The Journal of Development Studies

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/fjds20

Structural Change and Welfare: A Micro Panel Data Evidence from Ghana

Richmond Atta-Ankomah & Robert Darko Osei

To cite this article: Richmond Atta-Ankomah & Robert Darko Osei (2021) Structural Change and Welfare: A Micro Panel Data Evidence from Ghana, The Journal of Development Studies, 57:11, 1927-1944, DOI: 10.1080/00220388.2021.1939864

To link to this article: https://doi.org/10.1080/00220388.2021.1939864

The Journal of Development Studies, 2021
Vol. 57, No. 11, 1927–1944, https://doi.org/10.1080/00220388.2021.1939864

Structural Change and Welfare: A Micro Panel Data Evidence from Ghana

RICHMOND ATTA-ANKOMAH & ROBERT DARKO OSEI
Institute of Statistical, Social and Economic Research, University of Ghana, Legon, Ghana

(Original version submitted November 2020; final version accepted May 2021)

ABSTRACT *Ghana is an example of a developing economy where both output and employment have shifted from agriculture to services and where structural change has not followed the standard pattern observed for many industrialised countries. However, there appears to be a limited understanding of what this changing structure means for poverty reduction and welfare for Ghana, with previous studies focusing mainly on the growth effect of structural change. This article interrogates the welfare effects of cross-sector labour movements in Ghana using the first two waves of the Ghana Socio-economic Panel Surveys. Our results show that labour movements from agriculture to services improve welfare while a move from services to agriculture decreases welfare. We also find that women and younger people are more likely to undertake the welfare-enhancing move, from agriculture to services, than men and older people respectively. On the other hand, we find that men, older people and individuals with relatively high-risk profile are more likely to move from services to agriculture. These findings support the view that structural change in Ghana have played a significant role in Ghana's poverty reduction achievements in the last three decades.*

KEYWORDS: Structural change; cross-sector labour movements; welfare; poverty reduction

1. Introduction

This study interrogates the welfare implications of structural change in Ghana. Specifically, it investigates what the poverty reduction implications of structural change have been in Ghana using the first two waves of the nationally representative Ghana Socioeconomic Panel Surveys (GSPS). The study thus contributes to the literature on the economic impact of structural change with a particular focus on poverty and welfare which earlier studies on Ghana (for example, Breisinger, Diao, & Thurlow, 2009; Osei & Jedwab, 2016) have not paid much attention to. Meanwhile, as in many other developing countries, Ghana has witnessed a changing structure of its economy in terms of shifts in both output and employment shares from agriculture to services (Baymu & Sen, 2017; Osei & Jedwab, 2016). This trend is generally consistent with the basic idea behind the dual economy models, formalised by Lewis (1954), where a traditional and a modern sector co-exist with low and high productivities, respectively. This difference in productivity may then drive movements of labour from the low-productivity sector to the higher one, leading to changes in sectoral shares in employment.

Correspondence Address: Richmond Atta-Ankomah, Institute of Statistical, Social and Economic Research, University of Ghana, P O Box LG 74, Legon, Ghana. Email: attasnr@gmail.com
Supplementary Materials are available for this article which can be accessed via the online version of this journal available at https://doi.org/10.1080/00220388.2021.1939864

Although the dual economy models lost some flavour in development economics, there has been a resurgence of interest in them, and by implication, the role that structural change plays in economic growth (McMillan & Headey, 2014). This resurgence has come about because of the limitations of the neo-classical (Solow) growth models in adequately explaining economic growth. Now seen as rather complementary to the Solow model for explaining growth and development (Rodrik, McMillan, & Sepúlveda, 2016), the dual economy models emphasise structural change as an important determinant of growth particularly when it is driven by resource movement across sectors with different productivities (Paci & Pigliaru, 1997; also see Ahsan & Mitra, 2016). The growth effect occurs when resources move from the low-productivity sector to high-productivity sector (Diao & McMillan, 2018; Rodrik et al., 2016) or through intra sectoral reallocation of resources as long as there is a significant productivity gap between source and destination activity areas (Fagerberg, 2000). Empirical evidence on this growth effect abounds including those based on multi-sector extensions of Lewis dual-sector model (Chen, Jefferson, & Zhang, 2011; Fagerberg, 2000) and Solow growth models that incorporate mulitple sectors (Fan, Zhang, & Robinson, 2003).

In Africa, however, structural change has generally not followed the standard pattern, which involves resources initially moving from agriculture to industry and subsequently to services while the growth outcomes have generally been unfavourable (McMillan & Rodrik, 2011). Specifically, McMillan and Rodrik (2011) argued that structural change in Africa since the 1990s has been growth reducing because labour resources in most African countries moved from high-productivity sectors to low-productivity sectors. Rodrik et al. (2016) attribute this pattern of structural change in most African countries to what they refer to as 'fundamentals challenge', which arises from the limited investment in skills accumulation and institutional capabilities. In the case of Ghana, Osei and Jedwab (2016) found that structural change had been characterised by a decline in agriculture's share in total employment while the released labour had been largely absorbed by relatively low-productivity activities, largely the informal sector. However, contrary to the broad trends in Africa revealed in McMillan and Rodrik (2011), Osei and Jedwab (2016) found further that structural change in Ghana contributed to overall productivity growth, although, the impact was limited.

Structural change may also have implications for both poverty and inequality and an important strand of the existing literature interrogates this relationship. This body of work has its roots in the thesis of Kuznet which suggests that structural change should be associated with increasing growth but also high inequality (Baymu & Sen, 2017). Indeed, the foremost underlying mechanism suggested by Kuznet for his famous inverted-U relationship is the shift of population from traditional to modern activities (Anand & Kanbur, 1993). However, just as in the case of growth, one could argue that the welfare (poverty and inequality) implications of structural change depends on what drives the change. This is evident in Osmani (1990) observation that the remarkable shift in the structure of labour force in post-independence rural Bangladesh, where non-farm labour increased dramatically, did not lead to any reduction in poverty nor improve income distribution. Osmani (1990) shows that the shift merely reflected a re-allocation of surplus labour from farm to non-farm sector, resulting in a high degree of work-sharing in the latter. In essence, the structural change in rural Bangladesh was not driven by productivity gaps between the sectors but rather reflected sectorial differences in factor proportions, and corroborates a theoretical standpoint of Acemoglu and Guerrieri (2008) about the potential for differences in sectoral factor proportions to drive structural change.

In cases where productivity gap drives structural change, welfare effects have been realised in addition to growth effects. For instance, Hasan, Lamba, and Gupta (2013) provide empirical evidence showing that movement of labour from low- to high-productivity sectors engenders growth and poverty reduction. Baymu and Sen (2017) find for countries that are structurally developing and underdeveloped that a reduction in agriculture's share of employment and an increase in services' share of employment are both associated with increasing inequality. Sen (2017) also finds that in post 1990 India, there was a slow but steady shift of employment away from agriculture, to largely the services sector (which was the main driver of increases in aggregate labour productivity), and this was associated with high growth, poverty reduction, and increased inequality.

This article contributes to the empirical literature on the welfare impact of structural change by extending our knowledge beyond previous studies on Ghana which mainly focused on the growth impact of structural change. The next section presents trend analysis, depicting the changing structure of Ghana's economy as well as a brief overview of Ghana's poverty-reduction trends. Section 3 briefly discusses the GSPS data and descriptive analyses on the relationship between structural change and welfare in Ghana. Section 4 presents the econometric approach used to test the effect of structural change on welfare as well as the results. In Section 5, we provides summary of the key findings and the conclusion.

2. Trends in structural change and welfare in Ghana

2.1. Growth, labour productivity and employment trends

After a disappointing and highly variable growth episode in the 1970s through the early 1980s, Ghana's economy moved onto a steady growth trajectory, particularly from mid 1990s throughout the 2000s. In recent years, particularly from 2010, growth has been relatively high compared to the 1990s and 2000s; but it has also been more variable (Institute of Statistical Social and Economic Research, 2019). This relatively high variability in growth in recent years coincides with the onset of oil production in Ghana, which has emerged as a major driver of the country's economic growth (Institute of Statistical Social and Economic Research, 2019; Osei, Atta-Ankomah, & Lambon-Quayefio, 2020). The services sector has also experienced relatively high and stable growth in recent years, compared to the agriculture and manufacturing sectors which remained sluggish between 1981 and 2016 (Osei et al., 2020).

The pattern and trends in sectoral economic growth have had strong links with the nature of structural change observed over the last three decades. There has been a consistent decline in agriculture's share in GDP and employment from the 1980s. This sector accounted for 22 per cent of GDP in 2016, compared to about 45 per cent in the early 1980s (Figure 1(a)) while its share of employment declined from 60.5 per cent in 1984 to 37 per cent in 2016 (Figure 1(b)). In contrast, the services sector's share in GDP grew steadily over the same period and its employment share was 48 per cent in 2016, compared to less than 30 per cent in 1984 (Figure 1). Meanwhile, the GDP

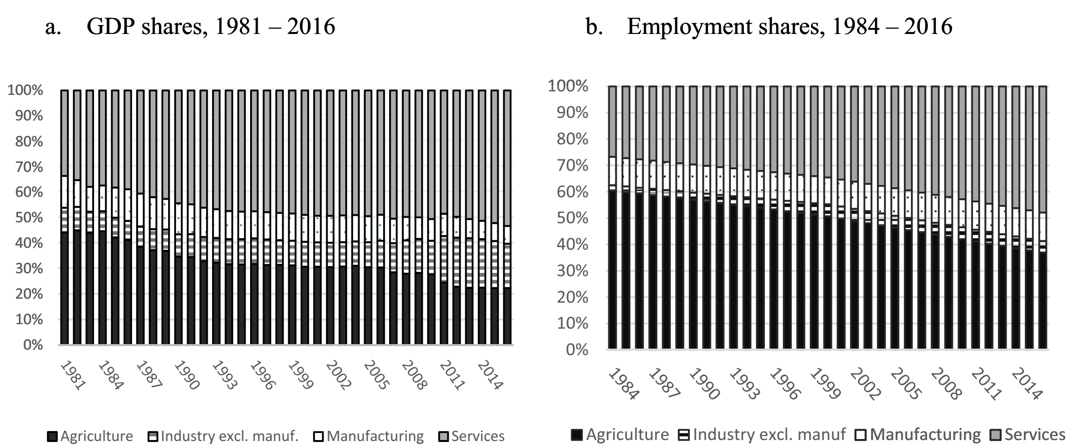

Figure 1. GDP and employment shares for major economic sectors.

Source: GDP and GDP shares were provided by Ghana Statistical Service (GSS). Employment data by sector for 1984, 2000 and 2010 are from Ghana censuses for the respective years and were taken from GSS (2005, 2013). The figures in between the census years were estimated the using compounding formula while those after 2010 were estimated using the sectoral employment growth rates between 2000 and 2010.

shares for the manufacturing and industry (excluding manufacturing) sectors, until the late 2000s, did not change much, and their employment shares have been consistently low (Figure 1). Following the discovery of oil in 2007, however, the GDP share of industry (excluding manufacturing) increased while that for manufacturing declined (Figure 1(a)). Interestingly, the recent increases in the GDP share for industry (excluding manufacturing), following the discovery and production of oil, has not translated into increasing employment shares for the sector.

Linked with the trends in sectoral GDP shares and cross sector labour movements observed in Figure 1 are the labour productivity gaps and trends between the economic sectors. The trends in sectorial labour productivity (defined as sectoral GDP divided by sectoral employment) in the four major economic sectors, shown in Figure 2, generally indicate an upward trend in labour productivity across all sectors. The agriculture sector has always had the lowest labour productivity, followed by manufacturing and then services sector. Industry (excluding manufacturing) has always had the highest labour productivity, and has seen a rapid growth since the discovery and production of oil in Ghana. The services sector has seen a relatively high growth in productivity following oil production, compared to the period before oil production. The productivity gaps between the sectors appear to drive the patterns and trends in cross sector labour movements, although industry (excluding manufacturing), which is the most productive sector, has not absorbed much of the released labour from agriculture. This is possibly due to the fact that the type of activities (such as mining and oil extraction) driving the increased productivity in this sector may be more capital and skill intensive. Thus, where the skill intensity requirement of the productivity growing sector is not matched by the skill levels of the labour migrating from agriculture, we could have growth in productivity in industry (excluding manufacturing) not matched by growth in the sector's employment share.

The trends and relationships discussed seem to suggest that structural change in Ghana has been characterised by a leapfrogging of the manufacturing sector. The fact that the productivity gap between services and agriculture is higher than that between manufacturing and agriculture means

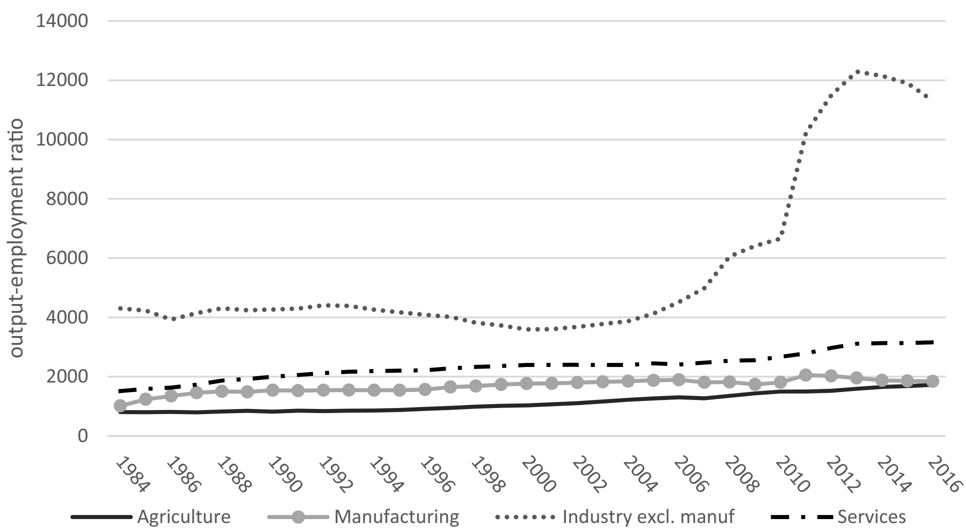

Figure 2. Labour productivity in major economic sectors, 1984–2016.

Note: Computed by authors based on data obtained from GSS.
Source: The real-output figures were obtained from GSS. The employment figures for the various sectors in 1984, 2000 and 2010 were taken from the Ghana Population and Housing Census Report for the respective years (GSS, 2005, 2013). The figures in between the census years were estimated the using compounding formula while those after 2010 were estimated using the sectoral employment growth rates between 2000 and 2010.

that, all things being equal, labour in agriculture would have more of an incentive to move into the services sector rather than to the manufacturing sector. This is reinforced by the relatively low barriers to entry and exit of the services sector due to low-skill intensities in many activities in this sector, particularly, for the informal segments. More recently, the productivity gap between agricultural and manufacturing sectors has almost disappeared (Figure 2), indicating that more labour movements from manufacturing to other sectors is more likely to occur.

2.2. Welfare trends

The relatively stable growth from the mid1980s to date has been associated with a significant reduction in the incidence of poverty (or headcount ratio) in Ghana (Osei et al., 2020). Ghana's headcount ratio based on both upper and lower poverty lines have declined significantly over the period. The headcount ratio, using the upper poverty line showed that nearly 51.7 per cent of Ghanaians were poor in 1992 but this had dropped to 23.4 per cent by 2017, and the decline in the incidence of poverty based on the lower poverty line was even sharper – from 36.5 per cent to 8.2 per cent over the same period (Ghana Statistical Service, 2007, 2018). However, inequality has risen though moderately within the same period (Atta-Ankomah et al., 2020; Cooke, Hague, & McKay, 2016). Our analyses based on the GSPS data also confirm the declining trend in poverty rate[1]: Using the upper poverty line as defined by the Ghana Statistical Service as the threshold, the GSPS data show a headcount ratio of 28.3 per cent in 2010, which declined to 22 per cent in 2014.

3. Data and descriptive analysis

3.1. Data

This study relies on data from the first two waves of GSPS. The two waves were respectively conducted in 2009/2010 and 2013/2014 through a collaboration between ISSER and the Economic Growth Centre (EGC) at Yale University. The first wave covered about 5000 households, selected through a multi-stage probability sampling technique that ensured representativeness at both the regional and national levels (Aryeetey, Osei-Akoto, Osei, & Udry, 2011) while the second wave involved 4774 households.

3.2. Descriptive analysis

3.2.1. Poverty trends and dynamics between 2010 and 2014. Taking advantage of the two waves of the GSPS data, we explore two types of transitions in poverty status: The first is the transition from a poor status in 2010 to a non-poor status in 2014, and the second relates to moving from being non-poor in 2010 to a poor status in 2014. We measure the probabilities for each type of transitions using percentages of row totals in a cross tabulation between poverty status in 2010 and that for 2014. The transition probabilities suggest that it is more likely for a poor household to move to a non-poor status than it is for non-poor household to become poor (Panel A of Table 1). However, in term of absolute numbers, the difference does not appear to be very large, as shown in the cross tabulations expressed as percentages of all households (Panel B of Table 1).

Figure 3 (which is a scatter plot of the monthly real-household consumption expenditure in the two periods) provides two additional insights into the dynamics of the welfare transitions. First, on average, poor households in both periods were closer to the poverty line than their non-poor counterparts, which means that all things being equal, a positive shock which can move a poor household into a non-poor status should be smaller in absolute magnitude than a negative shock that will cause a non-poor household to become poor. Second, if structural change is transformative (that is, people moving from low to high-productivity sectors) with a high-poverty reduction effect, then,

Table 1. Transitions in poverty status (2010–2014)

	Poverty status at Wave 2 (2014)		
Poverty status at Wave 1 (2010)	Non-poor	Poor	Total
Panel A: Cross tabulations as percentages (%) of row total			
Non-poor	83.0	17.0	100
Poor	64.10	35.90	100
Total	77.66	22.34	100
Panel B: Cross tabulations as percentages (%) of total number of households			
Non-poor	59.55	12.2	71.75
Poor	18.11	10.14	28.25
Total	77.66	22.34	100

Note: Authors' computations from GSPS, 2010 & 2014.

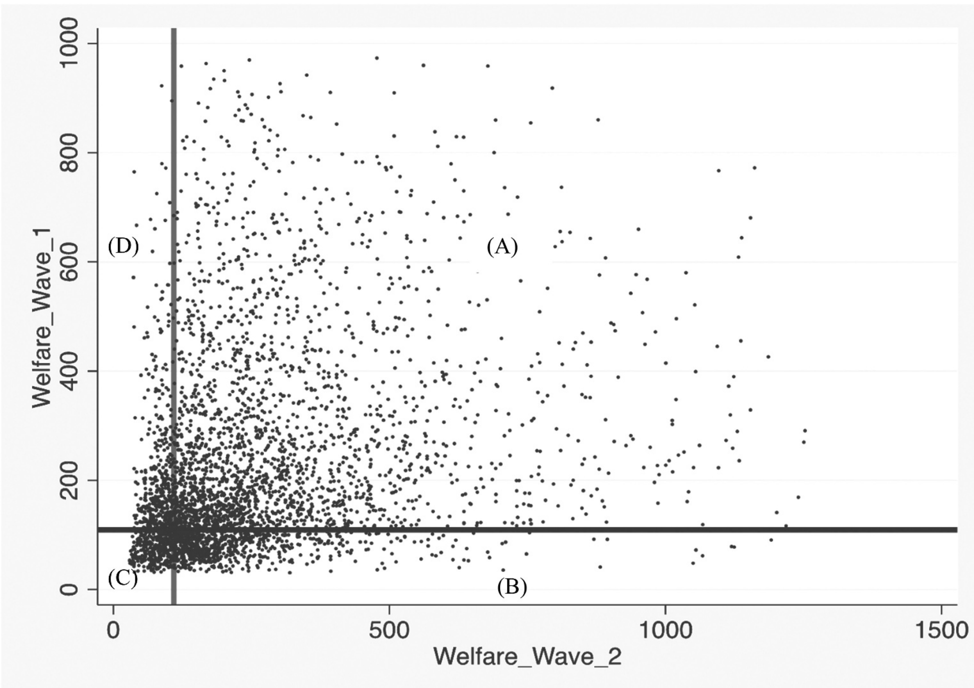

Figure 3. Scatter graphs depicting transitions in poverty status (2010–2014).

Source: Ghana Socioeconomic Panel Surveys, 2010 & 2014.

we will observe a significant increase in the number of households in quadrant A from one period to the next while the numbers in the other quadrants diminish over time.

3.2.2. Cross sector labour movements between 2010 and 2014. The trend and patterns of labour movement between the sectors observed in the GSPS data generally reflect those in Figure 1. Panel A of Table 2 shows that 45 per cent of people who were employed in 2010 worked in the services sector and this proportion increased to 50 per cent in 2014. Both Panel A and B of Table 2 show that most of the cross sector labour movements occurred between agricultural and services sector. This is followed by movement between manufacturing and services although this flow was mainly from manufacturing to services. Industry excluding manufacturing experienced the least inward flow of

Table 2. Transitions in sector of employment between 2010 and 2014

Sector of employment at Wave 1	Sector of employment at Wave 2				
	Agric	Manufacturing	Industry excl. manufacturing	Services	Total
Panel A: Cross tabulations as percentages (%) of row total					
Agric	85.47	1.35	1.09	12.09	100
Manufacturing	16.76	16.89	4.03	62.32	100
Industry excl. manufacturing	23.75	10.96	33.85	31.44	100
Services	14.48	3.05	1.34	81.14	100
Total	43.34	4.21	2.62	49.84	100
Panel B: Cross tabulations as percentages of total number of all individuals					
Agric	34.06	0.54	0.43	4.82	39.85
Manufacturing	1.91	1.92	0.46	7.09	11.38
Industry excl. manufacturing	0.78	0.36	1.12	1.04	3.3
Services	6.58	1.38	0.61	36.89	45.46
Total	43.34	4.21	2.62	49.84	100

Note: Authors' computations from GSPS, 2010 & 2014.

labour, which can be linked to our initial allusion that the limited labour movement into industry (excluding manufacturing) may be due to the fact that activities in this sector may require relatively high and specialised skills, compared to those of the other sectors, particularly the services sector. On the other hand, the relatively high movement into the services compared to agriculture and manufacturing may be accounted for, in part, by productivity differences in the sectors as shown in Figure 2. Thus, while movements into industry excluding manufacturing may be highly exclusive despite being the most productive sector, people prefer moving into services to moving into manufacturing because the productivity (and perhaps welfare) gains associated with the former are higher than those associated with the latter.

Table 3. Wave 2 poverty indicators by specific sectoral labour movements (2010–2014)

Nature of movement across sectors	Av. consumption per month		Poverty measures at 2014		
	Mean	Mean gap for poor	Head-count ratio	Av. normalised poverty gap	Av. squared normalised poverty gap
Agric to agric	176.50	30.09	0.37	0.10	0.04
Agric to manuf.	219.37	30.06	0.30	0.08	0.02
Agric to industry	227.25	5.06	0.16	0.01	0.00
Agric to services	240.09	27.75	0.16	0.04	0.02
Manuf. to agric	198.53	34.99	0.37	0.12	0.05
Manuf. to manuf.	283.19	31.81	0.22	0.06	0.02
Manuf. to industry	273.55	0.00	0.00	0.00	0.00
Manuf. to services	269.35	27.71	0.14	0.04	0.01
Industry to agric	290.19	23.94	0.14	0.03	0.01
Industry to manuf.	272.81	0.00	0.00	0.00	0.00
Industry to industry	336.93	25.39	0.04	0.01	0.00
Industry to services	337.99	26.65	0.03	0.01	0.00
Services to agric	216.02	37.59	0.23	0.08	0.03
Services to manuf.	279.61	30.38	0.23	0.06	0.02
Services to industry	358.08	0.00	0.00	0.00	0.00
Services to services	294.25	28.88	0.12	0.03	0.01

Source: Authors' computations from GSPS, 2010 & 2014, 2010 & 2014.
Note: 'manuf'. represents manufacturing sector and 'industry' stands for industry excluding manufacturing sector.

3.2.3. Cross sector labour movement and poverty status. With the four economic sectors, we decompose the headcount ratio at 2014 by 12 possible types of cross-sector labour movements, as presented in Table 3. We observe from Table 3 that all movements from agriculture are associated with lower headcount ratios. However, the ratios for movements from agriculture into industry and services (16 per cent in each case) are both lower than the ratio for movement from agriculture into manufacturing (30 per cent). Those who moved from manufacturing to agriculture experienced a higher poverty rate of 37 per cent compared to 22 per cent for those who remained in manufacturing. On the other hand, those who moved from manufacturing to services, and more importantly, from manufacturing to industry excluding manufacturing recorded much lower headcount ratios than those who remained in manufacturing. Similarly, the movements from services to industry excluding manufacturing were associated with lower headcount ratio, while movements from services to manufacturing and agriculture were associated with higher headcount ratios (23 per cent in each case), compared to those who remained in services. The general pattern observed here suggests that all movements out of agriculture seem to improve welfare. Similarly, all movements into services and industry excluding manufacturing are associated with higher welfare gains.

4. Econometric analysis

4.1. Empirical model

Our main research question relates to whether structural change, defined as the movement from one sector to the other, impacts on welfare outcomes. To do that we estimate a general model of the form:

$$W_i = X\delta + \gamma SC_i + \upsilon_i \tag{1}$$

Where W is a welfare variable; X is a vector of control variables; SC is the structural change variable; δ is a vector of parameters for the control variables; γ measures the effect of structural change on welfare; and ν is the error term. Four variants of this model are estimated based on different definitions of the welfare variable. The four definitions are as follows: (1) positive transition in poverty status which is a dichotomous variable, taking on a value of zero if the household was poor in both 2010 and 2014 (that is, the household is in quadrant C of Figure 3) but one if the household was poor in 2010 but became nonpoor in 2014 (that is, the household is in quadrant D of Figure 3); (2) negative transition in poverty status which is also dichotomous and takes on a value of zero if the household was nonpoor in both 2010 and 2014 (that is, the household is in quadrant A of Figure 3), but one if the household was nonpoor in 2010 but became poor in 2014 (that is, the household is in quadrant B of Figure 3); (3) the poverty status at 2014, which is also a dichotomous variable and takes on a value of one if the household was poor in 2014 but zero if the household was not poor in 2014; and (4) the real-monthly per capita consumption expenditure at 2014.

The different measures of welfare are regressed on measures of cross sector labour movement and a set of control variables. However, in the case of the models with transitions in poverty status (that, both positive and negative) as dependent variable, there could be reverse causality relationship between them and the cross sector labour movement variables; hence, we analyse the relationship using probit regressions as well as the instrumental variable (IV) regressions to formally test for endogeneity. We do not do IV regressions for poverty status at 2014 and real-consumption expenditure at 2014. The reason is that, unlike the poverty transition variables, these variables are realised at the end period (that, 2014), and hence, there is no empirical reason to expect reverse causality from these end period variables to cross sector labour movements, whose time of realisation precedes those for poverty status as well as real-consumption expenditure at 2014.

We also explore the determinants of labour movements across the sectors using probit regressions.[2] While we believe that productivity differentials may partly account for the movements, we also hypothesise that the demographic and socioeconomic backgrounds of individuals as well as their risk and time preferences can also explain the labour mobility across sectors. We estimate a probit regression model for each type of cross sector movement where the dependent variable (y_i) is defined as follows:

$$y_i = \begin{cases} 1 \; if \; the \; individual \; moved \; from \; sector \; A(for \; example, \; agric) \; to \; sector \; B \\ 0 \; if \; the \; individual \; remained \; in \; sector \; A(that \; is, \; agric) \; in \; both \; periods \end{cases}$$

Because GSPS consists of only two waves, we are able to measure only one temporal transition in both the sector of employment and poverty status. The regression analyses largely focus on two major types of cross sector labour movements in Ghana – namely, movement from agriculture to services and from services to agriculture – mainly due to limited degrees of freedom associated with the other types of cross sector labour movements in the data.

To avoid potential endogeneity between the dependent variables and control variables, we use the 2010 values for time-varying control variables (or covariates) in the regressions, except for two variables measuring risk and time preferences which are available only in the second wave of the survey. However, based on an argument that risk and time preferences of individuals are persistent and fairly stable over time (see Schildberg-Hörisch, 2018; Wölbert & Riedl, 2013), we do not expect these two variables to have any reverse causality effect on our dependent variables. The independent variables used in the models for both welfare and cross sector labour movement are defined as follows:

- *Agric_to_service* is a dichotomous variable which takes a value of one if an individual moved from the agricultural sector to the services sector, but zero if the individual remained in the agricultural sector in both periods.
- *Services_to_agric* is a dichotomous variable which takes a value of one if an individual moved from the services sector to the agricultural sector, but zero if the individual remained in the services sector in both periods.
- *Manuf_to_services* is a dichotomous variable which takes a value of one if an individual moved from manufacturing sector to the services sector, but zero if the individual remained in manufacturing sector in both periods.
- *Age*: Age of the individual in completed years.
- *rural2010* is a dummy variable and takes a value of one if the individual or household lived in rural locality at 2010; Otherwise zero.
- *hhsize2010* is the size of the household at 2010 measured by the number of individuals in the household.
- *Male* takes a value of one if the individual is a male and zero if the individual is a female
- *Outerwall2010* is measure for quality of housing and takes a value of one if the outer wall of household's dwelling was made of either cement block or sandcrete; otherwise zero.
- *School_attend2010* is a dummy variable taking on a value of one if the individual has ever been to school; otherwise zero.
- *futurebias* is a dummy variable taking on a value of one if individual is future biased; otherwise zero. The variable was derived from a set of hypothetical questions on time preference in the second wave of the survey and full details on how it was derived are presented in the Supplementary Materials (SM).
- *risk* is a dummy variable taking on a value of one if the individual is risk seeking; otherwise zero. The variable was also derived from a set of questions on a hypothetical game to determine the risk preferences of individuals in the second wave of the survey. The full details on how it was derived are presented in the SM.
- *Nine regional dummies*: Dummy variables for nine of the 10 regions of residence at 2010 are used while the remaining one is used as reference.

Let us note here that the regression results in this article are not weighted. This decision is informed by existing literature on the issues on applying sampling weights in regression analysis: Sampling weights help to derive unbiased estimates of univariate population parameters such as poverty rate; however, the decision to use them in regression analysis is more nuanced and they can also lead to biased, inefficient and inconsistent estimates (Solon, Haider, & Wooldridge, 2015; see also Friedman, 2013; Winship & Radbill, 1994). Solon et al. (2015) argue further that in cases where the focus of the analysis is on establishing causal effects, the potential motives for weighting (such as heteroscedasticity) sometimes do not apply, and when they do (for example, when heteroscedasticity is the issue), we are better off reporting the usual heteroscedasticity robust standard errors.

4.2. Econometric results

4.2.1. Effects of cross sector labour movement on welfare. This section presents regression results of the effect of cross sector labour movements on welfare, of which the results are shown in Table 4. Columns 1, 3, 5 and 8 of Table 4 respectively show the results on the effect of moving from agriculture to services on the four measures of welfare; namely, positive poverty transition, negative poverty transition, poverty status at 2014, and real-consumption expenditure at 2014. The results show that moving from agriculture to services has statistically significant effect on welfare, irrespective of the welfare indicator used. Specifically, a move from agriculture to services increases the probability of transitioning from being poor in 2010 to nonpoor in 2014 rather than remaining poor while it reduces the probability of transitioning from being nonpoor in 2010 to poor in 2014 instead of remaining nonpoor in the two periods. Additionally, it has a significant positive effect on real-consumption expenditure and also significantly reduces the probability of being poor at 2014. Indeed, a movement from agriculture to services may increase real-consumption expenditure by 16 per cent.

The effects of a movement from services to agriculture on the four measures of welfare are respectively presented in columns 2, 4, 6 and 9. We note that it has statistically significant coefficients for positive poverty transition (column 2) and real-consumption expenditure (column 9): A move from services to agriculture reduces the probability that a poor person in 2010 would become nonpoor in 2014 and also reduces the real-consumption expenditure by nearly 20 per cent. However, it has no significant effect on negative poverty transition and poverty status at 2014. Columns 7 and 10 show that moving from manufacturing to services reduces the probability of being poor at 2014 but has no statistically significant effect on real-consumption expenditure. Table 4 further shows that age, education, household size, living in rural locality as well as the quality of housing may also be important determinants of welfare.

4.2.2. Addressing potential endogeneity. In this section, we outline our strategy for addressing possible endogeneity between cross sector labour movements (that is, movements between agric and services sector) and transitions in poverty status between the two periods. We adopt the instrumental variable techniques to estimate the effects of cross sector labour movements on transitions in poverty status, formally test for endogeneity and compare the IV regression results to the probit results in sub section 4.2.1. We also perform several diagnostic and robustness checks on the IV regressions, particularly, for under identification, weak identification and over identification.

4.2.2.1. Instruments for cross sector labour movements. A crucial requirement of the instrumental variable approach is identifying variable(s) which are highly correlated with our potentially endogenous independent variable (in this case, cross sector labour movement) but only affect our outcome variable (that is, transition in poverty status) through its effects on cross sector labour movement. The instrumental variables used are sectoral employment shares at the level of communities (or enumeration areas) in 2014, of which there are 342 in the GSPS data.

Our choice of instruments is intuitively informed by the fact that the sectoral employment shares at the community level at the end period (that is, 2014) should reflect labour movements between the

Table 4. Probit and Ordinary Least Square (OLS) regression results

Independent variables	(1) ch_povP	(2) ch_povP	(3) ch_povN	(4) ch_povN	(5) pov_status2014	(6) pov_status2014	(7) pov_status2014	(8) ln_exp_real2014	(9) ln_exp_real2014	(10) ln_exp_real2014
Agric_to_services	0.417**		−0.484***		−0.470***			0.159***		
	(0.206)		(0.161)		(0.125)			(0.0493)		
Male	−0.117	0.199	−0.0503	0.0167	0.0598	−0.0511	0.312	−0.0401	0.0696**	0.0494
	(0.152)	(0.239)	(0.130)	(0.134)	(0.0966)	(0.115)	(0.251)	(0.0438)	(0.0354)	(0.0814)
Age	−0.00357	−0.00514	0.0104***	0.00786	0.00753***	0.00894**	0.00954	−0.00230**	−0.00412***	−0.00468
	(0.00345)	(0.00966)	(0.00357)	(0.00518)	(0.00241)	(0.00443)	(0.00824)	(0.00112)	(0.00147)	(0.00323)
School_attend2010	0.222*	0.236	−0.0335	−0.418***	−0.163*	−0.325***	−0.328	0.0795**	0.152***	0.0877
	(0.127)	(0.253)	(0.124)	(0.146)	(0.0851)	(0.123)	(0.281)	(0.0384)	(0.0491)	(0.0936)
outerwall2010	0.269*	0.426*	−0.122	−0.176	−0.175*	−0.207*	−0.319	0.129***	0.173***	0.0822
	(0.151)	(0.254)	(0.119)	(0.136)	(0.0894)	(0.117)	(0.241)	(0.0396)	(0.0406)	(0.0919)
hhsize_2010	−0.0339	−0.156***	0.0295	0.0848***	0.0419***	0.0928***	0.105**	−0.0293***	−0.0595***	−0.0378**
	(0.0211)	(0.0553)	(0.0219)	(0.0304)	(0.0144)	(0.0243)	(0.0495)	(0.00691)	(0.00863)	(0.0159)
rural	−0.0619	0.315	0.134	0.539***	0.122	0.424***	0.383	−0.0913*	−0.182***	−0.178*
	(0.238)	(0.287)	(0.146)	(0.137)	(0.122)	(0.119)	(0.265)	(0.0533)	(0.0385)	(0.0991)
futurebias	−0.00139	0.148	0.0285	0.0570	0.0350	0.0312	−0.484*	−0.0337	−0.0334	0.193**
	(0.114)	(0.242)	(0.113)	(0.149)	(0.0783)	(0.124)	(0.287)	(0.0349)	(0.0367)	(0.0745)
risk	0.211	−0.148	−0.103	−0.215	−0.131	−0.188	−0.276	0.000903	0.105**	0.0324
	(0.151)	(0.328)	(0.145)	(0.181)	(0.102)	(0.158)	(0.329)	(0.0438)	(0.0444)	(0.0870)
Services_to_agric		−0.449*		0.0965		0.185			−0.198***	
		(0.255)		(0.155)		(0.129)			(0.0471)	
Manuf_to_services							−0.502**			0.139
							(0.252)			(0.102)
Nine regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.354***	1.804**	−1.712***	−2.156***	−1.603***	−2.210***	−1.616**	5.576***	5.917***	5.749***
	(0.463)	(0.852)	(0.351)	(0.393)	(0.270)	(0.346)	(0.678)	(0.118)	(0.110)	(0.248)
Observations	660	186	792	1,018	1,508	1,270	217	1,508	1,270	271
(Pseudo R-squared)	0.0728	0.177	0.0701	0.223	0.0742	0.208	0.210	0.112	0.269	0.302
Loglikelihood	−400.6	−79.66	−421.1	−259.0	−860.2	−360.5	−81.93	−1413	−1096	−228.5
Chi2/F	61.41	32.95	58.80	99.98	127.0	125.5	44.99	10.44	25.29	8.724
P value (Chi2/F)	1.21e-06	0.0115	3.19e-06	0	0	0	0.000139	0	0	0

Notes: (1) Robust standard errors in parentheses; (2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; (3)ch_povP and ch_povN, respectively represent positive poverty transition and negative poverty transition; (4) Columns 1 to 7 are probit regression while 8 to 10 are OLS regressions; (4) We do not perform regression of the poverty transition variables on movement from manufacturing services because of limited degrees of freedom.

sectors prior to the end period, hence, they should be highly correlated with each other, a priori. This should be generally true even if one allows for the fact that the movement can also occur across communities. For example, if Mrs. A moves from the agriculture sector in community Y to the services sector in community Z, the employment share of agriculture in community Y decreases relative to the other sectors while the employment share of the services sector in community Z increases relative to the other sectors. Meanwhile, there appears to be weak or no empirical basis for anticipating a high correlation between the sectoral employment shares at the community level and transitions in poverty status at the individual or household level, and more so, when the employment shares are measured at the end period, after the poverty transitions have taken place. However, no matter how logical the reasoning leading to its selection may sound, an instrument is only as good as what the data say after subjecting it to robust tests of identification.

Table 5 provides details of the specific employment share variables used as instruments for cross sector labour movements for each type of poverty transition. Only the receiving sector's employment shares are used in the analysis for the positive poverty transition because a preliminary analysis using a linear combination of both agriculture and services' shares in employment as instrument led to a weak identification problem with the giving sector's share being a redundant instrument while only the receiving sector's share in employment passed both under identification and weak identification tests. For the negative poverty transition, however, a linear combination of the two employment shares passed all the test on identifications. Specific details of the various identification test are discussed later in this section.

4.2.2.2. Estimation method and results. Several econometric estimation techniques (such as two stage least squares [2SLS], generalised method of moment [GMM] and limited information maximum likelihood [LIML] methods) exist for deriving the regression parameters using instrumental variables. However, both theoretical and Monte Carlo exercises show that the LIML estimator may produce less bias and confidence intervals with better coverage rates than the 2SLS estimator (Poi, 2006; Stock, Wright, & Yogo, 2002). Moreover, while the LIML estimator is asymptotically equivalent to 2SLS, it has been found to outperform both 2SLS and GMM in finite samples (Cameron & Trivedi, 2010). The LIML may also be more robust to weak instruments than other estimators such as 2SLS (Stock et al., 2002; Stock & Yogo, 2005). We therefore perform our estimations using LIML method.

For robustness checks,[3] a set of three regressions with variations in the number of control variables were performed for each of the two types of cross sector labour movements. Table 6 presents the most parsimonious of the three regression results while the full set of results are presented in Table S3 as part of the SM for the reader's reference. The endogeneity tests following the estimations show that movements from agriculture to services and from services to agriculture are both not endogenous with positive poverty transition (Columns 1 and 2 of Table 6). The negative poverty transition variable is also not endogenous with movement from agriculture to services; however, it is

Table 5. Instruments for potentially endogenous variables

Dependent variable	Potentially endogenous variable (regressor)	Instrument(s)	Description of instrument(s)
Positive poverty transition	Agric_to_services	Serv_share	Receiving sector's share (services' share) in employment at community level
	Services_to_agric	Agric_share	Receiving sector's (agriculture's share) in employment at community level
Negative poverty transition	Agric_to_services	Serv_share; Agric_share	Both agriculture's and services' share in employment at the community level
	Services_to_agric	Serv_share; Agric_share	Both agriculture's and services' share in employment at the community level

Table 6. Positive and negative transitions in poverty status – IV LIML regression results

Independent variables	Dependent variable = Positive poverty transition		Dependent variable = Negative poverty transition	
	(1)	(2)	(3)	(4)
Agric_to_services	−0.3792		−0.0154	
	(0.3899)		(0.1421)	
Male	−0.1098	0.0860	0.0132	−0.0305
	(0.0749)	(0.0669)	(0.0455)	(0.0247)
Age	−0.0027*	0.0005	0.0038***	0.0003
	(0.0015)	(0.0026)	(0.0013)	(0.0010)
School_attend2010	0.0843**	0.1396**	−0.0319	−0.0889***
	(0.0419)	(0.0700)	(0.0357)	(0.0335)
outerwall2010	0.1507***	0.1124*	−0.0548	−0.0361
	(0.0537)	(0.0662)	(0.0350)	(0.0279)
hhsize_2010	−0.0154*	−0.0402***	0.0083	0.0110**
	(0.0084)	(0.0135)	(0.0066)	(0.0054)
rural	−0.0309	0.0670	0.0450	0.0774***
	(0.0691)	(0.0765)	(0.0411)	(0.0269)
Services_to_agric		−0.3067		0.2706**
		(0.2349)		(0.1331)
Constant	0.9546***	0.8062***	0.0304	0.0913
	(0.1702)	(0.1671)	(0.1130)	(0.0573)
Observations	672	198	795	1,023
R-squared	−0.0406	0.1144	0.0304	0.0211
Log Likelihood	−474.9	−93.50	−461.0	−212.1
Hansen J stat.	0	0	0.706	0.350
P value (J stat.)			0.401	0.554
Endogeneity stat.	1.911	0.554	0.680	3.226
P value (Endogeneity. stat.)	0.167	0.457	0.409	0.0725
Under identification. stat. (Kleibergen-Paap rk LM stat.)	14.04	14.03	48.76	42.27
P value (under ident. stat.)	0.0002	0.0002	0	0.0000
Weak identification stat. (Kleibergen-Paap rk F stat.)	13.92	16.29	30.72	24.34
Montiel Olea-Pflueger eff. F stat.			40.103	24.581
Second stage F Stat.	4.303	3.446	3.458	8.757
P value for 2nd stage F	0.0001	0.0017	0.0012	0.0000

Note: (1) Robust standard errors in parentheses; (2) *** p < 0.01, ** p < 0.05, * p < 0.1

endogenous with movement from services to agriculture (Columns 3 and 4 of Table 6). This means that except for the model on the effect of movement from services to agriculture on negative poverty transition, of which the IV regression results may be more robust, the probit regression results of Table 4 are more likely to reflect the true relationships.

Table 6 reports the Kleibergen-Paap rk *LM* statistics for under identification, which show that the null hypothesis of under identification is rejected, formally confirming the relevance of instruments used in the negative poverty transition regression. Also reported in Table 6 are Kleibergen-Paap rk *F* statistics and Montiel Olea-Pflueger effective *F* statistics (both of which are variants of the *F* statistics for the first stage regression) for weak identification. Andrews, Stock, and Sun (2019) however recommend the use of Montiel Olea-Pflueger effective *F* statistics for weak identification when more than one instrument are used because it applies a more robust correction factor in the presence of non-homoscedasticity than the Kleibergen-Paap rk *F* statistics. With the rule of thumb that the first stage *F* statistic should be greater 10 for rejecting the null hypothesis of weak identification, both Kleibergen-Paap rk *F* and Montiel Olea-Pflueger effective *F* statistics reported in Table 6 reject the case for weak identification. Also reported in Table 6 is Hansen *J* statistics with *p* value for over identification test, which has the joint null hypothesis that the instruments are valid instruments (that is, they are uncorrelated with the error term and are correctly excluded from the estimated equation for negative poverty transition). The result of the over identification test shows that we cannot reject the null hypothesis.

In contrast to the probit regression results of Table 4 on the effect of a movement from services to agriculture on negative poverty transition, the LIML IV regression results (in column 4 of Table 6) indicate that a movement from services to agriculture has statistically significant and positive effect on the probability of a nonpoor in 2010 becoming poor in 2014. This result aligns with those of the probit regressions for the other models, and together indicate that whether the poverty transition is positive or negative, a movement from agriculture to services may enhance welfare while a movement from services to agriculture may reduce welfare. They are also generally consistent with the analyses using the end period welfare indicators (that is, 2014 poverty status and 2014 real-consumption expenditure).

The above findings generally imply that the pattern of structural change in Ghana (where labour has predominantly moved from agriculture to the services) may partly account for the rapid reduction in Ghana's poverty rates in the last three decades. This welfare impact seems to be largely linked to the fact that labour productivity of services (that is, the largest destination sector) is higher than that of agriculture (that is, largest source sector). The results also indicate that Ghana could have reduced poverty by higher proportions over the years if industry (excluding manufacturing) had been able to absorb significant portions of the labour outflow from agriculture especially giving that labour productivity is highest in this sector and has been rising steadily since oil production began. The inability of industry (excluding manufacturing) to absorb labour appears to relate to what Rodrik et al. (2016) refer to as the fundamentals challenge, which arise from limited investment in skills accumulation and institutional capabilities. This challenge could also limit the extent of economic linkages that can be built with this sector, particularly with activities such as oil extraction and mining, further constraining the potential for structural change to become more transformative.

4.2.3. Determinants of cross-sector labour movements. This subsection explores in detail the determinants of cross sector labour movements. Table 7 presents the regression results for all individuals who made a movement from agriculture to services (in columns 1 and 2) and all individuals who made a movement from services to agriculture (in columns 3 and 4). The results of the first stage regressions (see Table S5 in the SM) associated with the IV regressions in Table 6 are analogous to those of Table 7 except for the difference in estimation method and the fact that those of Table S5 are respectively restricted to the number of individuals making a particular poverty transition.[4]

We observe generally from Table 7 that a sector's share in employment is positively associated with the probability of moving to that sector. We also find that being a male significantly reduces the probability of moving from agriculture to services but significantly increases the probability of moving from services to agriculture. Table 7 further shows that the probability of moving from agriculture to services reduces with age while that for the movement from services to agriculture increases with age. Being in a rural community at 2010 increases the probability of moving from agriculture to services but this has no statistically significant effect on a movement from services to agriculture. Also observed in Table 7 is that being risk seeking (or risk loving) increases the probability of moving from services to agriculture while it has no statistically significant effect on a movement from agriculture to services. Being a member of a household whose dwelling's outer wall is made from cement blocks or *sandcrete* significantly reduces the probability of moving from services to agriculture while it has no effect on a movement from agriculture to services (Table 7). Education has no effect on either ways of labour movement between agriculture and services.

Three key implications of these findings are worth reiterating: First, younger people are more likely to move from agriculture to services while they are less likely to move from services to agriculture. This is consistent with basic intuition that younger people generally find agriculture, which is largely a rural-based sector, less attractive and may also face more constraints in terms of access to land and capital than older people. Second, women are more likely to move from agriculture to services but less likely to make

Table 7. Probit regressions on determinants of cross sector labour movements

VARIABLES	(1) AS	(2) AS	(3) SA	(4) SA
Agric_share		−0.000964	0.0193***	0.00770
		(0.00711)	(0.00271)	(0.00515)
Serv_share	0.0298***	0.0288***		−0.0140***
	(0.00317)	(0.00768)		(0.00532)
Male	−0.666***	−0.666***	0.583***	0.569***
	(0.108)	(0.109)	(0.0955)	(0.0955)
Age	−0.0244***	−0.0244***	0.00977**	0.00989**
	(0.00334)	(0.00334)	(0.00389)	(0.00389)
School_attend2010	0.0602	0.0604	−0.0809	−0.0713
	(0.103)	(0.103)	(0.126)	(0.127)
outerwall2010	0.128	0.127	−0.286**	−0.279**
	(0.107)	(0.107)	(0.112)	(0.113)
hhsize_2010	−0.0255	−0.0256	0.0111	0.00936
	(0.0191)	(0.0191)	(0.0220)	(0.0221)
rural	0.444***	0.444***	−0.0332	−0.0573
	(0.147)	(0.147)	(0.130)	(0.131)
futurebias	−0.0470	−0.0467	−0.166	−0.150
	(0.0995)	(0.0993)	(0.105)	(0.106)
risk	−0.204	−0.205	0.211*	0.207*
	(0.134)	(0.134)	(0.125)	(0.126)
Nine regional dummies	yes	yes	yes	yes
Constant	−0.866***	−0.773	−2.157***	−1.002*
	(0.321)	(0.744)	(0.309)	(0.542)
Observations	1,581	1,581	1,318	1,318
Log Likelihood	−484.1	−484.1	−482.8	−479.9
chi2	202.5	202.5	186.0	183.5
p	0	0	0	0
Pseudo R-square	0.201	0.201	0.172	0.177

Note: (1) Robust standard errors in parentheses; (2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; (3) AS and SA respectively refer to movement from agriculture to services and movement from services to agriculture.

the reverse move. This can also be explained by the fact that in Ghana women seem to face more constraints than men regarding access to land and capital (see Deere, Oduro, Swaminathan, & Doss, 2013; Oduro, Baah-Boateng, & Boakye-Yiadom, 2011), and are therefore more inclined to move from agriculture to services, particularly to the relatively low-productivity areas (such as petty trading and food vending), where the barriers to entry and exit are relatively low. For example, no formal training or retraining may be required for petty trading which is in line with our finding that education may not matter for labour movement between agriculture and services. We also note that men are more likely to move from services to agriculture probably because they have savings accumulated from their previous employment in relatively more productive segments of the services sector. It could also be the case that men may have better access to finance and land than women. Third, uncertainties around production activities in agriculture in Ghana are known to be relatively high (Ullah, Shivakoti, Zulfiqar, & Kamran, 2016; Yeboah, Feng, Daniel, & Joseph, 2014), hence, it is not surprising to find that individuals who are relatively risk loving or seeking are more likely to move from services to agriculture compared with those who are more risk averse.

5. Conclusion

This study investigates the likely effects of structural change on welfare in Ghana. It does this by exploring two waves of a nationally representative household panel data, covering the period 2010 and 2014 and also drawing insights from trends in broad sectoral level indicators of labour productivity and employment shares. We observe from the analysis that although labour productivity is highest in industry (excluding manufacturing), cross sector labour movements are dominated by movements between agriculture and services sectors. Structural change in Ghana has therefore been largely driven by movements between agriculture and services sector just as in other developing countries as the literature suggests (see Baymu & Sen, 2017; Osmani, 1990; Sen, 2017).

We note the most crucial finding that cross sector labour movement between services and agriculture sector has statistically significant effect on welfare: A move from agriculture to services improves welfare while a move from services to agriculture decreases welfare. We find further that women and younger people are more likely to undertake the welfare-enhancing move (that is, from agriculture to services) than their respective counterparts. In contrast, men and older people are more likely to embark on the welfare-reducing movement from services to agriculture. These suggests that on average the poverty reduction gains from structural change in Ghana may have been more favourable to women and younger people. However, all other things being equal, the benefits for these groups could have been higher and Ghana's poverty reduction could have been faster, if the majority of them had rather moved from agriculture to industry (excluding manufacturing) giving the large productivity gap between these two sectors.

For the manufacturing sector, labour productivity has generally remained low and stymied, partly accounting for its limited role in structural change in Ghana so far, and perhaps, being a key reason why structural change in Ghana has departed from the standard pattern observed for many industrialised countries. In spite of this departure, we conclude that structural change in Ghana appears to have played an important role in Ghana's poverty reduction achievements over last three decades, thus, having more than a growth impact in Ghana.

Notes

1. It needs to be mentioned that consumption module in GSPS is not exactly the same as that of the GLSS.
2. As we explain in later sections, these probit regressions are analogous to the first stage regressions in the IV analyses.
3. The LIML IV estimation provides estimates to similar to the linear probability model (LPM) when the outcome variable is dichotomous (Nichols, 2011). Hence, we also perform bivariate probit regression analyses, in which the variables used as instruments in the LIML IV estimation are also used to meet the exclusion restriction requirement. Presented in Table S4 in the SM, the results of the bivariate probit regressions are not qualitatively different from the IV regression results.
4. While the results in Table 7 are interesting because they are for all individuals making a given cross sector movement, those of Table S5 are equally interesting because they allow us to examine whether the determinants vary by the type of poverty transitions. However, a comparison between the results show that the determinants largely do not vary much by the type of poverty transition and in relation to those in Table 7.

Acknowledgements

We acknowledge ISSER and EGC at Yale University for producing the GSPS data and making them publicly available at: https://yale.app.box.com/s/ww9pqfb1lf9bwvhtocs51ixd7v4qpv2s/folder/135707578976. The Stata codes used for this article will be provided upon request to the authors.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Richmond Atta-Ankomah http://orcid.org/0000-0001-9982-9377

References

Acemoglu, D., & Guerrieri, V. (2008). Capital deepening and non-balanced economic growth. *Journal of Political Economy*, *116*(3), 467–498.

Ahsan, R. N., & Mitra, D. (2016). Can the whole actually be greater than the sum of its parts? Lesson from India's growing economy and its evolving structure. In M. McMillan, D. Rodrik, & C. Sepúlveda (Eds.), *Structural change, fundamentals and growth: A framework and case studies* (pp. 39–80). Washington, DC: International Food Policy Research Institute.

Anand, S., & Kanbur, S. M. R. (1993). The Kuznet process and inequality-development relationship. *Journal of Development Economics*, *40*(1), 25–52.

Andrews, I., Stock, J. H., & Sun, L. (2019). Weak instruments in instrumental variables regression: Theory and practice. *Annual Review of Economics*, *11*(1), 727–753.

Aryeetey, E., Osei-Akoto, I., Osei, R. D., & Udry, C. (2011). *Ghana socioeconomic panel survey: Report of the baseline survey* (Yale/ISSER Technical Report). New Haven, CT and Accra: Yale University and Institute of Statistical, Social and Economic Research.

Atta-Ankomah, R., Osei, R. D., Osei-Akoto, I., Asante, F. A., Oduro, A. D., Owoo, N., & Afranie, S. (2020). *Inequality diagnostics for Ghana: An African Center of Excellence for Inequality Research (ACEIR) report*. Agence Française de Development. Retrieved from https://www.afd.fr/en/ressources/inequality-diagnostics-ghana

Baymu, C., & Sen, K. (2017, September). *What do we know about the relationship between structural transformation, inequality and poverty?* (ESRC GPID Research Network Working Paper No. 2). ESRC GPID Research Network.

Breisinger, C., Diao, X., & Thurlow, J. (2009). Modeling growth options and structural change to reach middle income country status: The case of Ghana. *Economic Modelling*, *26*(2), 514–525.

Cameron, A. C., & Trivedi, P. K. (2010). *Microeconometrics using Stata* (Revised ed.). College Station, TX: Stata Press.

Chen, S., Jefferson, G. H., & Zhang, J. (2011). Structural change, productivity growth and industrial transformation in China. *China Economic Review*, *22*(1), 133–150.

Cooke, E., Hague, S., & McKay, A. (2016). *The Ghana poverty and inequality report using the sixth Ghana living standard survey*. Accra: UNICEF Ghana

Deere, C. D., Oduro, A. D., Swaminathan, H., & Doss, C. (2013). Property rights and the gender distribution of wealth in ecuador, Ghana and India. *The Journal of Economic Inequality*, *11*(2), 249–265.

Diao, X., & McMillan, M. (2018). Toward an understanding of economic growth in Africa: A reinterpretation of the Lewis model. *World Development*, *109*, 511–522.

Fagerberg, J. (2000). Technological progress, structural change and productivity growth: A comparative study. *Structural Change and Economic Dynamics*, *11*(4), 393–411.

Fan, S., Zhang, X., & Robinson, S. (2003). Structural change and economic growth in China. *Review of Development Economics*, *7*(3), 360–377.

Friedman, J. (2013). *Tools of the trade: When to use those sample weights*. World Bank Group. Retrieved from https://blogs.worldbank.org/impactevaluations/tools-of-the-trade-when-to-use-those-sample-weights

Ghana Statistical Service. (2005). *Population data analysis report volume 1: Socio-economic and demographic trend analysis*. Accra: Ghana Statistics Service.

Ghana Statistical Service. (2007). *Pattern and trends of poverty in Ghana, 1991-2006*. Accra: Author.

Ghana Statistical Service. (2013). *2010 population & housing census: National analytical report*. Accra: Ghana Statistics Service.

Ghana Statistical Service. (2018). *Ghana Living Standard Survey 7 (GLSS7): Poverty trends in Ghana, 2005-2017*. Accra: Author.

Hasan, R., Lamba, S., & Gupta, A. S. (2013, November). *Growth, structural change, and poverty reduction: Evidence from India* (ADB South Asia Working Paper Series No 22). Asian Development Bank.

Institute of Statistical Social and Economic Research. (2019). *The state of the Ghanaian economy in 2018*. Accra: Author.

Lewis, W. A. (1954). Economic development with unlimited supplies of labour. *The Manchester School*, *22*(2), 139–191.

McMillan, M., & Headey, D. (2014). Introduction – understanding structural transformation in Africa. *World Development*, *63*, 1–10.

McMillan, M. S., & Rodrik, D. (2011, June). *Globalization, structural change and productivity growth* (No. w17143). National Bureau of Economic Research.

Nichols, A. (2011, July). Causal inference for binary regression with observational data. In *CHI11 stata conference*, Stata Users Group. Retrieved from https://EconPapers.repec.org/RePEc:boc:chic11:6

Oduro, A. D., Baah-Boateng, W., & Boakye-Yiadom, L. (2011). *Measuring the gender asset gap in Ghana*. Accra: University of Ghana and Woeli Publishing Services.

Osei, R. D., Atta-Ankomah, R., & Lambon-Quayefio, M. (2020, March). *Structural transformation and inclusive growth in Ghana* (WIDER Working Paper 2020/37). Helsinki: UNU-WIDER.

Osei, R. D., & Jedwab, R. (2016). Structural change in a poor African country: New historical evidence from Ghana. In M. McMillan, D. Rodrik, & C. Sepúlveda (Eds.), *Structural change, fundamentals and growth: A framework and case studies* (pp. 161–196). Washington, DC: International Food Policy Research Institute.

Osmani, S. R. (1990). Structural change and poverty in Bangladesh: The case of a false turning point. *The Bangladesh Development Studies*, *18*, 55–74.

Paci, R., & Pigliaru, F. (1997). Structural change and convergence: An Italian regional perspective. *Structural Change and Economic Dynamics*, *8*(3), 297–318.

Poi, B. P. (2006). Jackknife instrumental variables estimation in Stata. *The Stata Journal: Promoting Communications on Statistics and Stata*, *6*(3), 364–376.

Rodrik, D., McMillan, M., & Sepúlveda, C. (2016). Structural change, fundamentals, and growth. In M. McMillan, D. Rodrik, & C. Sepúlveda (Eds.), *Structural change, fundamentals, and growth: A framework and case studies* (pp. 1–38). Washington, DC: International Food Policy Research Institute.

Schildberg-Hörisch, H. (2018). Are risk preferences stable? *Journal of Economic Perspectives*, *32*(2), 135–154.

Sen, K. (2017). *Poverty, inequality, and structural change in India (GPID country note 2)*. Retrieved from https://gpid.univie.ac.at/wp-content/uploads/2017/09/Country_2.pdf

Solon, G., Haider, S. J., & Wooldridge, J. M. (2015). What are we weighting for? *Journal of Human Resources*, *50*(2), 301–316.

Stock, J., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. In D. W. K. Andrews (Ed.), *Identification and inference for econometric models* (pp. 80–108). New York: Cambridge University Press.

Stock, J. H., Wright, J. H., & Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business and Economic Statistics*, *20*(4), 518–529.

Ullah, R., Shivakoti, G. P., Zulfiqar, F., & Kamran, M. A. (2016). Farm risks and uncertainties: Sources, impacts and management. *Outlook on Agriculture*, *45*(3), 199–205.

Winship, C., & Radbill, L. (1994). Sampling weights and regression analysis. *Sociological Methods & Research*, *2*(2), 230–257.

Wölbert, E., & Riedl, A. (2013, July). *Measuring time and risk preferences: Reliability, stability, domain specificity* (CESifo Working Paper Series No. 4339). Retrieved from https://ssrn.com/abstract=2302494

Yeboah, N. E., Feng, Y., Daniel, O. S., & Joseph, N. B. (2014). Agricultural supply chain risk identification-a case finding from Ghana. *Journal of Management and Strategy*, *5*(2), 31–48.