years with zero aid flows in the sub-national WB data, I add one dollar to all aid flows before performing the log transformation.

Figure 5: Manufacturing and Aid at the Regional Level



Note: This plot represents the conditional relationship between the relative size of the manufacturing sector and the annual volume of aid flows in recipient SSA administrative regions between 2000 and 2014. The plot is based on the results of a panel regression of the share of employment on the log of World Bank aid flows received with controls and time and country fixed effects for 122 administrative regions with data from the SETD. Dashed lines are linear plots of the bounds of the the 95% confidence intervals.

excluded. The coefficient on Chinese aid in the same year is positive and significant at the 1% level; the effect after three years is not significant. This is again consistent with the national level results.

Within the context of this paper, I cannot go beyond OLS panel fixed effects in exploring the sub-national results. This is because the instrument for aid depends for inter-temporal variation on natural disasters in individual donor countries, and at the sub-national level I have aid data only on multilateral aid from the WB. The results presented in this section therefore do not go beyond establishing statistical links between aid and manufacturing at the sub-national level which are consistent with those at the national level.

Table 9: Panel FE Estimates of Effect of World Bank and Chinese Aid on Manufacturing Employment Share; *Regional Level*

	(1) [OLS FE] $ManEMP_t$	(2) [OLS FE] $ManEMP_t$	(3) [OLS FE] $ManEMP_t$	(4) [OLS FE] $ManEMP_t$
$lnWBAid_{i,t}$	-0.0005**			
	(0.0001)			
$lnWBAid_{i,t-3}$		-0.0001		
		(0.0002)		
$lnCHNAid_{i,t}$			0.0003***	
			(0.001)	
$lnCHNAid_{i,t-3}$				-0.0005
				(0.0003)
$SHDI_{i,t}$	-0.082	-0.039	-0.030	0.068
	(0.082)	(0.070)	(0.032)	(0.169)
$lnPop_{i,t}$	-0.007***	-0.003**	-0.000	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)
Controls	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
N	1880	1598	765	612

Clustered standard errors in parentheses

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

Notes: OLS Panel Fixed Effects estimations of equation (1) 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 three years. Dependent variable: share of total employment which is in manufacturing sector expressed as a decimal percentage. Independent variables of interest: logs of real dollar flow of World Bank aid or Chinese aid and third lags thereof. The row 'Controls' indicate whether or not controls other than time dummies are included in the regression.

Nevertheless, unlike with DAC aid as a whole, there is evidence that WB aid is targeted disproportionately at richer and more developed regions within recipient countries (Briggs, 2017). Therefore, reverse causality by which less industrialized regions attract more aid would seem less likely in the case of WB aid. The fact that the effects of both types of aid are not significant by the third lag in the sub-national results may be explained by labour reallocations taking place more rapidly in smaller spatial units, and by the fact that regions recieve considerably smaller and less frequent aid inflows from both sources than countries as a whole.

7 Conclusion

This paper has shown that, since 1990, development aid from the DAC has had on average a deindustrializing effect in terms of employment in recipient countries in sub-Saharan Africa. In the preferred specification a ten percent increase in the flow of DAC aid causes an approximately 0.09 percentage point decrease in the employment share of manufacturing after three years. This effect size is economically meaningful both in terms of number of persons in the average country-year, and as a proportion of the total manufacturing share of employment in the average country-year. By contrast, DAC aid has increased the agriculture share of employment. I find no effect of aid on the relative size of the non-government services sector. Results for the impacts of aid on the sector shares of real value added are more ambiguous and are not statistically significant in the preferred SSIV specifications.

Additional results show that aid has not increased manufacturing labour productivity, nor has it contributed to productivity gains in agriculture or services. The lack of impact on manufacturing productivity is not surprising given that the proportion of DAC aid directed towards industry has declined severely since around 1990 to an almost negligible one percent of the total DAC aid mix. Nevertheless, this also implies that a different aid mix may produce different results. Suggestive evidence for the proposition that aid need not necessarily be employment-deindustrializing is provided by the fact that aid from the largest non-DAC donor - China - is shown to have no significant association with the manufacturing share of employment in recipient countries. This is important from the perspective of policy, because a finding that results vary with aid types indicates that policymakers can exert influence over the impact of aid on structural change. The main results of this paper are qualitatively supported also when analysis is run at the sub-national level.

The results of this paper have policy implications both for aid practitioners and policymakers on the African continent. Structural transformation is once again at the centre of the policy conversation in sub-Saharan Africa, as illustrated by its prominent position in the African Development Bank (2024) Economic Outlook Report. This paper has shown that not only has DAC aid contributed neither to agriculture-to-manufacturing nor to agriculture-to-services reallocations of employment, it has plausibly come with structural change implications which were on average growth-reducing. The evidence presented does not prove that aid has caused growth reducing structural change, but it does show that it has led concomitantly to an employment share contraction in the above-average productivity manufacturing sector and an expansion in the lowest productivity sector, agriculture. Therefore, policymakers wishing to influence patterns of structural transformation in Africa and facilitate employment industrialization should consider the impact aid inflows are having on these relative sector sizes, and perhaps advocate for adjustments to the DAC aid mix or allocation priorities such that these effects can be mitigated.

In terms of future research, a key avenue will be the exploration of precisely how the DAC aid mix can be adjusted so as to facilitate desirable structural transformation outcomes, and whether aid can actually be used to drive industrialization or servicification paths. It is also essential to establish whether such changes to aid allocation priorities could be made without negatively impacting other development goals. Additionally, it will be valuable to broaden the analysis of the impacts of aid on structural change to countries beyond sub-Saharan Africa, and to further explore the impact of aid on within-sector reallocations such as between formal and informal manufacturing. Limitations of this paper are that it is not able to further subdivide the manufacturing sector, nor that it can confirm whether the decrease in the manufacturing share of employment and the increase in the agricultural share represent the same workers. Therefore, going forward the literature should seek to firmly establish whether it is indeed the same workers who are being displaced from manufacturing that are also reallocating to agriculture (or remaining in agriculture instead of moving to manufacturing); such questions may be answerable with household panel data within countries which follows the movement of individuals between sectors across multiple survey waves, and would constitute firmer evidence that the impact of aid on structural change has indeed been growth-reducing.

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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 [SETD]. The SETD is inspired by, and an offshoot of, the Economic Transformation Database [ETD] (de Vries et al., 2021; Kruse et al., 2023), 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 remain highly elusive.[25] Additionally, the SETD relies more on primary source microdata, as NSI census and survey publications and reports rarely present sectoral employment data by region.

The general construction procedure for the SETD is as follows. First, countries were selected to form the SETD 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 labour force surveys were conducted. Each benchmark year was then 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 inter-spacing. In some cases this procedure involved direct contact with representatives of NSIs. Generally speaking, the benchmark data came in one of three forms: population census or survey microdata obtained directly from the NSI, which I 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

[25] 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 substantial 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.

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 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. In between benchmark years, sectoral employment levels were 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. 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.

There are two further 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 statistical capacity tends to bias the sample towards relatively richer SSA countries (Diao et al., 2017). 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. Furthermore, the sample is biased towards 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 one highly reliable benchmark source (full population censuses or large scale labour force surveys), with the exception of Nigeria. During the sample period, Nigeria conducted only one full population census in 2006, and this was fraught with a variety of issues (Olorunfemi & Fashagba, 2021). 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 by classifying workers into the industries in which their occupation categories most commonly appear.

Generally speaking, data will be more reliable for the latter half of the sample during which there was more population census microdata, and for the broader, primary sectors than for the smaller sub-sectors. The latter point is a result of subdivisions of the sample across a larger number of matrices than is the case in national level sectoral datasets. This implies that the sector shares for smaller sectors in smaller regions may be estimated on the basis of basis of small numbers of sample observations. For example, a labour force survey of 30,000 in a country with twenty regions would imply samples of on average 1,500 observations per region, and smaller sector shares in that region such as mining or financial services might be estimated on the basis of fewer than 100 observations in those sectors. Aggregating in particular the smaller services sectors when using the data should mitigate this issue. This issue does not apply for benchmark years based on full-census microdata, and therefore for countries with predominantly benchmark years of this type such as Ghana or Mauritius.

Despite these shortcomings and caveats, the SETD represents an 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. The total panel contains 122 separate regions across 29 years, a total of 3538 region-years. Restricted to only the benchmark years, there are 392 unique region-year observations. This degree of coverage as well as the variety of sources used compares favourably to alternative regional-sectoral datasets for Africa, for example Baccini et al. (2023) which utilizes only data from IPUMS, and Bandiera et al. (2022) which utilizes only one or two benchmark years for most African countries in their analysis. Additionally, the link and normalization to the parent ETD database allows for interpolation between benchmark years and therefore a balanced panel dimension, which is not the case for these alternative datasets.

Table 10 contains a full list of the primary sources which underpin the benchmark years for each country of the SETD:

B Further Discussion of Shift-Share Instrument

An important literature has recently emerged which digs deeper into the conceptual understanding of 'Bartik'-style shift-share instruments, along with tests or visualizations which can provide suggestive evidence in favour of their validity (Borusyak et al., 2022; Christian & Barrett, 2017; Goldsmith-Pinkham et al., 2020). Goldsmith-Pinkham et al. (2020) extensively discuss shift-share instruments of the 'original' type used in Bartik (1991); i.e. those instruments where the trending/time-variant component is not exogenous. In these cases, the exclusion restriction depends on the shares/time-invariant component of the instrument, albeit an exclusion restriction which imposes weaker conditions than those of a standard IV. Specifically, the exclusion restriction imposed upon the shares component of the interacted IV is that they should be orthogonal to *changes* in the outcome variable driven by shocks to the trending component of the interacted IV, and not necessarily to the *levels* of the outcome variable. To be more concrete, an exclusion restriction violation would take place if the outcome-variable *reaction* to shocks to the trending component of the IV differed between the units of observation in a manner which was non-orthogonal to the shares - similar to violations of the parallel trends assumption in standard difference-in-differences methods.

This setting and the applications of Goldsmith-Pinkham et al. (2020) differ from this paper as they are concerned with research designs where the trending component of the interacted instrument is not plausibly exogenous to the observation-unit outcomes, whereas natural disasters in donor countries are plausibly exogenous to structural change outcomes in recipient countries. Furthermore, even if one does not fully accept this plausible exogeneity of donor country natural disasters - due, for example, to effects of natural disasters in donor countries on global commodity prices - the shift-share IV still removes a major additional source of endogeneity bias as compared to the standard panel FE OLS; namely that element of time-variant inter-recipient heterogeneity which stems from the location-specific correlation between the error term and the growth rates out the outcome variables; in this case industry shares.

Borusyak et al. (2022) discuss predominantly shift-share instruments of the type used in this paper; i.e. those where the trending/time-variant component is believed to be exogenous, and where the number of shocks is large - in the case of this paper, there are as many shocks as there are sample years. In these cases, the exclusion restriction depends on the trending/time-variant component of the instrument interaction term, which can be valid even if the shares/time-invariant component is exogenous. Nevertheless, such research settings are still vulnerable to type-1 error due to spurious correlation or non-parallel trends between units of observation with different degrees of shock-exposure; as was highlighted by Christian and Barrett (2017) in the comment on Nunn and Qian (2014). Whilst the shift-share IV research design I use differs from that of Nunn and Qian (2014), in particular in terms of the degree of serial-correlation in the trending component of the interaction IV, it is still important to discuss the setting of this paper in light of their critique. Bluhm et al. (2020), Dreher et al. (2021), etc. employ similar discussions and tests in support of their shift-share instruments.

The Christian and Barrett (2017) critique of Nunn and Qian (2014) condenses to two lines of argument: 1) that the relationship between the trending component of the instrument, the endogenous/instrumented regressor, and the dependent/outcome variable is spurious; and that 2) these spurious correlations lead to a type-1 error due to systematically different trends in the outcome variables between that subset of recipient-countries which are more exposed and that subset which is less exposed to exogenous shocks to the trending component of the IV. This first line of argument is demonstrated by the fact that long term trends dwarf year-on-year variation/volatility in the instrument, the endogenous/instrumented regressor, and the dependent/outcome variable; this second line of argument stems from non-parallel trends in country-sets with different degrees of shock-exposure. Christian and Barrett (2017) also perform a variety of placebo-style tests; some of which are highly context specific - such as the division of the Nunn and Qian (2014) sample period into periods of different US Food Aid policy; but others which are generalizable to other research settings - such as the randomization of the values of the endogenous/instrumented regressor whilst holding the other variables constant. First, I discuss the two Christian and Barrett (2017) lines of argument, with visualizations, in order to demonstrate that these issues are not applicable to the setting of this paper. Second, I perform the instrumented regressor randomization placebo test for the research setting of this paper so as to provide further reassurance.

Figure 6 presents key trends for the case of the DAC aid analysis. Panel (a) shows separately the trends in the logs of the temporal component the DAC natural disaster variables over time, these are the totals for the entire DAC.[26] I show the trends both for the frequency measure of natural disasters used in the main results, and the severity measure (deaths) used in the robustness appendix C. Panel (b) shows the trends in the aggregate aid flows and the separate aid flows to the below- and above- median countries in terms of their instrument exposure weights, and panel (c) shows the trends in the main outcome variable, manufacturing share of employment, also presented separately for the below- and above-median countries in terms of their instrument exposure weights. This figure is directly comparable to those of Christian and Barrett (2017) and Dreher et al. (2021), although unlike in the latter case, the detrended versions are omitted as the temporal components of the instruments do not follow a clear time trend as can be seen from Panel (a).

Figure 6 provides evidence in support of the use of the shift-share instruments of this paper. First, note the lack of a time trend in any of the trending components of the IV in panel (a) - clearly, the short-term volatility dominates any long-term trend in the natural disaster measures for DAC. This is in contract to the Christian and Barrett (2017) critique of Nunn and Qian (2014), where it is argued that a key problem is the longer-run trend dominating the year-on-year variation in the plausibly exogenous time series component of the instrument. Second, note that there are no clear similarities in the long run trends between Panels A and B - the trending component of the instruments and the instrumented variables, and especially no similarities in the non-linear pattern; this suggests that the strong first-stage relationship is not spurious. Third, and perhaps most important, there are no ways in which the above-median trends in panels (b) and (c) are *systematically more similar* to each other or to the trends in panel (a) than the below-median trends. Panel (c) should not be seen as a test of any kind of parallel trends assumptions as these are not pre-trends, and in fact completely parallel trends in these post-trends would be evidence against instrument relevance. What is important, however, is that the non-linearities are indeed similar, and that there is not a major difference in the extent to which the above- and below-median groups track the long run trends in the endogenous variable or the temporal component of the instrumental variables. Therefore, whereas Christian and Barrett (2017) paint a picture of Nunn and Qian (2014) which is one of long run trends dominating short run volatility and upper-quartile outcome variable trends which are systematically much more similar to the instrument trends than the outcome variable trends of the other quartiles, this is clearly very different in the context of this paper.

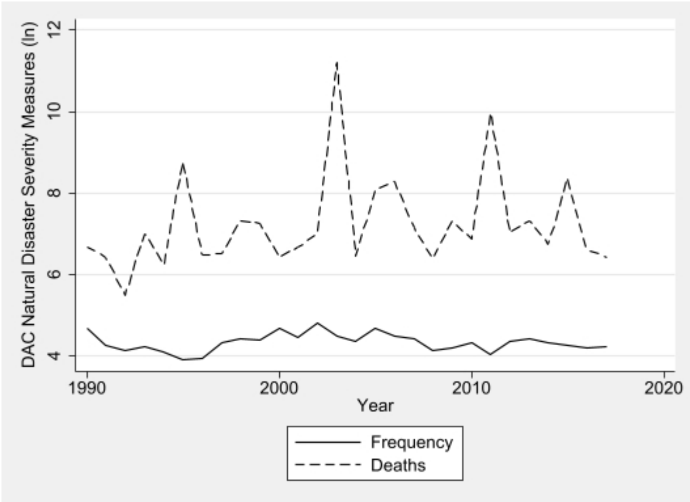
[26]The logarithm is used so as to ensure direct comparability with the aid flows in Panel B.

To further support the validity of the shift-share instruments of this paper, I perform a randomized inference style placebo check following Christian and Barrett (2017) on the SSIV estimation of the main result of this paper; ie the impact of aid on the manufacturing share of employment. The test works by randomly reshuffling the values of aid flows per recipient country in each year - that is, the aid flow which went to Senegal might now be randomly allocated to Burkina Faso, and that which went to Burkina Faso might now be randomly allocated to Kenya, etc., within each sample year. The values of the instrumental variables, control variables, and outcome variables are held constant. If the underlying driver of the significant results in this paper is a genuine first stage relationship with valid exclusion restriction, as opposed to spurious correlation or non-parallel pre-trends in the outcome variable, it would be expected to see a coefficient on aid which is not significantly different from zero once the aid flows have been randomized. Figure 7 presents density plots of the results of 1000 replications of the main SSIV specification of this paper in which the values of the aid flows have been randomly reshuffled across recipient countries within each year. It can be seen that the plot centres around an 'effect size' estimate of zero. This represents further evidence that the SSIV results for this paper are not being driven by spurious correlation or non-parallel pre-trends.

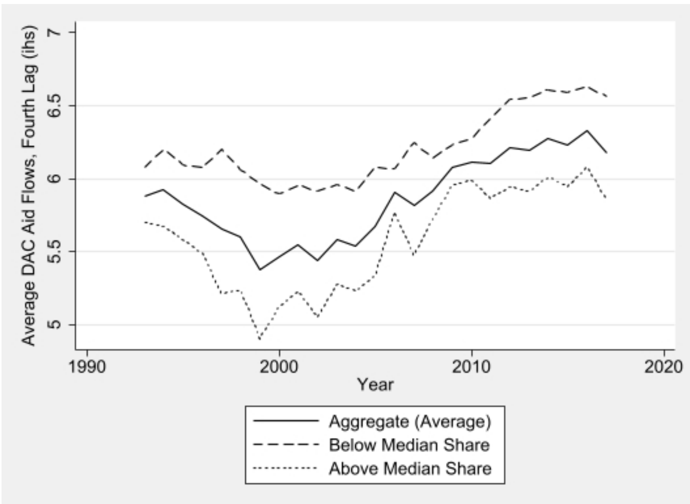
Finally, the SSIV estimates reflect *local average treatment effects* [LATE] in that, if the effects of different aid projects on structural change are heterogeneous, they estimate specifically the effects of the types of ODA which experience variation as a result of natural disasters in donor countries (Angrist et al., 1996). Therefore, if foreign aid is cut as a result of natural disasters occurring in donor countries, it is the effects of the marginal aid projects which are captured. In this case, it might be expected that the LATE is smaller than the ATE, if the marginal projects are those considered to be least effective. Similarly, as the variation in natural disasters across the DAC donors is driven largely by those countries with volatile climates, such as the USA and Japan, it may be that the LATE captured is biased towards the effects of aid from those countries rather than aid from the less environmentally volatile donors such as Germany and Switzerland, although the common DAC framework should reduce the heterogeneity of aid between different donors of the DAC.

Figure 6: IV, Endogenous, and Outcome Variable Trends

(a) Natural Disasters



(b) DAC Aid



(c) Manufacturing Share of Employment

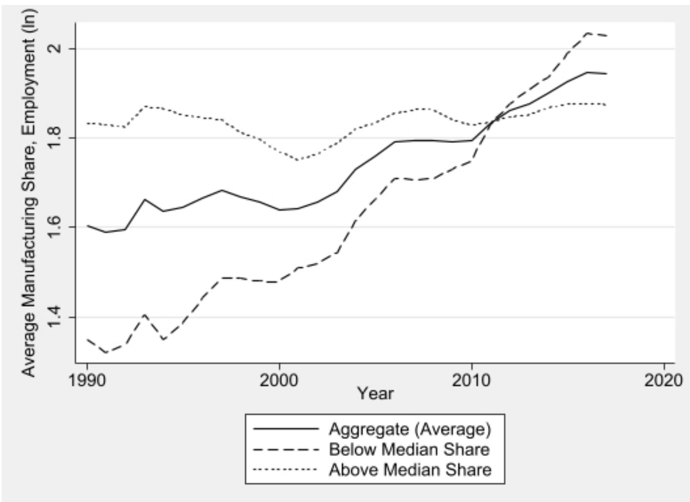


Figure 7: Randomized Inference Placebo Test

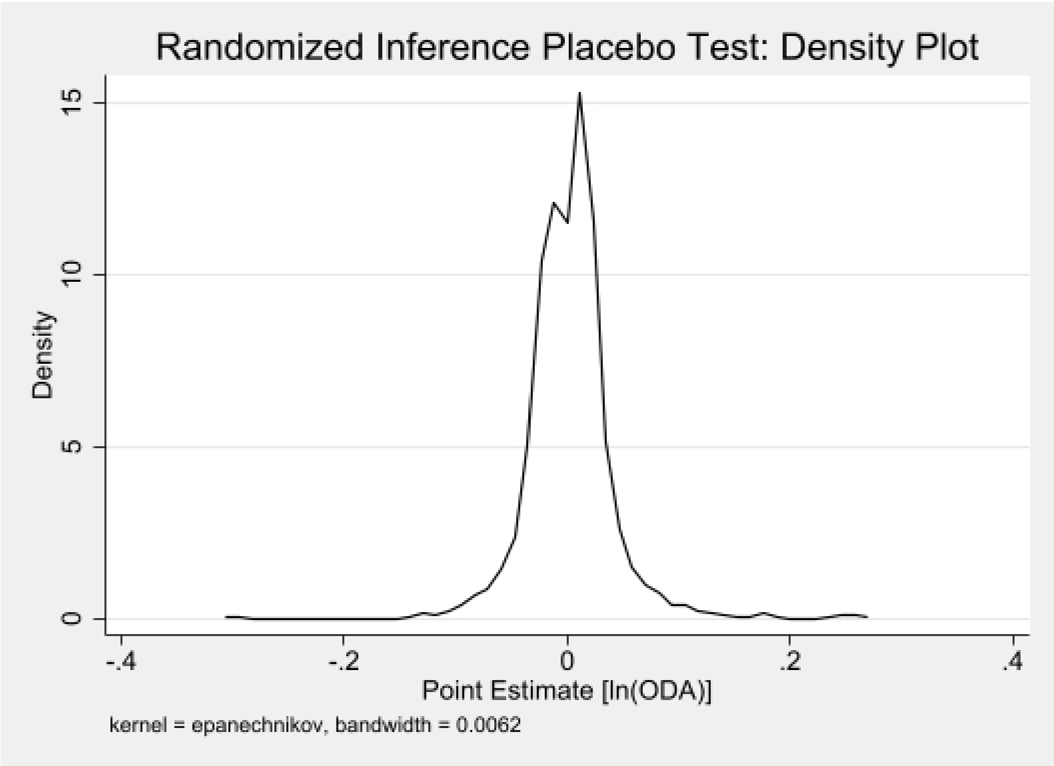


Table 10: SETD Primary Sources

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
Mauritius	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.

C Additional Robustness Checks

Table 11 shows the results of robustness checks for the main specifications of the paper - the impacts of DAC aid on the manufacturing share of employment - where inflows of DAC aid are normalized a) as a share of recipient country GDP, and b) as aid received per capita. The separate GDP per capita and population controls are excluded respectively from the regressions as they are implicitly controlled for by the denominators in the normalization. All coefficients on aid remain negative and statistically significant. Table 12 shows the results for the second and fourth lags of DAC aid, as opposed to the third lags as preferred in the main specifications. All coefficients on aid remain negative and statistically significant, although the instrument becomes weak in the case with the second lag. Table 13 shows the results where the control set is now that used in Rodrik (2016)-style premature deindustrialization regressions, which are common in the structural change literature, where the logs of GDP per capita and population are included as well as their quadratics; these regressions are not commonly used for estimating causal effects of independent variables, nevertheless some researchers may feel they more accurately control for the impact of demand on the manufacturing share. The coefficients on aid remain negative and statistically significant.

Table 14 shows the results of the main SSIV specification but with an additional instrument added to the instrument set. The main specifications derived intertemporal variation based on the frequency of natural disasters, this specification adds an additional instrument based on the severity of natural disasters as measured by the number of deaths due to natural disasters in donor countries per year. The construction procedure of the additional instrument is identical to equation (2) except now $D_{j,t}$ represents the number of deaths due to natural disasters in each donor country j in year t. Both instruments are included in the regressions of table 14, with and without controls. The coefficients on aid remain negative and statistically significant. This robustness check serves two purposes. First, as not all natural disasters are of equivalent magnitude, it introduces an adjustment for disaster severity into the first stage. Second, with two instruments for just one instrumented variable, the specification becomes over-identified which allows for the performance of a Sargan-Hansen test. Table 14 shows that this test fails to reject the null hypothesis that the over-identifying restrictions are valid, and the test therefore fails to provide evidence which would lead to the conclusion that the instruments are invalid.

Table 11: Panel FE and SSIV Estimates of Effects of DAC Aid over Recipient Country GDP and Population on Manufacturing Share of Employment.

	(1) [OLS FE] $ManEMP_{i,t}$	(2) [SSIV] $ManEMP_{i,t}$	(3) [OLS FE] $ManEMP_{i,t}$	(4) [SSIV] $ManEMP_{i,t}$
$ln(\frac{ODA}{GDP})_{i,t-3}$	-0.007**	-0.008***		
	(0.003)	(0.003)		
$ln(\frac{ODA}{Pop})_{i,t-3}$			-0.009***	-0.012***
			(0.002)	(0.002)
$lnGDPpc_{i,t}$	—	—	-0.022	-0.022
			(0.035)	(0.030)
$lnPop_{i,t}$	0.100	0.096	—	—-
	(0.121)	(0.112)		
$RelProd_{i,t}$	-0.003***	-0.002***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
$Conflict_{i,t}$	-0.002	-0.001	-0.001	0.000
	(0.005)	(0.005)	(0.004)	(0.003)
$OilRent_{i,t}$	0.000	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Time Dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	446	428	446	428
KP F-Statistic		51.0		59.8

Clustered standard errors in parentheses

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

Notes: OLS Panel Fixed Effects estimations of equation (1) and Shift-Share Instrumental Variables estimations of equation (4) with independent variables of interest normalized by recipient country GDP and population. Dependent variable: manufacturing as a share of total real value added (constant 2015 prices). Independent variable of interest: logarithm of dollar flow of ODA as a share of a) GDP and b) population three years prior. All standard errors clustered at country level. Reported F-Statistic is the Kleibergen-Paap rk Wald F statistic from SSIV first stage regressions.

Table 12: Panel FE and SSIV Estimates of Effects of DAC Aid on Manufacturing Share of Employment at Different Lag Lengths.

	(1) [OLS FE] $ManEMP_{i,t}$	(2) [SSIV] $ManEMP_{i,t}$	(3) [OLS FE] $ManEMP_{i,t}$	(4) [SSIV] $ManEMP_{i,t}$
$lnODA_{i,t-2}$	-0.008**	-0.031**		
	(0.003)	(0.013)		
$lnODA_{i,t-4}$			-0.006**	-0.027***
			(0.003)	(0.009)
$lnGDPpc_{i,t}$	-0.026	-0.014	-0.028	-0.017
	(0.032)	(0.029)	(0.029)	(0.028)
$lnPop_{i,t}$	0.109	0.081	0.110	0.106
	(0.119)	(0.090)	(0.106)	
$RelProd_{i,t}$	-0.003***	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
$Conflict_{i,t}$	-0.003	0.005	-0.003	0.003
	(0.004)	(0.006)	(0.003)	(0.006)
$OilRent_{i,t}$	0.000	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Time Dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	464	428	428	428
KP F-Statistic		4.0		13.3

Clustered standard errors in parentheses

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

Notes: OLS Panel Fixed Effects estimations of equation (1) and Shift-Share Instrumental Variables estimations of equation (4) with independent variables of interest normalized by recipient country GDP and population. Dependent variable: manufacturing as a share of total real value added (constant 2015 prices). Independent variable of interest: logarithm of dollar flow of ODA as a share of a) GDP and b) population three years prior. All standard errors clustered at country level. Reported F-Statistic is the Kleibergen-Paap rk Wald F statistic from SSIV first stage regressions.

Table 13: Panel FE and SSIV Estimates of Effects of DAC Aid on Manufacturing Share of Employment with Rodrik (2016) Controls

	(1) [OLS FE] $ManEMP_{i,t}$	(2) [SSIV] $ManEMP_{i,t}$
$lnODA_{i,t-3}$	-0.004	-0.010***
	(0.003)	(0.003)
$lnGDPpc_{i,t}$	0.379***	0.348***
	(0.101)	(0.104)
$lnPop_{i,t}$	-0.060	-0.074
	(0.073)	(0.068)
$lnGDPpc^2_{i,t}$	-0.033***	-0.031***
	(0.008)	(0.008)
$lnPop^2_{i,t}$	0.007	0.011
	(0.005)	(0.005)**
Time Dummies	Yes	Yes
Controls	Yes	Yes
N	446	428
KP F-Statistic		67.0

Clustered standard errors in parentheses

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

Notes: OLS Panel Fixed Effects estimations of equation (1) and Shift-Share Instrumental Variables estimations of equation (4). Dependent variable: total number of manufacturing workers in thousands. Independent variable of interest: logarithm of dollar flow of ODA three years prior. Control set are the Rodrik (2016) 'premature deindustrialization' controls, i.e. the logs of GDP per capita and population and their quadratics. All standard errors clustered at country level. Reported F-Statistic is the Kleibergen-Paap rk Wald F statistic from SSIV first stage regressions.

Table 14: SSIV Estimates of Effects of DAC Aid on Level of Manufacturing Employment with Additional Instrument

	(1) [SSIV] $ManEMP_{i,t}$	(2) [SSIV] $ManEMP_{i,t}$
$lnODA_{i,t-3}$	-0.028***	-0.016***
	(0.005)	(0.005)
$lnGDPpc_{i,t}$		-0.023
		(0.028)
$lnPop_{i,t}$		0.100
		(0.107)
$RelProd_{i,t}$		-0.002***
		(0.001)
$Conflict_{i,t}$		0.001
		(0.004)
$OilRent_{i,t}$		-0.001
		(0.001)
Time Dummies	Yes	Yes
Controls	No	Yes
N	446	428
KP F-Statistic	27.8	23.2
Hansen J-Statistic	0.680	1.122
Hansen p-value	0.410	0.290

Clustered standard errors in parentheses

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

Notes: Shift-Share Instrumental Variables estimations of equation (4) with additional instrument based on *severity* of natural disasters in donor countries. Dependent variable: total number of manufacturing workers in thousands. Independent variable of interest: logarithm of dollar flow of ODA three years prior. All standard errors clustered at country level. Reported F-Statistic is the Kleibergen-Paap rk Wald F statistic from SSIV first stage regressions; reported J-Statistic is from Sargan-Hansen test of overidentifying restrictions and p-value based on χ^2 distribution.